

Should I Stay or Should I Grow?

How Cities Affect Learning, Inequality and Aggregate Productivity

Hugo Lhuillier*
Princeton University
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Abstract

The spatial concentration of talent is a robust pattern of modern economies. While the sorting of individuals into cities begets regional disparities, it may benefit aggregate productivity by fostering human capital accumulation. To study this equity-efficiency tradeoff, I propose a theory wherein individuals learn from the other workers in their cities. Cities affect the stock of human capital by determining the frequency at which heterogeneous workers meet. Learning complementarities determine the existence of a tradeoff between productivity and spatial inequality. I estimate the model on French administrative data. I recover learning complementarities from a local projection of future wages on present wages and the wages of nearby individuals. I find that workers employed in relatively skill-dense cities experience faster wage growth, and disproportionately so if they are skilled. I address endogeneity concerns by using skill-density variations within firms across neighborhoods driven by past productivity shocks. The model explains two-thirds of the between-city wage growth variance and gives rise to a steep tradeoff between aggregate human capital and spatial inequality. I assess the implications of this tradeoff for the general equilibrium effects of moving vouchers. I find that large vouchers are effective at reducing spatial disparities in learning opportunities at the cost of decreased aggregate efficiency.

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1 Introduction

Spatial inequalities are pervasive across the globe. Cities such as New York, Paris, and Tokyo have become epicenters of talent, leaving remote regions deprived of such individuals. As workers exchange ideas with, collaborate with, and potentially learn from their neighbors, the spatial concentration of skills may have enduring effects on human capital accumulation while at the same time segregating learning opportunities in a few cities. Concerned by such regional disparities, national governments spend a sizable share of their budget every year to rebalance income across space. Yet, little is known about the aggregate effects of these policies on human capital. How does the sorting of workers into cities shape learning? To what extent are learning opportunities spatially concentrated, and how much does their concentration amplify regional disparities? Can policies spur higher productivity in conjunction with lower geographical inequalities?

This paper offers answers to these questions with four contributions. First, I propose a theory that sheds light on how the concentration of skills in space affects human capital accumulation. Second, I estimate the impact of cities' skill composition on wage growth using French administrative data. Third, I use the estimated model to quantify the extent to which learning opportunities are spatially segregated, and what are the consequences for spatial disparities and aggregate productivity. Fourth, I quantify the tradeoff between spatial inequality and human capital accumulation by evaluating the general equilibrium consequences of a large-scale moving voucher policy.

First, I propose a theory that sheds light on the importance of learning complementarities for the tradeoff between spatial inequality and human capital accumulation. Second, I estimate learning complementarities using French administrative data. Third, I use the estimated model to quantify the tradeoff between human capital accumulation and spatial inequality. Fourth, I evaluate the implications of this tradeoff for a large-scale moving voucher policy.

In the first part of the paper, I propose a theory of learning across space. The structure is an overlapping generation model with two key features. First, young workers are endowed with heterogeneous skills, cities differ in their productivity, and skill and productivity are complements in production. Second, young workers learn by randomly meeting other workers in their city. The learning depends on which workers are engaged in the interaction. Importantly, I impose minimal restrictions on the learning technology. Skilled individuals may disproportionately learn from other skilled workers. In this case, within-skill learning complementarities dominate between-skill complementarities. On the contrary, between-skill complementarities prevail if the marginal gains from meeting a high-skill are decreasing in workers' own skill. Individuals are forward-looking and freely choose where to work to maximize their lifetime utility.

The sorting of workers in cities shapes the spatial distribution of learning opportunities, which in turn may amplify the spatial concentration of skills. Holding constant future income, high-skill workers sort into productive cities as these locations offer relatively higher wages inherited from the production complementarities. Yet, their location decisions also reflect the local learning opportunities that shape future earnings. When skilled workers agglomerate in productive cities, individuals who learn relatively more from them view these locations as attractive learning centers.

The stronger the within-skill learning complementarities, the more skilled workers gain over time from working next to other skilled individuals, and the larger the spatial concentration of skills.

Spatial inequality feeds into the aggregate stock of human capital. When high-skill agglomerates next to each other, it increases the frequency at which they meet while reducing the opportunity for low-skill to learn from them. Whether a greater segregation of interactions enhances aggregate productivity relies on which workers learn the most from the high-skill. The stock of human capital expands with greater spatial inequality if skilled workers learn disproportionately from interacting with their peers. In contrast, the spatial concentration of learning opportunities reduces aggregate productivity if between-skill complementarities prevail.

Spatial policies have the potential to accelerate aggregate human capital accumulation. The competitive allocation is inefficient as workers do not internalize their impacts on others' learning. The marginal social value of interactions hinges on learning complementarities. When high-skill learn relatively more from each other, low-skill crowd out the learning opportunities of productive cities, and the competitive equilibrium features too little spatial skill concentration. The reverse occurs when between-skill complementarities are relatively stronger. Skilled workers do not consider how their location choice helps low-skills learn, and the decentralized equilibrium features too much spatial inequality. Regardless of the complementarities, the optimal allocation spurs human capital accumulation and can be decentralized by place-based policies that vary by skill.

The second part of the paper develops and structurally estimates a quantitative version of the framework with three main additions. First, workers consume local housing in addition to the freely traded good already present in the theory. Second, workers face migration costs. The migration costs imply that workers' birthplace shapes their lifetime opportunities. Third, I impose a flexible functional form on the learning technology according to which three elasticities govern skill growth: with respect to workers' own skill, the skill of the worker they interact with, and a cross-term that captures learning complementarities.

I estimate the quantitative framework using French administrative data. The estimation is split into two steps. I use the structure of the model to derive estimating equations that identify a first set of parameters. I then calibrate the remaining parameters in the second step to match salient features of the wage distribution in the aggregate, across cities, and across the lifecycle. The estimated framework replicates several non-targeted moments, such as how workers' location decisions vary by skill and age.

The learning complementarities are transparently estimated. The learning technology is recovered from a model-consistent local projection of future wages on workers' current wages and the average wage of the individuals working in the same city. I find the three elasticities governing the learning technology to be positive. First, relatively skilled workers experience faster skill growth holding constant their interactions. Second, every worker learns more from skilled individuals. Third, the returns to meeting a high skill are relatively larger for skilled workers. Altogether, the learning technology displays stronger within- than between-skill complementarities.

The equation estimating the learning technology allows me to derive clear-cut conditions that guarantee unbiased estimates. Specifically, the drivers of wage growth other than local interactions

must be identically and independently distributed across cities and individuals conditional on workers' wages. I use the granularity of the French matched employer-employee data to relax this identification assumption in three ways. First, I control for worker-level characteristics, such as age and tenure, known to shape wage growth. Second, I saturate the local projection with fixed effects to control for unobserved spatial heterogeneity in wage dynamics. In the most restrictive specification, the skill growth elasticities are estimated off variations in average wages across neighborhoods of employment for individuals who live in the same neighborhood and work in the same firm within the same city. Third, to generate quasi-random variations in skill density across space, I instrument present neighborhood wages with variations in the local share of white-collar twenty years ago. Armed with these controls and instrument, I find that neighborhoods with a greater skill density boost the wage growth of the individuals working there, and disproportionately so if they are skilled. The implied learning elasticities cannot be statistically differentiated from the baseline estimates.

The estimated returns to local interactions are substantial. The average worker experiences a wage growth 4.5 log points faster over five years when working in Paris (top 10% of the city-growth distribution) compared to when working in Troyes (bottom 10%). These growth gains differ considerably across workers due to the estimated complementarities. A worker in the bottom 10% of the wage distribution sees its wage growth accelerate by 2.8 log points when moving from Troyes to Paris, whereas these dynamic gains are 7.3 log points for individuals in the top 10%. Altogether, the model explains 64% of the between-city wage growth variance.

In the third part of the paper, I use the estimated model to quantify how much of the spatial differences in learning are caused by the segregation of learning opportunities, and what are the implications for spatial disparities and human capital accumulation. To do so, I compare the baseline equilibrium in which cities segment learning interactions with a counterfactual economy in which individuals learn randomly from workers in the entire economy.

I find that the spatial segmentation of interactions, rather than the sorting of fast-learning workers, explains the vast majority of the learning gaps between cities. This, in turn, engenders spatial learning inequality. Workers born in remote cities experience slower human capital accumulation caused by their reduced access to learning opportunities: workers born in the bottom 25% of the city-growth distribution have a lifetime skill growth 10% lower than the average French worker. In addition, the concentration of opportunities in a few cities amplifies spatial wage inequality. Productive cities get bigger as workers need to live there to accumulate human capital faster. In addition, the spatial concentration of high-skill rises as they benefit more over time from working in skill-dense locations. Combined, spatial wage inequality increases: the between-city wage variance grows from 0.007 to 0.024 when learning occurs within cities.

The confinement of learning opportunities to productive cities also boosts human capital accumulation. The aggregate stock of human capital is 1.2% higher when learning takes place within cities. Learning complementarities explain the majority of this productivity gain: the average skill of old workers would only be 0.5% higher were all workers to learn equally from skilled workers. The learning gains are concentrated at the high end of the skill distribution. Skilled workers agglomerate in productive locations, increasing the frequency at which they learn from each other. As a result,

individuals in the top 10% of the skill distribution experience a lifetime skill growth 26% higher when they only interact with their neighbors. In contrast, workers at the bottom of the skill distribution neither gain nor lose from the spatial concentration of learning opportunities as they do not sort and learn relatively less from skilled workers.

Combined, the estimated model suggests the existence of a steep tradeoff between spatial inequality and human capital accumulation. In the fourth part of the paper, I quantify this equity-efficiency tradeoff by evaluating the consequences of a moving voucher policy. Specifically, I study a policy subsidizing every worker born in the bottom 25%

The moving voucher policy is spatially redistributive. On the one hand, the policy improves the opportunities of treated workers by helping them reallocate to skill-dense locations. When the subsidy covers 80% of the average migration costs, which represents 1.5% of GDP, the probability that treated workers migrate to the three largest French cities rises from 7% to 45%. Treated individuals have an easier access to learning centers, and their lifetime skill growth coincides with that of the average worker. As a result, their welfare increases by 2% on average. On the other hand, the moving vouchers depress the learning of the non-treated. The policy attenuates the spatial concentration of skills by reallocating marginally less skilled workers to productive cities. The local learning opportunities worsen, and workers born there, as well as the other non-treated workers who were migrating to these cities to learn, experience slower human capital accumulation. Combined with the financial cost of the policy, non-treated workers suffer average welfare losses of 2.3%.

While the policy reduces spatial disparities, it acts negatively on aggregate efficiency. The stock of human capital is 0.3% lower when the policy reaches 1.5% of GDP. The general equilibrium effect of the policy more than offset its partial equilibrium gains. Holding the quality of local opportunities constant, human capital would rise by 0.8% as the policy expands the pool of workers with access to fast-learning opportunities. Absent learning complementarities, the general equilibrium feedback would be a third smaller, and aggregate human capital would neither rise nor fall from the policy. I conclude that learning complementarities are crucial for the tradeoff between spatial inequality and human capital accumulation.

Related literature This paper primarily adds to two strands of the literature. The first strand studies how social interactions shape productivity growth. Started by the seminal work of Jovanovic and Rob (1989), and later developed by Lucas (2009a), Lucas and Moll (2014), Perla and Tonetti (2014), and Akcigit et al. (2018), amongst many others, this literature initially abstracted from space. The idea that cities facilitate knowledge diffusion is however not novel and can be traced back to Marshall (1890) and Jacobs (1969).¹ In particular, if interactions spur learning and mainly occur between individuals who work next to each other, then the spatial distribution of talent must matter for human capital accumulation. Two papers have recently quantified this insight.²

¹Since then, a long list of papers have documented how proximity shapes knowledge diffusion (e.g. Jaffe et al., 1993; Audretsch and Feldman, 2004; Moretti, 2021; Atkin et al., 2022; Baum-Snow et al., 2023).

²Several other recent papers have studied the impact of space on aggregate growth through trade and technology diffusion, e.g. Lucas (2009b), Alvarez et al. (2013), Sampson (2016), Desmet et al. (2018), Buera and Oberfield (2020), Perla et al. (2021), and Cai et al. (2022).

Martellini (2022) finds that local peer effects explain the majority of the faster lifecycle wage growth of large cities in the United States. Crews (2023) builds a dynamic model in which the vibrancy of cities, defined by their size and skill composition, shapes how workers learn. He concludes that relaxing land-use regulations in New York and San Francisco spur aggregate growth.³

I contribute to this literature by characterizing the crucial role of learning complementarities in determining how cities affect human capital accumulation. In particular, by not imposing restrictions on learning complementarities, I show that the spatial segmentation of learning opportunities may be detrimental to learning, an insight already noted by Benabou (1993).

I also contribute to the literature that estimates the dynamic returns to interactions between neighbors and coworkers. Across space, Baum-Snow and Pavan (2012), de la Roca and Puga (2017), and Eckert et al. (2022), among others, find the wage age-profile of large cities to be relatively steeper. Within the firm, Nix (2020) and Jarosch et al. (2021) document that workers employed in high-wage firms experience faster wage growth. I add to this literature in three ways. First and foremost, I estimate how the returns to local interactions vary across workers. The granularity of the French matched employer-employee allows me in particular to estimate these learning complementarities while addressing some of the endogeneity concerns present in the peer effect literature (Angrist, 2014). Second, I find the effect of cities' skill composition on wage growth to be one order of magnitude larger than that of city size. Third, I show that the neighborhood where individuals work shapes their wage growth even after controlling at which establishment and firm they are employed.

This paper also connects more broadly with several papers in economic geography. First, it adds to the literature that investigate the sources of spatial agglomeration (Duranton and Puga, 2004; Behrens and Robert-Nicoud, 2015). Two papers in particular have studied theoretically how learning within cities triggers spatial agglomeration. Glaeser (1999) shows that urbanization rises when the ability to learn by imitation increases. More recently, Davis and Dingel (2019) finds that local interactions can provide a motive for sorting even when cities are *ex-ante* similar. I contribute to this literature by quantifying the strength of these agglomeration forces. I find that learning within cities amplifies the skill concentration in space, an empirical pattern documented by Combes et al. (2008), Eeckhout et al. (2014), and Diamond (2016), among others. Second, this paper adds to the literature that studies optimal spatial policies.⁴ Most related are the papers by Rossi-Hansberg et al. (2019) and Fajgelbaum and Gaubert (2020) who study optimal policy in the presence of worker sorting and static production spillovers.⁵. Related to these papers, I characterize the optimal spatial policy when spillovers are dynamic.

The rest of this paper is organized as follows. Section 2 presents the theory and characterizes how learning complementarities shape the tradeoff between spatial inequality and human capital accumulation. Section 3 turns to the French matched employer-employee to estimate these com-

³Another strand of the literature focuses on the joint evolution of city sizes and aggregate growth (Rossi-Hansberg and Wright, 2007; Herkenhoff et al., 2018; Hsieh and Moretti, 2019; Duranton and Puga, 2023).

⁴See Glaeser and Gottlieb (2008) and Kline and Moretti (2014) for reviews of the estimated consequences of place-based policies on productivity.

⁵Gaubert (2018) and Bilal (2023) also derives the optimal spatial policy in the presence of firm sorting.

plementarities. Section 4 estimates the rest of the model, and Section 5 quantifies the impact of local interactions on human capital accumulation and agglomeration. Section 6 then proceeds to study the consequences of spatial policies on spatial inequality, productivity, and welfare. Section 7 concludes.

2 A Theory of Learning across Space

In this section, I shed light on the tradeoff between spatial inequality and human capital accumulation by offering a model of learning across space. The model puts learning complementarities front and center. The remaining ingredients are standard in the quantitative spatial literature (Redding and Rossi-Hansberg, 2017).

2.1 Setup

I model workers that sort into cities. Every period, a unit mass of young workers enter the labor market. Workers live for two periods and discount the future at rate β . Denote their first and second life period as young (y) and old (o). Old workers express no altruism towards future generations. Workers choose in which city to work at any point in time.⁶ Cities are indexed by ℓ , and the total number of cities L is fixed. I study the steady state of this economy and omit time subscripts.

Preferences Individuals consume a single, freely-traded good taken to be the numéraire. I abstract from local consumption for the sake of tractability in this section. I add housing in the quantitative version of the model. Individuals hold linear utility over their consumption, which they finance using their current income. They supply inelastically one unit of labor per period, so that wages and incomes are interchangeable. They do not have access to a saving device.

In addition, individuals have idiosyncratic preferences for the city they work in, denoted by $\boldsymbol{\varepsilon} = \{\varepsilon_\ell\}_{\ell=1}^L$. These preferences are drawn from independent Gumbel distributions with city- and age-specific location parameters B_ℓ^a , $a \in \{y, o\}$, and scale parameter ϑ^{-1} . The location parameter B_ℓ^a reflects the amenities offered by city ℓ to workers with age a . Young workers may prefer cities with a vibrant nightlife whereas old workers may value more the quality of the opera, and I impose no relationship between B_ℓ^y and B_ℓ^o . Local amenities are taken as given. Finally, I assume that location preferences are independent across the lifecycle.⁷

Finally, I assume that consumption and location preferences are perfect substitutes. Hence, the per-period utility of workers with income y and preferences $\boldsymbol{\varepsilon}$ when working in city ℓ is $y + \varepsilon_\ell$.

Human capital Young workers are endowed with an initial skill s^y . This skill is drawn from an aggregate skill distribution N^y . The young skill distribution is a primitive of the model. I suppose

⁶I define a city as a commuting zone in the data and thereby abstract from commuting decisions.

⁷I later add migration costs in the model. Migration costs and inter-temporal persistence of location preferences are isomorphic except for welfare accounting.

that the support of N^y is connected, positive, and bounded, $[\underline{s}^y, \bar{s}^y]$, with $\bar{s}^y < \infty$.⁸ I also assume that skills are uni-dimensional.⁹

Workers learn in their youth. This learning is shaped by the interactions they encounter. Learning interactions are governed by three assumptions.

First, they are spatially segmented: interactions take place between workers who work in the same location. Second, interactions are random. Hence, while workers cannot target specific interactions, they can choose to locate in a particular city to increase their chance to meet a particular skill-type. In this section, I assume for the sake of tractability that interactions happen only between young workers. The likelihood of an interaction with a skill s_p in city ℓ is then given by the local density of this skill, $\pi_\ell^y(s_p)$. I relax this assumption in the quantitative model. Third and most importantly, the return to an interaction depends on which workers are engaged in it. If a worker with skill s interacts with a partner with skill s_p , they obtain new skill $s^o = e\gamma(s, s_p)$.¹⁰ The learning technology γ encapsulates how workers' skill and that of their partners determine their human capital accumulation. In addition, workers experience an idiosyncratic learning shock, e , which captures the other possible sources of learning (e.g. on-the-job training). These learning shocks are drawn from the city-independent distribution F with support \mathbb{R}_+ .¹¹

I impose minimal restrictions on the learning technology.

Assumption 1 (Learning technology).

The learning technology γ is positive, bounded, and twice differentiable in (s, s_p) .

Assumption 1 allows my framework to nest different learning complementarities across skills. First and foremost, it encompasses the case in which interactions are irrelevant for learning, $\gamma(s, s_p) = g(s)$ for some function g . In this case, workers' capacity to learn may still depend on their own skill, e.g. if skilled workers are better at learning-by-doing (Huggett et al., 2011). Second, interactions may affect all workers equally, $\gamma(s, s_p) = g(s) + h(s_p)$, for h another function. In this case, while interactions shape learning, the learning technology does not feature any complementarities. Third, the learning complementarities may be stronger within-skill than between-skill. In that case, the learning technology is supermodular:

$$\frac{\partial^2 \gamma(s, s_p)}{\partial s \partial s_p} > 0, \quad \forall (s, s_p).$$

Supermodularity requires that the marginal gains from a skilled interaction are greater for skilled individuals. This occurs for instance when workers are better able to learn from each other when they share similar skills (Jovanovic, 2014). Alternatively, the learning technology may display complementarities that are stronger between than within-skill. Then, the learning technology is

⁸A bounded support simplifies the proofs, but all that is required is the existence of the first moment, $\int s dN^y(s) < \infty$.

⁹For papers with multi-dimensional skill and sorting across firms or occupations, see Lindenlaub (2017), Guvenen et al. (2020) and Lise and Postel-Vinay (2020).

¹⁰I assume for simplicity that workers interact with a single partner in their youth.

¹¹The idiosyncratic shocks are not required for the theory but smooth the aggregate old skill distribution. They help quantitatively to match the wage distribution of old workers.

submodular,

$$\frac{\partial^2 \gamma(s, s_p)}{\partial s \partial s_p} < 0, \quad \forall(s, s_p),$$

and the marginal gains from a skilled interactions are greater for low-skilled individuals. This is for instance the case if knowledge diffuses from skilled workers to relatively less skilled individuals (e.g. Lucas and Moll, 2014; Perla and Tonetti, 2014).

The simple learning technology

$$\gamma(s, s_p) = g_0 + g_1 \times s + g_2 \times s_p + g_{12} \times s \times s_p \quad (1)$$

illustrates well when within- or between-skill complementarities prevail. The parameter g_0 governs the average skill of old workers, whereas $g_1 > 0$ implies that skilled workers experience on average faster learning. When $g_2 > 0$, interactions with skilled partners yield higher future skills, and the learning complementarities are fully determined by g_{12} . If $g_{12} > 0$, the learning technology is supermodular, and skilled workers learn relatively more from skilled partners. On the contrary, the learning technology is submodular when $g_{12} < 0$.

Learning takes time, and the skill obtained from an interaction can only be used in the next period. The aggregate skill distribution of old workers is denoted by N^o . To the contrary of the young workers' skill distribution, this is a general equilibrium object that reflects the learning of every young workers.

Production Production takes place within cities. In each city, there is a single representative competitive firm with productivity T_ℓ , which reflects the industries and firms present there. The representative firm produces the tradable good using labor as sole input. If the firm hires a bundle of skill $\mathbf{n}_\ell = \{n_\ell(s)\}_s$, it produces output

$$Y_\ell(\mathbf{n}_\ell) = T_\ell \int s n_\ell(s) ds.$$

This production function has two properties. First, cities' TFP and workers' skills are complements: high-skill workers produce relatively more in productive cities than their low skill counterparts.¹² Second, skills are perfect substitutes. I assume away skill complementarities in production, which has been the focus of the spatial literature thus far (e.g. Diamond, 2016; Giannone, 2022), to put the emphasis on skill complementarities in the learning process.¹³ Quantifying jointly the spatial consequences of static and dynamic skill complementarities is a promising avenue of research for future work.

I assume that labor markets are segmented by city and by skill. The zero profit condition faced

¹²TFP and skills are complements in that a marginal increase in the city's TFP increases the marginal productivity of a skill; that is, the production technology is supermodular in (s, T_ℓ) . This definition of complementarity is standard in the monotone comparative statics literature (e.g. Topkis, 1998).

¹³The estimation of the learning technology in Section 3 can however accommodate complementarities in production.

by the representative firm pins down the local wage schedule, $w_\ell(s) = sT_\ell$. Wages therefore inherit the complementarity between TFP and skill.

Feasibility The spatial allocation of workers must be feasible. Specifically, the aggregate demand for workers with skill s must be less or equal to the aggregate supply of that skill:

$$\sum_{\ell} n_{\ell}^a(s) \leq n^a(s), \quad \forall s, \forall a \in \{y, o\}, \quad (2)$$

where $n_{\ell}^a(s)$ is the measure of workers with age a and skill s employed in city ℓ , and $n^a(s) = dN^a(s)$ is the aggregate density of skill s for workers with age a . Accordingly, the density of skill s in city ℓ amongst workers with age a is

$$\pi_{\ell}^a(s) = \frac{n_{\ell}^a(s)}{N_{\ell}^a}, \quad \forall s, \forall \ell, \forall a, \quad (3)$$

for $N_{\ell}^a = \int n_{\ell}^a(s)ds$ the mass of workers with age a employed in ℓ .

2.2 The Steady State Equilibrium

The steady state equilibrium is represented by three equations governing the spatial allocation of young and old workers as well as the aggregate distribution of old workers' skills.¹⁴

Old workers Old workers solve a static location choice problem. They choose a city ℓ that maximizes their present utility conditional on their skill s and their location preferences ε ,

$$V^o(s, \varepsilon) = \max_{\ell} \{w_{\ell}(s) + \varepsilon_{\ell}\}, \quad \forall s, \forall \varepsilon.$$

Workers' idiosyncratic preferences ensure that every skill is present in every location. In particular, the number of old workers with skill s employed in city ℓ is given by

$$n_{\ell}^o(s) = n^o(s) \left(\frac{e^{\vartheta(w_{\ell}(s) + B_{\ell}^o)}}{\sum_{\ell'} e^{\vartheta(w_{\ell'}(s) + B_{\ell'}^o)}} \right), \quad \forall s, \forall \ell. \quad (4)$$

The first term captures the aggregate supply of skill s amongst the old and follows from the feasibility condition (2). The second term is the probability that skill s chooses to work in city ℓ and is given by the Gumbel-distributed location preferences.

Young workers Young workers solve a dynamic location choice problem,

$$V^y(s, \varepsilon) = \max_{\ell} \left\{ w_{\ell}(s) + \varepsilon_{\ell} + \beta \int \int \mathcal{V}^o[e\gamma(s, s_p)]dF(e)\pi_{\ell}^y(s_p)ds_p \right\}, \quad \forall s, \forall \varepsilon,$$

¹⁴The young spatial allocation is decoupled from that of the old. As a result, the economy is independent from its initial condition and converges to its steady state in one period.

where $\mathcal{V}^o(s) \equiv \mathbb{E}[V^o(s, \boldsymbol{\varepsilon}') | s]$ is the expected utility of an old worker with skill s prior to observing their idiosyncratic preferences.¹⁵ Young workers' location decision depends on three considerations. The first two are static and are common to old workers. The third consideration is dynamic and reflects where are located the best learning opportunities. The expected future utility of working in city ℓ is indeed given by the weighted average of the expected gains from particular interactions, $\mathcal{V}^o[e\gamma(s, s_p)]$, with weights given by the local likelihood of such interactions, $\pi_\ell^y(s_p)$. A location constitutes an attractive learning center if it provides a large density of individuals from whom workers learn relatively more. When interactions do not shape human capital accumulation, $\gamma(s, s_p) = g(s)$, this dynamic consideration disappears.

As for the old, the number of young workers with skill s employed in city ℓ follows from the Gumbel location preferences and the feasibility condition (2),

$$n_\ell^y(s) = n^y(s) \left(\frac{e^{\vartheta(w_\ell(s) + B_\ell^y + \beta \mathbb{E}[\mathcal{V}^o(E\gamma(s, S_\ell^y))])}}{\sum_{\ell'} e^{\vartheta(w_{\ell'}(s) + B_{\ell'}^y + \beta \mathbb{E}[\mathcal{V}^o(E\gamma(s, S_{\ell'}^y))])}} \right), \quad \forall s, \forall \ell, \quad (5)$$

where $\mathbb{E}[\mathcal{V}^o(E\gamma(s, S_\ell^y))] = \int \int \mathcal{V}^o[e\gamma(s, s_p)] dF(e) \pi_\ell^y(s_p) ds_p$ is the expected future utility of young workers with skill s employed in city ℓ . This expectation is a general equilibrium object that depends on the location choices of the other young workers. When deciding where to work, individuals take the location choice of others as given.

Skill distribution The aggregate skill distribution of old workers is a general equilibrium object that reflects the learning experienced by young individuals. Specifically, the fraction of old workers with skill less than s_o is given by

$$N^o(s_o) = \sum_\ell \int \int \int \mathbb{1}\{e\gamma(s_y, s_p) \leq s_o\} dF(e) n_\ell^y(s_y) \pi_\ell^y(s_p) ds_p ds_y, \quad \forall s_o. \quad (6)$$

The spatial allocation of young workers determine the skill distribution of old workers, and thus the aggregate stock of human capital, by shaping the aggregate probability of two skills meeting.

Equilibrium Equations (4) to (6) describe the steady-state spatial equilibrium. Young workers choose a city where to work taking as given the spatial distribution of learning opportunities. In equilibrium, their expectations must be consistent with the other workers' location choices. The spatial allocation of young workers determine the aggregate skill distribution of old workers, and the spatial allocation of old workers must be feasible.

Definition 1 (Steady state equilibrium).

A steady state equilibrium is a young and old allocation, $\{n_\ell^y, n_\ell^o\}_\ell$, city-specific skill densities amongst young workers, $\{\pi_\ell^y\}_\ell$, and a skill distribution of old workers, n^o , such that:

1. Taking the behavior of other young workers as given, the young spatial allocation satisfies (5);
2. Given the old workers' skill distribution, the old spatial allocation satisfies (4);

¹⁵The expected utility has the usual closed-form expression: $\mathcal{V}^o(s) = c + \log \left(\sum_\ell e^{\vartheta w_\ell(s)} \right) / \vartheta$ for c a constant.

3. The local skill densities are consistent with the location decisions of young workers (3);
4. The skill distribution of old workers satisfies (6).

The steady state equilibrium is the outcome of an infinitely-dimensional non-linear fixed point in the local skill densities. Existence of an equilibrium is guaranteed by the idiosyncratic location preferences which, together with cities' TFP, coordinate expectations.

Proposition 1 (Existence).

A steady state equilibrium exists.¹⁶

Characterizing the steady state equilibrium amounts to solving for the spatial allocation of young workers. I highlight two special types of allocation that may prevail in equilibrium. In the first, the skill densities are the same in every city, and therefore so are the learning opportunities. I refer to this allocation as the symmetric allocation.

Definition 2 (Symmetric allocation).

An allocation is symmetric if the local skill densities are identical, $\pi_\ell^a(s) = n^a(s)$ for all s, ℓ and a .

Alternatively, productive locations may feature a higher density of skilled workers. In this case, I say that the allocation satisfies stochastic positive assortative matching (SPAM).¹⁷

Definition 3 (Stochastic positive assortative matching).

An allocation satisfies stochastic positive assortative matching if the local skill densities can be ordered in the first-order stochastic dominance sense by cities' productivity: $\pi_\ell^a \succ_{FOSD} \pi_{\ell'}^a \iff T_\ell > T_{\ell'}$.

In the absence of restrictions on the learning technology, the steady state equilibrium depends on the entire skill distribution of every city. To gain analytical tractability without imposing structure on the technology, I solve for the steady state equilibrium when city TFP are not too dispersed, $T_\ell \approx \bar{T}$ for all ℓ . When cities share a common TFP, the production complementarities vanish. Workers no longer have an exogenous motive to sort across cities, and an equilibrium with a symmetric allocation exists (Proposition A.1). This equilibrium is unique when the dynamic gains of cities, summarized by $\vartheta\beta$, are not too large.¹⁸ Approximating the equilibrium around the symmetric allocation thus simplifies how to keep track of the local skill densities.

Sections 2.3 and 2.4 characterize the equilibrium under this perturbation approach. Throughout, \bar{x} refers to the value of x in the homogeneous TFP equilibrium, and I use capital letters to denote random variables. For instance, S^y is the aggregate skill distribution of young workers, and S_ℓ^y the skill distribution of young workers in city ℓ . I return to the global solution from Section 2.5 onward.

¹⁶Appendix A presents the proofs of all propositions.

¹⁷This definition generalizes the notion of positive assortative matching in a context of many-to-one matching in which every skill is present in every city due to the presence of idiosyncratic location preferences.

¹⁸For a framework where local interaction alone generate asymmetric equilibria, see Davis and Dingel (2019).

2.3 Local Interactions as a Source of Agglomeration

I first show how the spatial segmentation of learning opportunities affect where individuals choose to work. I start by characterizing the location decisions of old workers, which is independent from these learning considerations, to then contrast it with that of the young. When between-city differences in TFP are small, (4) implies that the number of old workers with skill s employed in city ℓ is to a first order given by¹⁹

$$n_\ell^o(s) \approx \underbrace{\frac{\bar{n}^o(s)}{L}}_{\text{Symmetric}} + \underbrace{\vartheta \left(\frac{\bar{n}^o(s)}{L} \right) (T_\ell - \bar{T}) s}_{\text{Sorting for working}}, \quad \forall s, \forall \ell,$$

where $\bar{n}^o(s)$ is the density of old workers with skill s when cities are homogeneous. When cities share a common TFP, old workers locate in cities that maximize their idiosyncratic preferences, and the resulting allocation is symmetric. When some cities are more productive than others, the local wages are relatively higher, which attracts more workers. Furthermore, the between-city wage gaps are larger for relatively skilled workers due to the production complementarities. High-skill workers are therefore relatively more present in productive cities, and the old allocation satisfies SPAM.²⁰ The dispersion in idiosyncratic location preferences modulates the amount of sorting.

The location decisions of young workers differ from the old in that they also care about local learning opportunities. Specifically, from (5), the measure of young workers with skill s in city ℓ is to a first order given by

$$n_\ell^y(s) \approx \underbrace{\frac{n^y(s)}{L}}_{\text{Symmetric}} + \underbrace{\vartheta \left(\frac{n^y(s)}{L} \right) (T_\ell - \bar{T}) s}_{\text{Sorting for working}} + \underbrace{\vartheta^2 \beta \left(\frac{n^y(s)}{L} \right) (T_\ell - \bar{T}) \Theta(s)}_{\text{Sorting for learning}}, \quad \forall s, \forall \ell.$$

Similarly to old workers, young individuals prefer to work in relatively productive cities to earn higher wages everything else equal. The third, new term captures the learning considerations. Specifically, the function $\Theta(s)$ summarizes how much young workers with skill s value the learning opportunities of relatively productive cities. When $\Theta(s) > 0$, these opportunities are relatively attractive, and young workers with skill s have a greater incentive to work in productive cities to learn from the individuals who are there. When $\Theta'(s) > 0$, skilled workers value disproportionately the learning opportunities of productive cities, which intensifies their concentration across space. I define the total willingness to sort of young workers with skill s as the sum of the sorting for working and sorting for learning motives, $\eta(s) \equiv s + \vartheta \beta \Theta(s)$.

How much young workers value the learning opportunities of productive cities depend on who

¹⁹For ease of exposition, I present in the main text the expression for the case of homogeneous local amenities. Appendix A presents the general expressions. Amenity differentials affect city size but not the local skill densities, and as a result, do not affect the qualitative predictions of the model.

²⁰Proposition A.2 shows that SPAM always prevail for old workers for any spatial distribution of TFP.

works there and how much individuals learn from them,

$$\Theta(s) = \int \underbrace{(\gamma(s, s_p) - \mathbb{E}[\gamma(s, S^y)])}_{\text{Relative learning from } s_p \text{ interaction}} \underbrace{(s_p + \vartheta\beta\Theta(s_p))}_{\text{Willingness to sort of } s_p} dN^y(s_p), \quad \forall s. \quad (7)$$

The first term in the integrand captures how much workers with skill s relatively learn from a partner with skill s_p . The second term reflects how much more likely are interactions with s_p in productive cities, which itself depends on the willingness of these individuals to work there. That is, how attractive are the learning opportunities of productive cities for workers s depends on how all the other workers value these opportunities. Formally, $\Theta(s)$ is the solution to a infinite-dimensional linear fixed point.²¹ I show in Appendix A.6 that this fixed point has a unique solution when the dispersion forces, captured by $\vartheta\beta$, are large enough.

Were workers not to learn from who's around them, the willingness to sort of young workers would solely rely on their sorting for working motive. The spatial allocation of young workers would then also display stochastic positive assortative matching. The sorting for learning motive could *a priori* offset this technological force if low-skill were to disproportionately value the learning opportunities of productive cities. A higher density of low-skill workers in productive cities would however contradict the empirical evidence on sorting patterns found in this paper and others (e.g. Combes et al., 2008; Card et al., 2023, amongst others). I therefore focus on the part of the parameter space that generates a SPAM allocation for young workers.

Lemma 1 (Stochastic positive assortative matching).

If $T_\ell \approx \bar{T}$ for all ℓ and $\vartheta\beta\text{Cov}[\gamma_1(s, S^y), S^y] \geq -1$ for all s , the young allocation exhibits SPAM.

Lemma 1 bounds the relative strength of the between-skill learning complementarities. For instance, when the learning technology takes the form of (1), the condition simplifies to $\vartheta\beta g_{12}\text{Var}[S^y] \geq -1$, which imposes a bound on how submodular the learning technology can be. I assume that the condition of Lemma 1 holds for the remainder of Sections 2.3 and 2.4.

In a SPAM equilibrium, individuals who work in productive cities are more likely to interact with skilled workers. Productive cities are therefore attractive learning centers to workers that disproportional learn from high-skill. Formally, $\gamma(s, \cdot)$ increasing implies $\Theta(s) > 0$, and the spatial segmentation of learning opportunities increases the number of young workers with skill s in productive cities. Two consequences follow on the spatial distribution of economic activity.

First, the concentration of skilled workers in productive cities may constitute a source of agglomeration that make these cities bigger. Specifically, if every young individual learns relatively more from skilled workers, the size of productive cities is larger in the presence of spatially segmented learning interactions as individuals agglomerate there to learn from the local workers.

Second, the concentration of skilled workers in space may rise as they agglomerate in a few cities

²¹These infinite-dimensional linear fixed points are referred to as Fredholm integral equation of the second kind. Similar integral equations can be found in Allen and Arkolakis (2014).

to learn from each other. To a first order, the average skill of young workers employed in city ℓ is

$$\mathbb{E}[S_\ell^y] \approx \underbrace{\mathbb{E}[S^y]}_{\text{Symmetric}} + \underbrace{\vartheta(T_\ell - \bar{T}) \text{Var}[S^y]}_{\text{Sorting for working}} + \underbrace{\vartheta^2 \beta (T_\ell - \bar{T}) \text{Cov}[S^y, \Theta(S^y)]}_{\text{Sorting for learning}}, \quad \forall \ell,$$

where $\mathbb{E}[S_\ell^y]$ is the average skill of in ℓ , $\text{Var}[S^y]$ is the aggregate skill variance, and $\text{Cov}[S^y, \Theta(S^y)]$ is the covariance between workers' skill and their valuation of productive cities' learning opportunities. Local interactions affect the spatial concentration of skilled workers by shaping their willingness to sort. When the within-skill complementarities dominate the between-skill complementarities, young skilled workers have relatively greater incentives to interact with their own peers. They therefore place a higher value on the learning opportunities present in productive cities, and the local density of high-skill rises. Greater between-city wage inequality follows (equation (37) in Appendix A.5). In contrast, if the between-skill complementarities prevail, the learning motive in workers' location choice reduces the concentration of skilled workers in productive cities.

I summarize the consequences of the spatial segmentation of learning opportunities on spatial inequality in Proposition 2.

Proposition 2 (Spatial inequality).

When $T_\ell \approx \bar{T}$ for all ℓ , $\gamma(s, \cdot)$ increasing implies $\Theta(s) > 0$, and conversely, $\gamma(s, \cdot)$ decreasing yields $\Theta(s) < 0$. As a result:

1. If $\gamma(s, \cdot)$ is increasing for all s , (un)productive cities are (smaller) larger when interactions are spatially segmented; the converse holds when $\gamma(s, \cdot)$ is decreasing;
2. If γ is supermodular, the average skill of young workers in (un)productive cities is (smaller) larger when interactions are spatially segmented, which leads to greater between-city wage variance amongst young workers; the converse holds when γ is submodular.

2.4 The Human Capital Consequences of Local Interactions

Between-city differences in skill growth arise endogenously from the sorting of young workers. In particular, if workers learn more from relatively skilled interactions, young workers accumulate human capital faster in productive cities and slower in low TFP locations.

Do these spatial differences in learning matter for aggregate productivity? In the aggregate, the average skill of old workers is given by

$$\mathbb{E}[S^o] = \sum_\ell \int \int \int e\gamma(s_y, s_p) n_\ell^y(s_y) \pi_\ell^y(s_p) dF(e) ds_p ds_y. \quad (8)$$

This equilibrium stock of human capital can be contrasted with the average skill of old workers that prevails under the symmetric allocation:

$$\mathbb{E}[\bar{S}^o] = \int \int \int e\gamma(s_y, s_p) n^y(s_y) n^y(s_p) dF(e) ds_p ds_y. \quad (9)$$

This also coincides with the stock of human capital were interactions not segmented by cities since the spatial allocation of workers is then irrelevant for human capital accumulation. Comparing (8) and (9), cities affect aggregate productivity by shaping the aggregate probability of complementarity meetings. Absent learning complementarities, i.e. $\gamma(s, s_p) = g(s) + h(s_p)$, (8) and (9) indeed coincides and the location choices of young workers do not shape aggregate productivity. In that case, the faster human capital accumulation of individuals working in productive cities is indeed exactly offsetted by the slower learning of workers employed in the other locations.

Cities however have the potential to amplify or dampen aggregate human capital accumulation. To a second order, (8) implies that the average skill of old workers is²²

$$\mathbb{E}[S^o] \approx \mathbb{E}[\bar{S}^o] + \vartheta^2 \text{Var}[T_\ell]\Omega, \quad (10)$$

where $\mathbb{E}[\bar{S}^o]$ is given by (9) and $\text{Var}[T_\ell]$ is the variance of cities' TFP. The constant Ω fully encapsulates how the spatial segmentation of learning opportunities affect aggregate productivity. The stock of human capital is larger when interactions are spatially segmented if $\Omega > 0$, and smaller otherwise. This aggregate effect is given by

$$\Omega = \int \int \gamma(s, s_p) (\eta^y(s) - \mathbb{E}[\eta^y(S^y)]) (\eta^y(s_p) - \mathbb{E}[\eta^y(S^y)]) dN^y(s_p) dN^y(s).$$

The aggregate impact of cities on human capital accumulation thus relies on three terms. The first term captures how much skill s learns from s_p . The second and third terms reflect the willingness of these two skills to work in productive cities which, combined, determine the aggregate probability that they meet.

Learning complementarities shape the impact of cities on aggregate human capital accumulation. In a SPAM equilibrium, cities increase the chance that workers with similar skills interact. When within-skill complementarities are strong, the marginal gains from skilled interactions are increasing in workers' skills. In such case, the agglomeration of skilled individuals in productive locations boost aggregate human capital accumulation. On the contrary, if the between-skill complementarities dominate, low skill workers gain relatively more from meeting skilled partners. The spatial segregation of skilled workers in productive cities prevents low-skill workers to frequently learn from them, and lower aggregate productivity follows.²³

Proposition 3 (Human capital accumulation).

Suppose that $T_\ell \approx \bar{T}$ for all ℓ . If γ is supermodular, the average skill of old workers is larger when interactions are spatially segmented, i.e. $\Omega > 0$. Conversely, γ submodular implies a lower average skill of old workers, $\Omega < 0$.

As a corollary to Proposition 3, learning complementarities determine the existence of a tradeoff

²²Cities do not have a first-order effect on the average skill of old workers as the between-city differences in learning necessarily cancel each other.

²³Appendix A.9 presents the consequences of local interactions on human capital accumulation across the skill distribution. When every worker learns relatively more from skilled interactions, local interactions increase learning inequality across skills by boosting the average learning of skilled workers and dampening that of low-skill individuals.

between spatial inequality and human capital accumulation.²⁴ In a SPAM equilibrium, a larger degree of between-city wage inequality is necessarily associated with a stronger concentration of skilled workers in productive cities, and therefore a greater segregation of learning opportunities across space. When within-skill learning complementarities prevail, an equity-efficiency tradeoff therefore exists as greater spatial wage inequality enhances aggregate productivity. Such tradeoff is not present when the between-skill learning complementarities are stronger. Then, a policy that reduces spatial wage inequality also increases the stock of human capital.

Corollary 4 (Equity-efficiency tradeoff).

Suppose that $T_\ell \approx \bar{T}$ for all ℓ . In equilibrium, a greater between-city wage variance amongst young workers leads to a greater (smaller) stock of human capital if γ is supermodular (submodular).

Learning complementarities therefore shape the tradeoff between spatial inequality and aggregate productivity. They also determine whether spatial inequalities are inefficiently too large.

2.5 Optimal Policies

To study whether the spatial allocation of workers is efficient, I solve for the allocation chosen by a utilitarian planner. I assume that the planner has homogeneous Pareto weights across skills and cities to focus on the learning externalities rather than redistributive concerns. I further suppose that the planner cannot condition its allocation on workers' idiosyncratic location preferences, either because these preferences are unobserved or because it is not politically feasible to do so. This restriction is standard in models with idiosyncratic location preferences (e.g. Rossi-Hansberg et al., 2019; Fajgelbaum and Gaubert, 2020).

Given these restrictions, the planner chooses a sequence of spatial allocation of workers, $\{n_{t\ell}^{y\star}(s), n_{t\ell}^{o\star}(s)\}_{t,\ell}$, together with a sequence of consumption allocation across cities and skills, $\{c_{t\ell}^{y\star}(s), c_{t\ell}^{o\star}(s)\}_{t,\ell}$, to maximize the discounted sum of each cohort's expected lifetime utility,²⁵

$$\sum_{\ell} \int \mathbb{E}[V_0^{o\star}(s, \boldsymbol{\varepsilon}) | s] n_{0\ell}^{o\star}(s) ds + \sum_{t>0} \beta^t \sum_{\ell} \int \mathbb{E}[V_t^{y\star}(s, \boldsymbol{\varepsilon}) | s] n_{t\ell}^{y\star}(s) ds. \quad (11)$$

The function $V_0^{o\star}(s, \boldsymbol{\varepsilon})$ is the utility of old workers with skill s and preferences $\boldsymbol{\varepsilon}$ in the initial period under the planner's allocation. Likewise, $V_t^{y\star}(s, \boldsymbol{\varepsilon})$ is the lifetime utility of young workers in cohort t . The planner cannot observe workers' idiosyncratic preferences, and thus maximizes workers' expected utility. The consumption allocation must not exceed the aggregate output produced in each period.²⁶ Meanwhile, the spatial allocation of workers must be consistent with the aggregate supply of each skill and workers' idiosyncratic location preferences. These preferences act as an

²⁴Formally, from (10), the equilibrium average skill of old workers can be rewritten $\mathbb{E}[S^o] - \mathbb{E}[\bar{S}^o] \propto \Omega \text{Var}[\mathbb{E}(W_{\ell}^y)]$, where $\text{Var}[\mathbb{E}(W_{\ell}^y)]$ is the between-city wage variance. To a second-order, the equilibrium is always located on this equity-efficiency loci. In particular, the impact of any policy that affects the spatial allocation of workers on aggregate productivity is given by this technological frontier.

²⁵By the property of the Gumbel distribution, the expected utility of workers who choose to work in city ℓ is identical to the unconditional expected utility, $\mathbb{E}[V_0^{o\star}(s, \boldsymbol{\varepsilon}) | s, \ell \succ \ell' \forall \ell' \neq \ell] = \mathbb{E}[V_0^{o\star}(s, \boldsymbol{\varepsilon}) | s]$.

²⁶Same as for consumers, the planner cannot transfer resources across time.

incentive constraint: to increase the supply of workers in a particular city, the planner needs to compensate them for their foregone location preferences.²⁷ I solve first for the global, non-linearized planner's allocation. I focus on the steady state allocation, which I refer to as the (constrained) optimal allocation.²⁸

Old workers do not affect the learning of young workers, and therefore do not exert externalities. As a result, the decentralized allocation of old workers coincides with that of the planner.²⁹

In contrast, the allocation of young workers need not be efficient. Young workers do not internalize that where they work shape the learning of others, whereas the planner does. To correct for the potential resulting spatial misallocation, the planner, who faces the location choices of young workers as incentive constraints, modulates the spatial allocation of consumption. Specifically, the difference between the optimal and decentralized consumption of young workers with skill s employed in city ℓ is given by

$$c_\ell^{y\star}(s) - c_\ell^y(s) = \tau_\ell^\star(s) - \sum_{\ell'} \left(\frac{n_{\ell'}^{y\star}(s)}{n^y(s)} \right) \tau_{\ell'}^\star(s), \quad \forall s, \forall \ell. \quad (12)$$

The right-hand side of (12) represents the wedge between the social and private incentives of young workers with skill s to locate in city ℓ . When it is positive, the decentralized equilibrium features too few of these workers there. This wedge is given by the net welfare gains (or losses) brought by a marginal increase in the number of skill s in city ℓ . The welfare gains brought by this reallocation for city ℓ alone are given by

$$\tau_\ell^\star(s) = \beta \int \int (\mathcal{V}^o[e\gamma(\sigma, s)] - \mathbb{E}[\mathcal{V}^o(e\gamma(\sigma, S_\ell^{y\star}))]) dF(e) \pi_\ell^{y\star}(\sigma) d\sigma, \quad \forall s, \forall \ell, \quad (13)$$

where $\mathbb{E}[\mathcal{V}^o(e\gamma(\sigma, S_\ell^{y\star}))] = \int \mathcal{V}^o[e\gamma(\sigma, s_p)] \pi_\ell^{y\star}(s_p) ds_p$ is the expected future utility of working in city ℓ for skill s . These local welfare gains are positive if workers in ℓ learn relatively more from skill s than from the average worker present in the city. The second term on the right-hand side of (12) is the employment-weighted average of the welfare gains for all the locations. Hence, the optimal spatial allocation features a greater number of skill s in city ℓ if the workers employed in that city learn disproportionately from that skill.

The decentralized equilibrium is therefore inefficient to the extent workers learn from others. When workers' human capital accumulation depends solely on their own skill, $\gamma(s, s_p) = g(s)$, the decentralized equilibrium is efficient. Otherwise, the optimal and decentralized spatial allocation of young workers differ from one another. Characterizing the spatial misallocation in the decentralized equilibrium amounts to solving for (13). The function $\tau_\ell^\star(s)$ appears on both side of the equation as

²⁷Appendix B.1 describes the full set of constraints faced by the planner.

²⁸As for the decentralized equilibrium, the planner's allocation converges to its steady state in one period.

²⁹The efficiency of the old allocation highlights that, absent learning externalities, the planner has no incentives to redistribute resources across cities. Idiosyncratic location preferences alone thus do not create inefficiencies. While this may appear in contradiction with the conclusions of Fajgelbaum and Gaubert (2020), the two results are reconciled by noting the absence of local non-traded goods in the present framework. The marginal utilities of consumption are then trivially equalized across space, and the planner does not redistribute across space.

it affects the spatial allocation of young workers π_ℓ^{y*} through the consumption allocation (12). The optimal allocation is therefore the solution to a non-linear infinitely dimensional fixed point. As in Sections 2.3 and 2.4, I simplify this fixed point by studying the optimal allocation when the spatial TFP gaps are small, $T_\ell \approx \bar{T}$. Appendix B.3 derives in detail the first-order approximation.

I find that local learning interactions generate spatial misallocation through two channels. First, productive cities may be too large in the decentralized equilibrium. When skilled interactions are relatively more productive, young workers agglomerate in productive cities (Proposition 2.1). In doing so, they forego their idiosyncratic location preferences for less productive locations.³⁰ However, high-TFP cities do not offer *ex-ante* better learning opportunities, and these opportunities could *a priori* be anywhere. Holding learning complementarities constant, the planner thus desires to decentralize learning centers. When spatial TFP gaps are small, this is achieved by reallocating workers from high to low TFP locations independently of their skills.

Second, the decentralized equilibrium may feature too much or too little skill segregation across space. When the within-skill learning complementarities dominate the between-skill complementarities, skilled workers benefit disproportionately from interacting with their own peers. The planner takes into account these spillovers, and increases the frequency of interactions between relatively skilled workers by augmenting the concentration of skilled workers in productive cities. On the contrary, relatively low-skill workers experience too little skilled interactions in the competitive equilibrium when the between-skill complementarities prevail. The planner corrects this misallocation by reallocating skilled workers towards low-TFP cities that are abundant in low skills. In both cases, the optimal allocation corrects the learning externalities and increases the aggregate stock of human capital.

Proposition 5 (Optimal allocation).

The decentralized equilibrium is efficient if interactions do not shape learning, $\gamma(s, s_p) = \gamma(s)$. Otherwise, the decentralized equilibrium is inefficient. Furthermore, when $T_\ell \approx \bar{T}$ for all ℓ :

1. *If $\gamma(s, \cdot)$ is increasing for all s , productive cities are too large in the decentralized equilibrium: $N_\ell^* < N_\ell \iff T_\ell > \bar{T}$; conversely, productive cities are too small if $\gamma(s, \cdot)$ is decreasing for all s .*
2. *If γ is supermodular, there is too little young skill concentration in productive cities: $\mathbb{E}[S_\ell^{y*}] > \mathbb{E}[S_\ell^y] \iff T_\ell > \bar{T}$; conversely, there is too much young skill concentration in productive cities when γ is submodular.*

The optimal allocation implies a larger stock of human capital, $\mathbb{E}[S^{o}] > \mathbb{E}[S^o]$.*

Which policy instruments can decentralize the optimal allocation? Equation (13) implies that efficiency is restored through place-by-skill transfers, $t_\ell^y(s)$, equal to the right-hand side of (13). These transfers complement workers' wage, and the income of young workers with skill s employed in city ℓ becomes $I_\ell^y(s) = w_\ell(s) + t_\ell^y(s)$.³¹ When the spatial TFP gaps are small, the transfers

³⁰In a different setting, Waldfogel (2003) coined this externality the “preference externality”.

³¹These transfers can alternatively be expressed as city-specific income tax schedules.

can further be decomposed into two components. First, a city-specific tax which corrects the size distortion found in Proposition 5.1. Second, skill-by-city subsidies which generate the optimal amount of spatial skill segregation (Proposition 5.2).

Taking stock, the spatial segmentation of learning opportunities may shape spatial inequality and aggregate human capital accumulation, and call for place-based policies. To evaluate quantitatively their consequences, I add several extensions to the framework that allow me to bring it to the data.

2.6 Quantitative model

I add two key elements to the model, housing and migration costs, that are frequently mentioned to explain the presence of spatial inequality and justify the need for local policies (e.g. Chetty et al., 2014). I also let young workers interact with old partners. I solve for the global, non-linearized solution of the model numerically. Appendix C provides a formal description of the quantitative model and the numerical algorithm used.

Housing In addition to the freely traded numéraire, households consume a local good sold at (rental) price p_ℓ . I refer to this good as housing. Households have Cobb-Douglas preferences over the two goods, with α representing the housing expenditure share.³² In each city, local land-owners supply a stock of housing $H_\ell = \mathcal{H} p_\ell^\delta$, for \mathcal{H} a constant and δ the housing supply elasticity.³³ I take these land owners to be absentee, and in particular exclude them from any welfare calculation.³⁴

Migration costs While workers remain free to change location whenever they please, they now incur a migration cost upon moving. I let these migration costs vary across the lifecycle, e.g. if young workers face tighter borrowing constraint or if old workers have accumulated more social capital. I assume that workers are born in the location where their parents lived when young; that is, the probability to be born in city ℓ is given by N_ℓ^y .³⁵ A young worker born in city ℓ that moves to city ℓ' incurs a utility cost $\kappa_{\ell\ell'}^y$.³⁶ Likewise, an individual who lived in ℓ in their youth and migrates to location ℓ' in their old period pays a cost $\kappa_{\ell\ell'}^o$. I assume that the migration costs are symmetric, $\kappa_{\ell\ell'}^a = \kappa_{\ell'\ell}^a$ for $a \in \{y, o\}$, and I normalize $\kappa_{\ell\ell}^a = 0$ for every ℓ and $a \in \{y, o\}$. The presence of migration costs implies that the expected lifetime utility of young workers now depends on their skill and their birthplace. In particular, expected utilities are no longer equalized across space.

Learning I also relax the assumption that young workers interact only between themselves, and let young workers interact both with young and old workers. Furthermore, I assume that the

³²For empirical evidence using U.S. data in support of the constant housing expenditure share implied by the Cobb–Douglas functional form, Davis and Ortalo-Magné (2011).

³³This reduced-form supply function can be micro-founded by assuming that land-owners have to provide effort subject to convex cost to turn the land they own into rentable housing.

³⁴The model would have the same positive predictions if I were to assume that land-owners use their revenues to consume the freely traded good. Abstracting from them in the welfare computation would however be inconsistent.

³⁵I could alternatively assume that workers' birthplace is given by their parents' location when old. The probability to be born in ℓ would be N_ℓ^o . In the data, I define a young as a worker between 25 and 40 year old. I stick with the first formulation to stick closer to the empirical timing of birth. This will not matter quantitatively since $N_\ell^y \approx N_\ell^o$.

³⁶Alternatively, these migration costs can represent auto-correlation in workers' location preferences. The two interpretations are isomorphic from a positive standpoint and differ only in terms of welfare considerations.

learning technology takes the form

$$\log \gamma(s, s_p) = g_0 + g_1 \log s + g_2 \log s_p + g_{12} \log s \log s_p. \quad (14)$$

The learning technology therefore relies on four parameters that altogether shape workers' skill growth.³⁷ The first, g_0 , determines the average skill growth. The parameter g_1 governs how workers' own skill shapes their human capital accumulation regardless of who they interact with. In particular, $g_1 > 1$ implies that skilled worker learn relatively faster. The two other parameters, g_2 and g_{12} , affect how workers learn from others. Workers learn relatively more from skilled partners on average when $g_2 > 0$, and, in particular, if they are themselves skilled when $g_{12} > 0$.

The learning technology (14) differs from (1) as it is expressed in logs rather than in levels. While the latter functional form was useful to exemplify the between and within-skill learning complementarities, it is harder to bring to the data because it does not feature any concavity.³⁸ In contrast, g_1 , g_2 and g_{12} in (14) are skill growth elasticities, and therefore can be directly estimated from wage growth data. In addition, this functional form is more flexible as it entertains learning technologies that are neither super nor submodular.

Distributions Finally, I suppose that the skill distribution of young workers is log-normal with mean μ_y and standard deviation σ_y , and I parametrize the idiosyncratic learning shocks to be log-normally distributed with zero mean and standard deviation σ_e .³⁹

Relationship to theory To what extent the results derived in Sections 2.3 to 2.5 hold in the quantitative model? The introduction of migration costs and housing consumption alters the analytical tractability of the model. Rather, I rely on numerical methods. In Section 5, I compare the estimated framework with a counterfactual economy in which interactions are not spatially segmented. The numerical results align with the qualitative predictions of Proposition 2 and 3.

3 Estimating the Returns to Local Interactions

As highlighted in the previous sections, learning complementarities are crucial in determining how the spatial segmentation of learning opportunities affect spatial disparities and productivity. In this section, I present evidence on the role of cities' skill composition in shaping workers' wage growth. I argue that these evidence can be used to estimate the model's learning technology.

³⁷The log skill growth of a young worker endowed skill s is $\log[\gamma(s, s_p)/s] = g_0 + (g_1 - 1) \log s + \log s_p + g_{12} \log s \log s_p$.

³⁸Alternatively, one could include higher order terms in (1) to introduce curvature in the learning technology. This would however require to estimate many more parameters and open the door to over-fitting concerns.

³⁹Normalizing the mean of the learning shocks distribution to zero is without loss of generality since it is not separately identified from g_0 in the learning technology.

3.1 Data

I estimate the model on French matched employer-employee data (DADS).⁴⁰ This dataset comes in two formats. The first format is a 4% representative panel that tracks the entire history of individuals on the labor market (DADS panel).⁴¹ The second format is a repeated yearly cross-section covering the universe of employed workers (DADS salariés). Both datasets provide information on workers' wages, the number of hours worked, the location where they work and live, along with demographic information. The data goes back to 1976 but frequent changes of variables make it difficult to use the observations collected prior to 1993.

This dataset has several advantages over other data sources used in the literature. First, its long-panel dimension allows me to measure individual wage growth at a long-term horizon. Second, the cross-sectional format is useful to measure precisely the local skill composition at a granular geographical level. Third, it is one of the few matched employer-employee dataset that provides joint information on where individuals work (firm, establishment, and neighborhood) and where they live.

I apply the same sample restrictions on both datasets. I focus my analysis on full-time employed workers between 25 and 55 year old. Workers employed in the public sector in France have their wage determined nationally by their tenure, and as such, their wage may not fully reflect their productivity. I therefore keep in the sample workers employed in the private sector, and I exclude the education and health industries due to the large fraction of workers that are public servants. I measure workers' wages by their gross yearly salaries divided by the number of hours worked, and I truncate the hourly wage distribution at the 5% and 99.9% percentile to minimize measurement errors in hours worked.⁴² Appendix D.1 provides further details on the construction of the sample.

Over time, wages grow for two reasons. First, workers experience idiosyncratic changes. Second, wages fluctuate for all workers as the economy grow and fluctuates around the business cycle.⁴³ Aggregate trajectories are absent from the framework laid down in Section 2. To abstract from them empirically, I normalize the average log wage to zero every year. These trajectories may also differ across space, e.g. for cities impacted by the deindustrialization of the French economy. I therefore focus the study to the 2009-2019 time window. In that decade, aggregate growth was evenly spatially distributed in France (Figure D.2), guaranteeing that I do not conflate faster lifecycle wage growth with faster aggregate growth.

I define a city as a commuting zone. A commuting zone is a statistical area defined by the French statistical agency (INSEE). It consists of a collection of contingent municipalities clustered

⁴⁰DADS stands for “*Declarations Annuelles de Données Sociales*”. The dataset is constructed from employer tax records which are compiled by the French statistical agency (INSEE).

⁴¹Individuals' employment history is recorded in the dataset if (a) they have at least one employment spell, and (b) they are born in the first fourth days of each quarter.

⁴²In France, between 5% and 10% of the overall workforce is paid at the minimum wage (INSEE, 2021). For these workers, wages are not a valid proxy of their skills. I focus on workers paid above the minimum wage by truncating the left-tail of the wage distribution at the 5%.

⁴³This relationship is mechanical. The log wage growth of worker i can always be decomposed $\omega_{it+1} - \omega_{it} = \tilde{\omega}_{it+1} - \tilde{\omega}_{it} + \mathbb{E}[\omega_{it+1}] - \mathbb{E}[\omega_{it}]$, for $\omega_{it} = \log w_{it}$ and $\tilde{\omega}_{it} \equiv \omega_{it} - \mathbb{E}[\omega_{it}]$. The first term is the worker-level wage growth and the second is aggregate wage growth.

together to reduce the commuting flows across them. There are 297 such areas in metropolitan France, which span the whole territory.⁴⁴ Commuting zones are the natural geographical unit when thinking of local labor markets. In particular, their relatively large size (40,000 employed workers on average) are well-suited to capture all the interactions that a worker may experience locally. I use the terms commuting zones and cities interchangeably for the rest of the paper.

I also use a second, more granular geographical unit for the empirical analysis. Specifically, I define a neighborhood as a municipality (“commune” in French). Municipalities are legal areas which also span the French metropolitan territory. They are however smaller than commuting zones: in 2019, France was split in 34,839 municipalities with an average size of 1,800 inhabitants and an average area of 15 square kilometers.⁴⁵ They compare to ZIP codes in the United States. Figure D.1 displays a map of the French commuting zones alongside the municipalities contained in Paris and Lyon to highlight how granular these spatial units are. I restrict the analysis to metropolitan municipalities with more than 50 employed workers to reduce local measurement errors. I am left with 12,320 municipalities, representing 99% of the French workforce and with an average size of 950 employed workers.

3.2 The Geography of Wage Growth

Wage growth across the lifecycle is very unevenly distributed across space in France.⁴⁶ Figure 1a plots the average five-year wage growth at the worker-level by commuting zones.⁴⁷ On average, young workers experience a wage growth of 10.6 log points over five years. Workers in Paris see their wage increase by 15 log points. Meanwhile, the average wage growth in Lyon, the city in the 75th percentile of the growth distribution and the second biggest French city, is 12 log points, and the growth in Troyes, the city in the 10th percentile of the growth distribution, is 8 log points. In total, half of the cities (20% of the population) offer wage growth below 9 log points.

Fast wage growth is concentrated in cities where wages are also relatively high. Figure 1b displays the average wage growth at the city level against the local average wage. In the cross-section, an increase of the city wage by one standard deviation is associated with an increase of wage growth by 2 log points at the five-year horizon. This relationship is not mechanically caused by high-wage cities diverging away from the other places (Figure D.2) or by housing prices dynamics (Figure D.3). I now argue how this pattern can be used to identify the learning technology.

3.3 Identification

In the framework laid down in Section 2, the learning technology determines the effect of local interactions on skill growth. Consequently, between-city variations in skill growth can be used to recover the learning technology.

⁴⁴Metropolitan France excludes the French overseas regions (Guadeloupe, Réunion, etc.).

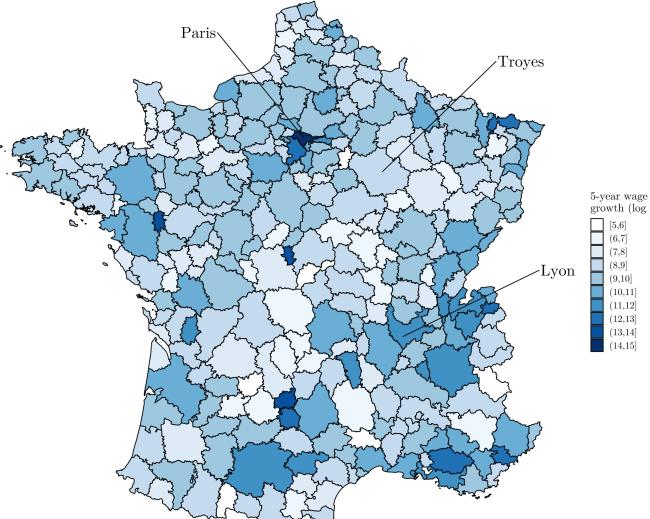
⁴⁵Municipalities were introduced with the French revolution in 1789. Since the 20th century, the number of municipalities have been rather stable over time. Appendix D.2 provides more details on their history and characteristics.

⁴⁶While the between-city difference in growth are large, they explain a small fraction (4%) of the total variance.

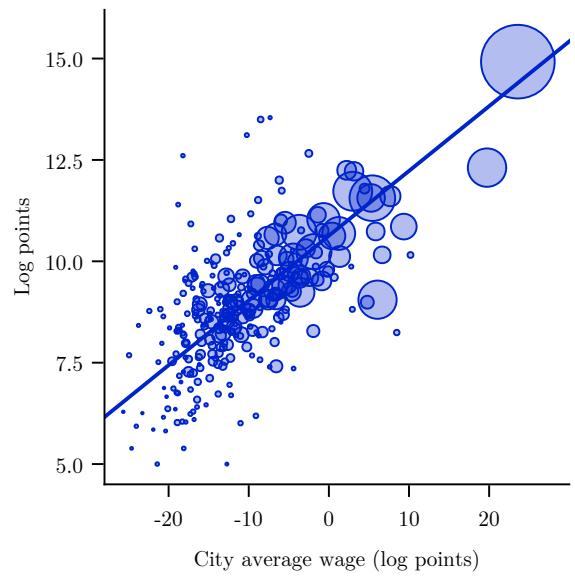
⁴⁷Consistent with the model, these averages are computed on “young” workers under 40 years old.

Figure 1: The geography of wage growth

(a) Average wage growth by commuting zone



(b) Wage growth and local wages



Note: left-panel plots the average log wage growth at the five-year horizon by commuting zones for workers under 40 year old. Right-panel plots the average log wage growth at the five-year horizon against the average wage of the commuting zones. The size of the markers is proportional to the city size. In both panels, wage growth is measured at the worker level, i.e. $\log w_{it+1}/w_{it}$.

Specifically, given the learning technology (14), the next period's skill of a worker i given their present skill, s_{it} , and the skill of their learning partner, s_{pit} , is

$$\log s_{it+1} = g_0 + g_1 \log s_{it} + g_2 \log s_{pit} + g_{12} \log s_{it} \log s_{pit} + \log e_{it+1}, \quad (15)$$

where e_{it+1} is the idiosyncratic learning shock experienced by i . These shocks represent for instance enrollments in training programs, returns to on-the-job tenure, or strokes of genius. They are however assumed to be identically and independently distributed across space, workers and partners. Through the lens of the model, the learning technology can therefore be estimated via a local projection of future skills on today's skills, both for i and their partner.

Estimating (15) poses however two empirical challenges: how to observe learning interactions, p_{it} , and how to measure skill, s_{it} . I use the structure of the model to solve these challenges.

First, very few datasets track workers' interactions, and even less the skills or wages of the workers engaged in them.⁴⁸ However, when interactions are random within cities, the average skill of individuals working in the same location as i constitutes a valid proxy for their interactions. Specifically, substituting s_{pit} in (15) for the average skill in the location where i is employed,

⁴⁸Recent papers have made significant advances in how to measure face-to-face interactions (e.g. Atkin et al., 2022; Emanuel et al., 2023). Yet, they lack a measure of worker productivity that they can track over time.

$\mathbb{E}_{\ell_{it}}[\log s_{it}]$, returns

$$\log s_{it+1} = g_0 + g_1 \log s_{it} + g_2 \mathbb{E}_{\ell_{it}}[\log s_{it}] + g_{12} \log s_{it} \mathbb{E}_{\ell_{it}}[\log s_{it}] + \log e_{it+1} + \nu_{it}. \quad (16)$$

The term $\nu_{it} = (g_2 + g_{12} \log s_{it})(\log s_{p_{it}} - \mathbb{E}_{\ell_{it}}[\log s_{it}])$ captures the gap between the particular interaction experienced by worker i and the average interaction in city ℓ . Random interactions imply that ν_{it} is orthogonal to s_{it} and $\mathbb{E}_{\ell_{it}}[\log s]$ (Appendix D.3).

Second, in the theory, skill and wages are related through $w_{it} = s_{it} T_{\ell_{it}}$, for $T_{\ell_{it}}$ the TFP of the city where i works.⁴⁹ While skills are rarely measured, wages are easily observed. Substituting wages for skills in (16), the theory predicts that future wages are related to today's wages through

$$\log w_{it+1} = g_0 + g_1 \log w_{it} + g_2 \mathbb{E}_{\ell_{it}}[\log w_{it}] + g_{12} \log w_{it} \mathbb{E}_{\ell_{it}}[\log w_{it}] + \log e_{it+1} + \nu_{it} + \zeta_{it}. \quad (17)$$

The added term, $\zeta_{it} = \log T_{\ell_{it+1}} - (g_1 + g_2) \log T_{\ell_{it}} - g_{12} (\log w_{it} + \mathbb{E}_{\ell_{it}}[\log s_{it}] - \log T_{\ell_{it}}) \log T_{\ell_{it}}$, synthesizes the difference between workers' skills and wages.

The learning technology can therefore be estimated from a local projection of future wages on current wages, the average wage of the workers employed in the same city, and the control for cities' TFP,

$$\log w_{it+1} = \alpha_t + \beta \log w_{it} + \gamma \overline{\log w}_{\ell_{it}} + \delta \log w_{it} \overline{\log w}_{\ell_{it}} + \zeta_{it} + u_{it}. \quad (18)$$

In (18), α_t is a year fixed effect that controls for aggregate trends in wages and $\overline{\log w}_{\ell}$ is the average log wage in city ℓ . I measure future wages at the five-year horizon to smooth out transitory wage shocks while keeping sufficient statistical power.⁵⁰ I compute local average wages on all the workers in the sample, but I only include in the regression young workers under 40. Finally, cities' TFP are not empirically observed. However, when the spatial dispersion in TFP is small, wages closely track skills and $\zeta_{it} \approx 0$.⁵¹ I thus estimate (18) in two steps. First, I estimate the local projection under the assumption of small TFP gaps. I then estimate structurally the other parameters of the model, including cities' TFP (Section 4). In the second step, I re-estimate (17) controlling for ζ_{it} .⁵²

Similar local projections have been used in the learning from coworkers literature. For instance, Nix (2020) and Jarosch et al. (2021) project respectively future wages on the average education within the firm and the average wage within the establishment where workers are employed. My empirical design differ from theirs in two ways. First, it studies the returns to local interactions within cities rather than within firms. Second, it includes an interaction term between workers' wage and the wage of the city where they work to estimate learning complementarities.

I summarize the two assumptions essential to the identification of the learning technology in the

⁴⁹As a robustness, in Section 3.5 I control for work characteristics (e.g. industry or occupation) that may affect wages beyond workers' skills.

⁵⁰Section 4.2 describes how the 5-year estimates produced by (17) are turned into structural 15-year estimates.

⁵¹Recall that mean log wages are normalized to zero. Hence, small TFP differentials across cities imply $\log T_{\ell} \approx 0$ and $\zeta_{it} \approx 0$.

⁵²In practice, I find the spatial dispersion in TFP to be small as it explains less than 2% of the wage variance.

following proposition.

Proposition 6 (Identification).

Suppose that

1. Interactions are random within cities, $(w_{it}, w_{pit}) \perp \mathbb{E}_{\ell_{it}}[\log w]$,
2. The idiosyncratic learning shocks are i.i.d. across workers and cities, $e_{it} \perp (w_{it}, \mathbb{E}_{\ell_{it}}[\log w_{it}])$.

Then, (18) produces unbiased estimates of the learning technology: $\hat{\beta} = g_1$, $\hat{\gamma} = g_2$ and $\hat{\delta} = g_{12}$.

3.4 Endogeneity concerns

The assumptions underlying Proposition 6 may not hold empirically. Skilled workers may be able to target interactions with skilled partners, $(w_{it}, w_{pit}) \not\perp \mathbb{E}_{\ell_{it}}[\log w]$. The learning complementarities estimated by (18) would then be biased upward, $|\delta| > |g_{12}|$. To investigate how large is this bias, I estimate (18) separately for small and large cities as well as for more or less unequal locations. To the extent that skilled workers can better target skilled interactions in larger or more unequal cities, the estimated complementarity should be higher in those places.

Meanwhile, the distribution of learning shocks may vary across workers and cities, $e_{it} \not\perp (w_{it}, \mathbb{E}_{\ell_{it}}[\log w_{it}])$. For instance, young workers may learn faster for reasons other than local interactions while also earning lower wages. Meanwhile, the faster wage growth of productive cities may be due to other form of agglomerations than local interactions, e.g. a steeper local job ladder.

I alleviate this second set of endogeneity concerns in three ways. First, I control for worker-level characteristics known to shape wage growth (Adda and Dustmann, 2023). I include age fixed effects to control for the faster growth of younger workers. To control for long-term contracting and decreasing returns to experience, I add fixed effects for tenure at the job, at the occupation, and at the industry level. Finally, to account for the effect of job switching on wage dynamics, I include a dummy for employer switching.

Second, I control for potential unobserved differences in learning shocks across cities through a set of granular spatial fixed effects. Specifically, I estimate the augmented local projection

$$\log w_{it+1} = \alpha_{tn_{it}^r}^R + \alpha_{tg_{it}}^W + \beta \log w_{it} + \gamma \overline{\log w}_{n_{it}^w} + \delta \log w_{it} \overline{\log w}_{n_{it}^w} + \Psi' \mathbf{X}_{it} + \zeta_{it} + u_{it}. \quad (19)$$

In the above, n_{it}^r and n_{it}^w are the neighborhoods where worker i resides and works. The parameters $\alpha_{tn_{it}^r}^R$ are therefore year by neighborhood of residence fixed effects, and $\overline{\log w}_{n_{it}^w}$ is the average wage of the workers employed in neighborhood n^w . Meanwhile, $\alpha_{tg_{it}}^W$ are fixed effects that control for the work environment of i . I adopt two different specifications for these fixed effects. First, I set g_{it} to be the city where i is employed. In this case, (19) effectively compares two workers who live in the same neighborhood but work in different neighborhoods in the same city. Second, I set g_{it} as the firm-city where i is employed. Then, (19) compares workers who live in the same neighborhood and work in the same firm but in establishments located in different neighborhoods within the same city. In both cases, I control for the geographic distance between the neighborhood of residence and work.

The two sets of fixed effects control flexibly for unobserved spatial and firm heterogeneity in wage dynamics. The residence fixed effects take into account that workers who live in wealthier neighborhoods may enjoy steeper wage profiles, e.g. due to a better access to public transportation. Meanwhile, productive firms may offer higher wages and more lucrative promotions to its workers, which is controlled for by the city-firm fixed effects. Finally, by comparing workers who live in the same neighborhood and work in the same firm, the fixed effects also reduce workers' unobserved heterogeneity.⁵³

Third and last, I rely on an instrumental variable strategy to generate quasi-random variations in the quality of neighborhoods' learning opportunities. Equations (18) and (19) are effectively peer effect models. These models are often subject to a reflection problem (Manski, 1993; Angrist, 2014). Individuals working in the same neighborhood may indeed be exposed to common productivity shocks that affect their present and future wages.⁵⁴ In that case, measuring the quality of the local learning opportunities through the local wage conflates the returns to local interaction with the effect of the productivity shocks.

I therefore identify spatial variations in skill density that are plausibly unrelated to local productivity shocks. To do so, I instrument neighborhoods' average wage by past changes in their white-collar employment share. I define white-collar workers through their occupations. I use the change in their employment share between 1993 and 2000. The instrument is relevant to the extent that past changes in the occupational mix of neighborhoods have long-term consequences on their skill composition. Meanwhile, the exclusion restriction holds if the underlying shocks that triggered these changes are not correlated with the present productivity shocks. I provide indirect evidence in support of the relevance and exclusion restrictions in Table D.2. First, past changes in the white-collar employment share are strongly correlated with the current employment share (column 2). Meanwhile, there is no statistical relationship between the change in the white-collar employment share between 1993 and 2000 and their change between 2010 and 2019 (column 4).

By isolating variations in local skill density due to past *changes* in occupation composition, the instrument estimates the effect on neighborhoods' skill composition on wage growth net of time-invariant local characteristics. Over twenty years, changes in neighborhoods' skill composition may however affect other local characteristics than the quality of the learning interactions (e.g. the physical stock of capital), and indirectly through those wage growth. My identification strategy cannot separate the "interaction" channel from those other forms of agglomeration. However, to the extent that both channels capture how the local skill composition affects workers' human capital accumulation, I view them as theoretically isomorphic.

How to interpret the elasticities estimated by (19)? The parameters obtained from the local

⁵³An alternative is to include worker fixed effects in (19). In this case, present wages need to be instrumented à la Arellano and Bond (1991). However, this instrument requires $T \geq 3$. In my setting, by using five-year wage growth and restricting my sample to the 2009-2019 period, most of my individuals are observed for $T \leq 3$, making it difficult to obtain precise estimates of the learning technology.

⁵⁴The second assumption of Proposition 6 rules out local correlated shocks, which allows (18) to produce unbiased estimate of the learning technology. Table D.1 further confirms through Monte-Carlo simulations that the reflection problem is not present in (18).

projections (18) and (19) can be interpreted as reduced-form elasticities. In that case, γ measures the average treatment effect of the local skill composition on skill growth, and δ estimates the heterogeneity in treatment effects across the skill distribution. With this reduced-form interpretation, the elasticities can be quantitatively compared across specifications to study what are the implications of relaxing the assumptions behind Proposition 6. Interpreting the elasticities estimated by (19) as structural parameters is more challenging. Through the lens of Proposition 6, the controls present in the augmented local projection may indeed soak relevant structural variations – the so-called “bad controls” (Angrist and Pischke, 2009) – and generate biased structural estimates. This tension between endogeneity concerns and structural estimation is inevitable and goes beyond this paper. Nevertheless, I still consider the elasticities produced by (19) as informative of the impact of locations’ skill composition on workers’ human capital accumulation.

3.5 Results

Table 1 presents the estimates of the learning technology. Columns 1 to 4 use spatial variations in average wages at the city level, and columns 5 to 8 use variations at the neighborhood level. Standard errors are clustered at the same level as the spatial wage variation. The first and second columns present the estimates produced by the model-consistent local projection (18). The first column does not control for city TFP whereas the second does. In both cases, the three elasticities are estimated to be positive and significant at the 0.1%. In addition, the two sets of estimates are very similar and not statistically different from each other at the 5%. I take the estimates of the second column as the baseline. Three predictions emerge out of them.

First, high-wage workers enjoy faster wage growth ($\hat{\beta} > 1$): a wage increase of one standard deviation boosts wage growth by 0.4 log points over five years for workers in the average city.⁵⁵ Workers starting their career with lower wages therefore do not catch-up to high-wage individuals – although this effect alone is quantitatively small. The estimated wage process is therefore non-stationary.⁵⁶ This result rests however on the time horizon considered. In Figure D.4, I estimate the local projection for time horizons between one and five years. For shorter-term wage growth, I do estimate an auto-correlation parameter β close but under the unit root, in accordance with estimates from the literature (e.g. Guvenen, 2009). I take this as indirect evidence that, by considering longer-term variation, I estimate a learning technology that captures permanent variations in human capital rather than transitory, mean-reverting shocks.

Second, individuals employed in high-wage cities experience faster growth ($\hat{\gamma} > 0$). An increase by one standard deviation of the city wage implies an additional growth of 1.6 log points for the average worker. Through the lens of the model, this implies that workers learn on average more from skilled individuals.

⁵⁵The average wage is normalized to zero, and therefore so is the wage of the average French city. Hence, $\beta - 1$ represents the marginal effect of increasing workers’ wages on wage growth for workers in the average French city. Similarly, γ estimates the marginal growth effect of increasing the city’s average for the average French worker.

⁵⁶The non-stationarity of the wage process is not a problem in my setting due to the overlapping generation structure that guarantees the existence of an ergodic skill distribution.

Table 1: The returns to local interactions

Dep. variable: 5-year wage	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS
Wage (β)	1.010 (0.003)	1.010 (0.003)	1.010 (0.003)	1.010 (0.003)	1.000 (0.001)	0.935 (0.002)	0.998 (0.002)	0.935 (0.003)
Local wage (γ)	0.122 (0.005)	0.107 (0.015)	0.095 (0.012)	0.111 (0.005)	0.078 (0.008)	0.032 (0.008)	0.099 (0.022)	0.053 (0.021)
Wage \times local wage (δ)	0.102 (0.008)	0.108 (0.032)	0.102 (0.007)	0.104 (0.009)	0.062 (0.014)	0.071 (0.013)	0.078 (0.026)	0.077 (0.023)
Log city size			0.002 (0.001)					
<hr/>								
Controls								
City TFP	.	✓
Worker-level	.	.	.	✓	✓	✓	✓	✓
Distance work-residence	✓	✓	✓	✓
Establishment growth	✓	.	✓
<hr/>								
Fixed effects								
Residence	✓	✓	✓	✓
City	✓	.	✓	.
City \times firm	✓	.	✓
Obs.	971,401	971,401	971,401	971,401	971,401	974,401	974,401	974,401
F-stat.	55,244	53,539

Standard errors clustered at the city level for columns 1 to 4 and at the neighborhood level for columns 5 to 8. Sample includes all workers between 25 and 40 year old. Wage growth distribution truncated at the 5% within cities. Local wage defined as the city average wage in column 1 to 4 and the neighborhood average wage for columns 5 to 8. TFP estimates in column 3 obtained from the model (Section 4). Worker-level controls include age, job tenure, occupation tenure, and industry tenure fixed effects, as well as a dummy if the worker changed employer between the five years. Columns 1 to 4 include a year fixed effect, and all the fixed effects in column 5 to 8 are fully interacted with year fixed effects. Column 7 and 8 instrument for the neighborhood (of work) wage by the change in the white-collar employment share between 1993 and 2000.

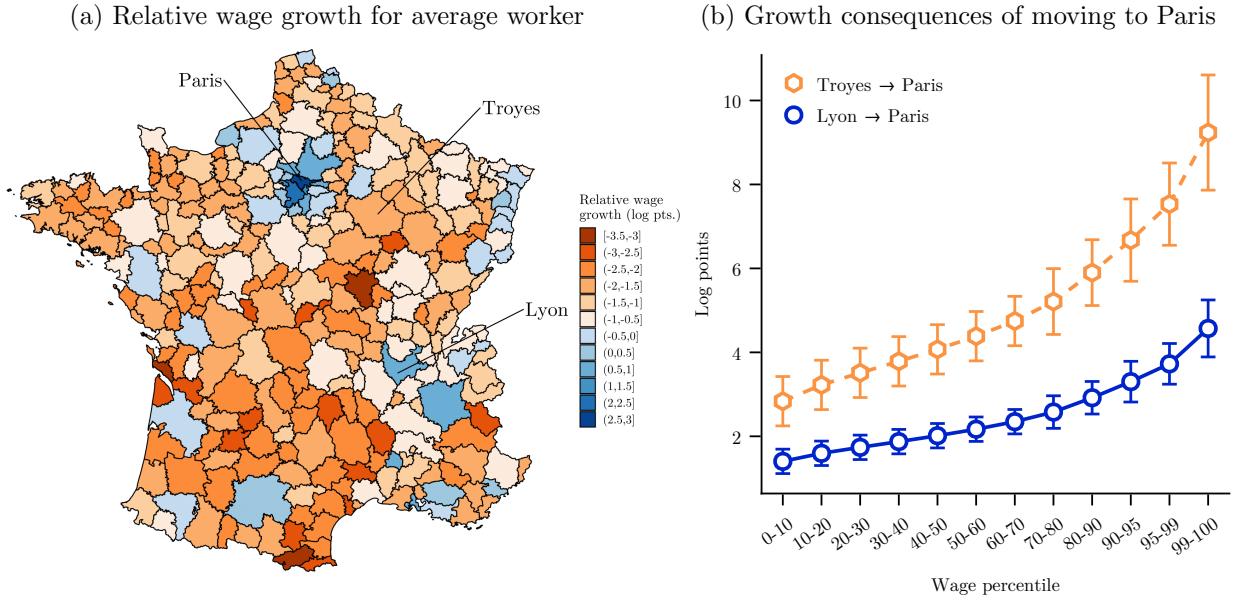
Third and last, high-wage individuals working in high-wage cities see their wage grow faster than their low-wage counterparts in the same location ($\hat{\delta} > 0$). An increase by one standard deviation of the city average wage implies an additional growth of 1 log points for workers at the 10th percentile of the wage distribution, compared to an increase of 2.6 log points for workers at the 90th percentile. From (18), this implies that the learning technology displays strong within-skill complementarities: skilled workers learn relatively more from skilled partners than their low skill counterpart.

The estimated returns to local interactions are substantial. Figure 2a displays the predicted relative wage growth by commuting zones for a worker with the average skill.⁵⁷ Migrating from Troyes to Paris triggers a wage growth increase of 4.5 log points per five year for the average French worker, while moving from Lyon to Paris implies wage growth gains of 2.2 log points. Altogether, the predicted wage growth explain 64% of the between-city wage growth variance.

The between-city difference in growth are very heterogeneous across workers due to the estimated learning complementarities. Figure 2b plots the difference in predicted growth between Paris, Lyon and Troyes across the wage distribution. All workers, both low- and high-wage, experience faster

⁵⁷These estimates are computed as $\hat{\gamma}\mathbb{E}_\ell[\log w]$. They correspond to the change in wage growth from a migration for the average French worker. These estimates do not take into account the sorting of workers across cities.

Figure 2: The estimated growth gaps across space and workers



Note: left-panel displays the relative average growth by commuting zone for the average French worker, $\hat{g}_2 \mathbb{E}_{\ell_{it}} [\log w_{it}]$. Right-panel displays the predicted growth difference between Paris and Troyes (orange hexagons) and Paris and Lyon (blue circles) across the wage distribution, $(\hat{g}_2 + \hat{g}_{12} \log w_{it}) (\mathbb{E}_{\ell'} [\log w_{it}] - \mathbb{E}_{\ell} [\log w_{it}])$. Both set of statistics are computed using the estimates of column 1 in Table 1.

growth employed in Paris relative to the other two cities. High-wage workers benefit however more over time from working in high-wage locations. For instance, the wage growth gap between Paris and Troyes is 2.8 log points for workers in the bottom 10% of the wage distribution. It is 3.7 log points for workers in the top 10%. The same pattern holds between Paris and Lyon, although the gaps are smaller as the two cities have a more similar skill composition.

Robustness The remaining columns of Table 1 provide a battery of robustness exercises to address the endogeneity concerns mentioned in Section 3.4.⁵⁸ Column 3 investigates the role of large cities in shaping the estimated elasticities. A vast literature, started by de la Roca and Puga (2017), finds indeed that larger cities boost workers' wage growth. In column 3, I thus control for city size to net out the correlation between city size and local wages. In accordance with the previous literature, I also find that workers in larger city experience faster growth. However, the effect of city size is one order of magnitude smaller than the effect of skill composition: an increase in city size by one standard deviation implies a 0.4 log points increase in wage growth for the average worker.⁵⁹ The difference in magnitude justifies why I abstract from city size in the quantitative model.⁶⁰ In

⁵⁸In all of the exercises, I do not control for cities' TFP. Controlling for cities' TFP is indeed computationally costly since it requires to solve the entire estimation routine presented in Section 4. Since the estimates of the first and second columns of Table 1 were not statistically different from each other, I abstract from this computation cost.

⁵⁹Most papers in this literature, to the exception of Eckert et al. (2022), identify the effect of size on growth from spatial correlation between city size and wage growth. In fact, the empirical model of de la Roca and Puga (2017) coincides with (18) under the restriction that $\beta = \delta = 1$.

⁶⁰See Duranton and Puga (2023) for a spatial growth model without heterogeneous workers in which size shapes aggregate human capital accumulation.

addition, the point estimates are not statically different at the 5% from the baseline estimates.⁶¹

Columns 4 to 8 displays the point estimates produced by (19), gradually adding the worker-level controls, the spatial fixed effects, and the instrument variable. The fourth column introduces the worker-level controls: age, tenure and employer transition fixed effects. The point estimates are not statistically different from the baseline estimates. The same hold when adding occupation by industry fixed effects to control for productivity trends, or when instrumenting workers' wage by their past wage to net out transitory shocks (Appendix D.5). The standard drivers of wage growth thus do not affect the estimated wage growth elasticities.

The fifth column adds the neighborhood of residence and city fixed effects to control for unobserved spatial heterogeneity in wage growth, and the sixth columns adds the firm by city fixed effects to soak unobserved heterogeneity in wage dynamics across firms.⁶² All the fixed effects are fully interacted with year fixed effects. In addition, to account for establishment-specific productivity shocks, e.g. at the headquarter level, I control for the growth in average wages at the establishment level in column 6. In both columns, the two elasticities governing how workers' skill growth depends on the skill composition of where they work, γ and δ , remain positive. Comparing two workers employed in the same firm, in the same city, and living in the same neighborhood, the individual working in the relatively high-wage neighborhood experiences faster wage growth – and disproportionately so if these workers earn initially higher wages.

The last two columns introduce the instrument variable to address the potential presence of confounding shocks at the neighborhood level. In both cases, the F-statistics are well above the conventional thresholds for weak instruments (Stock and Yogo, 2002; Andrews et al., 2019). I find the 2SLS estimates to be slightly larger than the OLS ones, although they cannot be statistically differentiated from each other at the 5%.⁶³ I therefore conclude that neighborhoods with a greater skill density boost the wage growth of the individuals working there, and disproportionately so if they are skilled. Furthermore, the two elasticities determining the magnitude of this dynamic effect, γ and δ , are not statistically different from the baseline estimates of column 2.

Columns 3 to 8 of Table 1 therefore confirm that the skill composition of where individuals work shape over time their human capital accumulation.⁶⁴ In addition, I view the stability of the estimated wage growth elasticities in Table 1 as suggestive evidence of the robustness of the learning technology estimates. I now turn to estimating the remaining parameters of the quantitative model.

⁶¹I also show in Appendix D.5 that the estimated elasticities are not driven by a few large cities.

⁶²Table D.3 in Appendix D.5 further adds city by industry by occupation fixed effects. Beyond controlling for heterogeneity in wage growth across occupations and industries, these fixed effects also allow for skill complementarities, decreasing returns to scale, and productivity spillovers in the production function at the city level.

⁶³The downward bias of the OLS estimates could in part be caused by mean-reverting productivity shocks at the neighborhood level.

⁶⁴In addition, Appendix D.5 shows that the wage growth elasticities are similar in large and small cities, are increasing in the time horizon considered, and remain positive after controlling for the skill composition of the establishment where workers are employed.

4 Model Estimation

The remainder of the structural estimation is split into three parts. In the first part, I define the geography and the time horizon of the model, and accordingly externally calibrate the discount factor. In the second part, I use the structure of the model to derive estimating equations that identify a first group of parameters without the need for simulation. In the third part, I calibrate the remaining parameters to match salient features of the wage and city-size distributions. The estimated parameters are presented in Table E.2.

4.1 Definitions

Consistent with the evidence of Section 3, I define a location in the model as a commuting zone. Solving the model for the 297 commuting zones is computationally challenging as it requires to solve for the entire skill distribution within each city. Instead, I create 30 types of cities and restrict all cities within the same type to be homogeneous. Importantly, there are still 297 cities in the model and learning interactions happen within cities. I define the first 10 types as the 10 largest French cities.⁶⁵ To construct the remaining 20 types, I divide France into four geographic districts (North-East, North-West, South-East and South-West). I then subdivide each district into five types using a k-mean algorithm that clusters cities based on variables that proxy for the geographic primitives of the model.⁶⁶ Appendix E.1 contains details on the variables used in the algorithm, and Figure E.1 plots the resulting city types.

Regarding the model's time horizon, the model features two lifecycle periods covering the entire career of workers.⁶⁷ In the young phase, individuals work and learn while they only work in the old period. In the data, the wage-age profile plateaus around 40 year old. Accordingly, I set a lifecycle period to fifteen years and map the young period to ages 25 to 40 and the old period to ages between 40 and 55. The model does not provide an explicit moment to estimate the discount factor. I therefore calibrate it externally, take a yearly discount factor of 0.975, and set $\beta = 0.975^{15}$.

4.2 Model Inversion

In the second step, I invert the model to estimate the parameters dictating the housing supply and demand, the migration costs, and the the learning technology as described in Section 3. The estimating equations are derived in Appendix E.2.

⁶⁵The ten largest commuting zones are Paris, Lyon, Roissy, Saclay, Toulouse, Bordeaux, Marseille, Nantes, Lilles, and Rennes.

⁶⁶While this classification is not without loss of generality, it is likely to have little impact on the counterfactuals since cities within each city-type are rather homogeneous. Figure E.2 plots the within-cluster to total sum of square residuals as a function of the number of clusters within each district. With five types, the clustering algorithm captures 83% of the total variation.

⁶⁷Adding more lifecycle periods would make the model's learning technology more comparable to the estimates reported in Table 1. However, it would also increase its computation complexity without much effects on the counterfactuals of interest.

Housing From the Cobb-Douglas preferences, α is the housing expenditure share. I therefore read off α from the French national accounts and set $\alpha = 0.2$ (INSEE, 2020). Regarding the housing supply parameters, the housing market clearing conditions relate housing prices to local expenditures through

$$\log p_\ell = \left(\frac{1}{1 + \delta} \right) \log \left(\frac{1 - \alpha}{\mathcal{H}} \right) + \left(\frac{1}{1 + \delta} \right) \log Y_\ell, \quad \forall \ell, \quad (20)$$

where p_ℓ and Y_ℓ are the housing rental price and total expenditures in city ℓ . I obtain p_ℓ from the “Carte des Loyers” (Rental Map), which provides estimates for the average monthly rent per meter square at the municipal level.⁶⁸ Meanwhile, the expenditures in city ℓ are given by the payments to the labor inputs, $Y_\ell = N_\ell \mathbb{E}[W_\ell]$, where N_ℓ and $\mathbb{E}[W_\ell]$ are the employment share and average wage of city ℓ that I compute from the cross-sectional matched employer-employee dataset. To match the frequency of the rent data, I set wages at the monthly frequency in euros of 2018. Given $\{p_\ell, N_\ell, w_\ell\}_{\ell=1}^L$ and α , the housing supply parameters, \mathcal{H} and δ , can be recovered from (20) by OLS. Figure E.5c compares the rent prices in the data with the prices in the model. While simple, the model captures 71% of the between-city rent variations.

Migration costs The migration costs are recovered non-parametrically from the observed migration flows. Using workers’ optimal location decisions and the assumption of symmetric costs, the model predicts that the cost to move from city l to city ℓ for workers with age $a \in \{y, o\}$ is⁶⁹

$$e^{-2\vartheta \kappa_{l\ell}^a} = \int \left(\frac{n_{ll}^a(s)}{n_{ll}^a(s)} / \frac{n_{\ell\ell}^a(s)}{n_{\ell\ell}^a(s)} \right) dN^a(s), \quad \forall l, \forall \ell. \quad (21)$$

In equation (21), $n_{l\ell}^a(s)$ is the number of workers with age a and skill s who migrates from l to ℓ . The cost to move between these two cities is thus identified from the size of the bilateral migration flows relative to the numbers of individuals who do not move. Measuring the right-hand side of (21) requires to observe workers’ skill and migration decisions. I proxy workers’ skill with their wage quartile.⁷⁰ Consistently with the model, I measure migration decisions differently for young and old workers. For young workers, I compute $n_{l\ell}^y(s)$ as the number of workers under 40 born in city l and currently living in city ℓ with skill s . For old workers, I compute $n_{l\ell}^o(s)$ as the number of workers with age above 40 that lived in city l 15 years ago and are currently living in city ℓ with skill s .⁷¹ Both flows are computed from the long-panel.

Figure E.3 plots the estimated migration costs by city of origin. Empirically, 45% of young

⁶⁸These rents are residualized and correspond to the rent paid for a typical 40m² apartment in France. I compute p_ℓ at the city-level by taking the population weighted average of the municipal rents.

⁶⁹As mentioned in Section 2.6, these migration costs can alternatively capture correlated location preferences – up to welfare considerations. In this case, (21) captures the autocorrelation in location preferences.

⁷⁰Proxying workers’ skill with their wage quartile may lead to biased migration costs as wages are the product of workers’ skill and city TFP. The biases are likely to be small in practice for two reasons. First, the estimated TFP variance explains less than 2% of the wage variance. Second, (21) estimates migration costs off double difference in migration flows, and $n_{l\ell}(s)/n_{ll}(s)$ partially nets out the biases that emerge from using wages as a proxy for skills.

⁷¹Equation (21) can be used to the extent that $n_{l\ell}^a(s) \neq 0$ for all ℓ . To guarantee that this is the case for all cities in my sample, I directly compute the flows $n_{l\ell}^a(s)$ at the city-type level.

workers live in cities different than their birthplace, whereas 20% of old workers change locations between their youth and their old age. Through the lens of the model, this is rationalized with higher migration costs for old workers. The average migration cost for young workers is 1,255€, which corresponds to 43% of their income. For old workers, the average migration costs is 1,594€(44% of their earnings).⁷²

The model predicts substantial heterogeneity in migration probabilities across workers. In particular, young skilled workers born in productive cities are relatively more likely to work there, whereas young skilled workers born in low-TFP locations are more likely to move out. Appendix E.3 provides more details on the migration heterogeneity.

Learning technology The learning technology parameters g_1 , g_2 and g_{12} are estimated according to Proposition 6. In the model, the young period lasts fifteen years. In the data, I use wage growth at the five year horizon to have enough statistical power. To get a learning technology with the appropriate time horizon, I therefore estimate (18) for three age bins: 25 to 30, 30 to 35 and 35 to 40 (Figure D.5). I then set $g_1 - 1$, g_2 and g_{12} as the sum of their respective estimated age-specific skill growth elasticities.⁷³

4.3 Indirect Inference

The remaining 95 parameters govern workers' productivity and location preferences. I calibrate them jointly to match salient features of the wage and city-size distributions. I provide first arguments that justify the identification strategy. I then show numerically how the chosen moments affect the calibration of the model.

City productivity I set the productivity of each city to match its average wage in the data. In the model, the average wage of city ℓ is given by

$$\mathbb{E}[W_\ell] = T_\ell \int s\pi_\ell(s)ds, \quad \forall \ell, \tag{22}$$

where $\int s\pi_\ell(s)ds$ is the average skill of the workers employed in ℓ . The average wage on the left-hand side can be measured from the matched employer-employee dataset. Holding constant the skill distribution, a greater TFP implies higher local wages. However, the average skill in city ℓ is not observed, and it is an equilibrium object that depends on the spatial distribution of TFPs. Equation (22) therefore cannot be directly inverted to recover T_ℓ . Nevertheless, given $\{T_\ell\}_{\ell=1}^L$ and the other parameters, the spatial distribution of skills can be recovered in equilibrium from the model. Equation (22) therefore defines a fixed point over $\{T_\ell\}_{\ell=1}^L$ that can be solved for numerically to obtain cities' TFP without taking a stance on how to measure skills empirically.

⁷²The estimated migration costs are in utils. The reported estimates are converted to monetary unit through $\kappa_{\ell e}^a P_\ell$. The reported average cost are computed as unweighted average, excluding $\kappa_{\ell e}^a$. As such, they do not represent the migration costs *actually* paid by workers.

⁷³That is, I set $g_1 - 1 = \hat{\beta}_{25-30} + \hat{\beta}_{30-35} + \hat{\beta}_{35-40} - 3$, $g_2 = \hat{\gamma}_{25-30} + \hat{\gamma}_{30-35} + \hat{\gamma}_{35-40}$ and $g_{12} = \hat{\delta}_{25-30} + \hat{\delta}_{30-35} + \hat{\delta}_{35-40}$.

Worker-level productivity Four parameters govern the distribution of worker-level productivity. The first two, μ_y and σ_y , are the mean and the standard deviation of the exogenous skill distribution of young workers. The level of workers' skill and cities' TFP are not separately identified. I thus normalize the economy-wide average log skill to zero, and set μ_y to ensure that this normalization holds.⁷⁴ Holding cities' TFP constant, a greater skill dispersion implies a greater wage variance. I therefore calibrate σ_y to match the aggregate wage variance of young workers.

The other two parameters implicitly shape the skill distribution of old workers in equilibrium. First, g_0 in the learning technology (14) dictates the overall amount of human capital accumulation. The higher g_0 , the higher the average skill of old workers, and thus the higher their average wage. I therefore set g_0 to match the wage ratio between old and young workers. Second, the variance of the idiosyncratic learning shocks, σ_ν , influences the dispersion in the skills of old workers. I thus calibrate σ_ν to match the variance of log wages for old workers.

Location preferences The remaining parameters – cities' amenities and the dispersion in the taste shocks – determine workers' location preferences. The higher the amenities offered by a city, the more workers want to live there. I therefore set the age-specific local amenities to match the cities' age-specific employment share.⁷⁵ The dispersion in idiosyncratic location preferences, ϑ , governs the amount of sorting that prevails in equilibrium. When $\vartheta \approx 0$, the idiosyncratic location preferences are very dispersed, and the skill distributions are homogeneous across cities. As a consequence, there are no spatial differences in within-city wage inequality. As ϑ increases, skilled workers concentrate in productive cities, and those places become relatively more unequal. I therefore set ϑ to match the cross-sectional correlation between cities' average wage and wage variance.⁷⁶

Sensitivity How precise is the calibration exercise? Figure E.8 reports how the targeted moments vary as a function of the parameters in the model. Across the board, the targeted moments are sensitive in the parameters they are supposed to identify, with a 1% change in the parameter associated with a change in the targeted moment between 0.5% and 2%. Appendix E.4 describes in more details this sensitivity exercise and reports the sensitivity measure of Andrews et al. (2017).

4.4 Estimation Results and Over-identification Exercises

The estimated model implies a large degree of spatial sorting (Figure E.6). 30% of workers in the top 10% of the skill distribution choose to work in Paris, and this fraction goes as high as 46% for workers in the top 1%. In contrast, low-skill workers are much less spatially concentrated: only 10% of workers in the bottom half of the skill distribution decide to work in Paris. These between-skill differences in willingness to work in productive cities also vary across the lifecycle. In Appendix E.6,

⁷⁴That is, I impose $0 = \mathbb{E}[\log S] = (\mu_y + \mathbb{E}[\log S^o])/2$, where $\mathbb{E}[\log S^o]$ is the (equilibrium) average skill of old workers. I also ensure that this normalization holds when estimating the learning technology in Section 3.

⁷⁵As for their TFP, cities' employment share can theoretically be expressed as a function of the their amenities and a residual (equation (49) in Appendix E.2). The residual can be computed within the model, and cities' amenities $\{B_\ell^y, B_\ell^o\}_{\ell=1}^L$ are recovered as a solution to a second fixed point. Figure E.4b plots the estimated amenities.

⁷⁶The level of ϑ depends on the monthly wage frequency adopted, making it hard to compare its value with previous estimates from the literature.

I show as an over-identification exercise that, in the model and in the data, young skilled workers have a relatively higher propensity to work in productive cities than their old counterparts.

Worker sorting explains the vast majority of the between-city wage differentials. In the model, the between-city wage variance can be decomposed into three terms:

$$\text{Var}[\mathbb{E}(\log W_\ell)] = \text{Var}[\log T_\ell] + \text{Var}[\mathbb{E}(\log S_\ell)] + 2\text{Cov}[\log T_\ell, \mathbb{E}(\log S_\ell)].$$

The first term captures how much the spatial segmentation of productivity affects spatial wage inequality. I find the dispersion in cities' TFP to be small as it rationalizes only 16% of the between-city wage gap – and 1.7% of the total wage variance. The second and third terms capture the spatial differences in skill composition that emanates from the sorting of workers into cities. Together, they explain the remaining 84% of the between-city wage variance. These estimates align with those of the literature that quantifies the impact of cities on wage inequality through movers designs (Dauth et al., 2022; Lhuillier, 2022; Card et al., 2023). In Appendix E.6, I follow this literature and, as a second over-identification exercise, re-estimate cities' TFP using a two-way fixed effect model à la Abowd et al. (1999).⁷⁷ The newly estimated TFPs can barely be distinguished from the baseline estimates. I therefore conclude that the small dispersion in TFP across space is a robust feature of the French labor market.

Finally, through the sorting of workers across space and the estimated learning technology, the model explains 64% of the between-city wage growth variance in the data. To what extent are these differences in wage growth caused by the spatial segmentation of learning opportunities? And what are the implications for spatial inequality and aggregate productivity? I now use the estimated model to answer these questions.

5 The Tradeoff Between Human Capital and Inequality

In this section, I compare the baseline equilibrium with a counterfactual economy in which interactions are not segmented by cities. In the counterfactual world, interactions continue to be random, but the likelihood of an interaction is given by the aggregate skill density rather than the skill density of the city where individuals work.⁷⁸ I compare the two economies in steady state. Table 2 summarizes the key results.

5.1 Learning within Cities and Spatial Inequality

I find that learning opportunities are very spatially concentrated. Figure 3a plots the average skill growth by workplace in the baseline equilibrium (blue circles). On average, workers' skills grow by 15 log points throughout their lifetime. Individuals who work in high-wage cities experience faster human capital accumulation. For instance, workers in Paris experience a skill growth of 23

⁷⁷This approach is not used as the baseline as it requires to take a stance on how to empirically measure skills.

⁷⁸The aggregate skill density of the counterfactual economy may in turn differ from the baseline skill distribution to the extent that cities shape human capital accumulation.

Table 2: The impacts of spatially segmented learning opportunities on inequality and productivity

	No segmentation	Segmentation	Change
Average skill of old workers	1.231	1.246	1.21%
.. due to learning complementarity	.	.	58.5%
Average wage (€)	3,210	3,296	2.68%
Between-city wage variance	0.007	0.024	0.017
Between-city wage growth variance (log points)			
.. by workplace	0.016	13.85	13.85
.. by birthplace	0.000	3.281	3.281

Table contains aggregate statistics on inequality and productivity under two different assumption regarding the segmentation of learning interactions. First column corresponds to the case in which interactions are random in the whole economy. Second column is when interactions are fully segmented by cities (baseline, estimated model). The third column is the change between the two equilibrium.

log points. In the model, these differences in learning can originate from the sorting of fast-learning workers in productive cities, or from the concentration of learning opportunities in the locations. To quantify the relative importance of each channel, the orange hexagons in Figure 3a displays the average skill growth by workplace were interactions not segmented by cities – holding the spatial allocation of workers constant. Skilled individuals are disproportionately in productive cities, and these workers accumulate faster human capital on their own ($g_1 > 1$). As a result, workers in Paris continue to experience relatively faster skill growth in this counterfactual economy. Yet, this sorting channel is quantitatively small as it explains only 2% of the model-predicted between-city skill growth variance. I conclude that the segmentation of learning opportunities is the main driver of the spatial differences in human capital accumulation.

The concentration of learning opportunities in a few cities has two consequences on spatial disparities. First, it engenders learning inequality. Figure 3b displays the average skill growth by birthplace against the city's average wage.⁷⁹ When workers learn from the individuals around them and face migration costs, workers born in or near skill-dense cities have an easier access to the local learning opportunities, and they enjoy faster human capital accumulation.⁸⁰ This birthplace learning premium is substantial. For instance, workers born in Paris have a lifetime skill growth 3 log points higher than the average French worker, and as a result, their human capital at the end of their career is 5% larger. In contrast, workers born in the bottom 25% of the city-growth distribution have a lifetime skill growth 1.6 log points lower.⁸¹ The impact of individuals' birthplace on their lifetime learning are exacerbated for middle and skilled workers for whom being able to learn from other skilled workers is crucial for their human capital accumulation (Figure F.1).

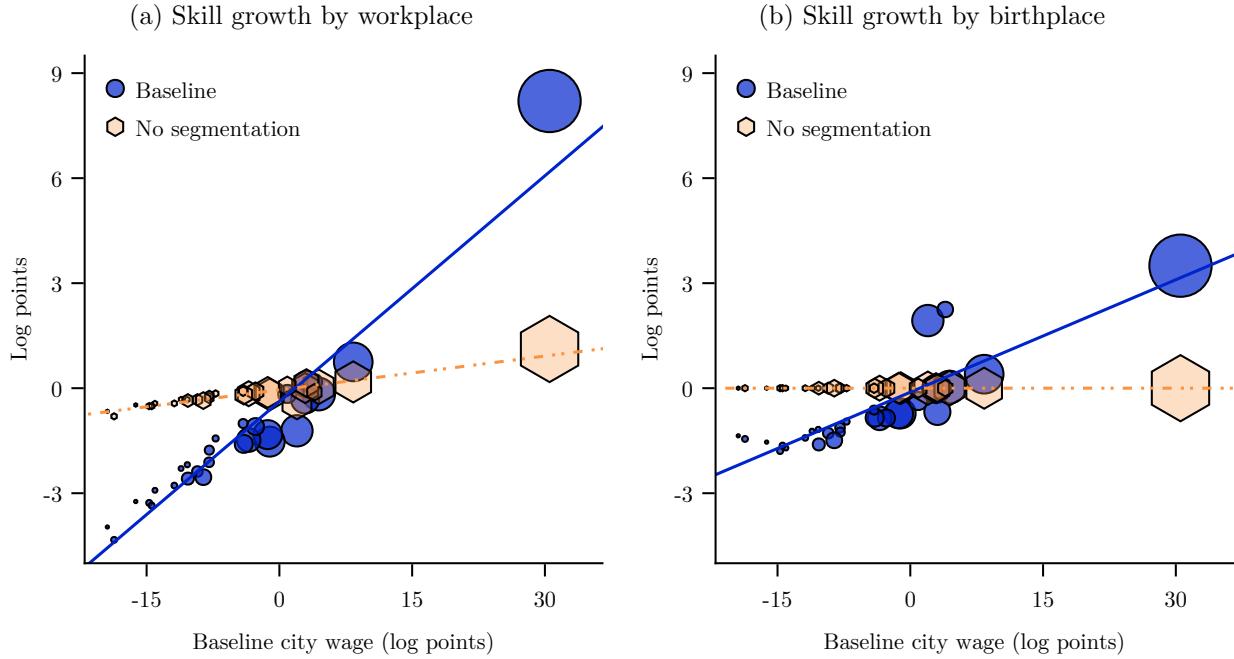
Second, the confinement of learning opportunities to productive cities amplifies spatial wage

⁷⁹The model explains 55% of the wage growth variance across birthplaces in the data.

⁸⁰Workers born near Paris indeed experience relatively faster skill growth, as shown in Figure F.2.

⁸¹The spatial differences in learning feeds into lifetime income inequality. When opportunities are spatially concentrated, the lifetime income of workers born in the bottom 25% of the city-growth distribution is 4% lower than the average French worker, compared to 2% when interactions are not segmented.

Figure 3: Between-city differences in skill growth in the model and in the data



Note: panel (a) displays the average skill growth by workplace in the equilibrium with segmented interactions (blue circles) and in the equilibrium without segmented interactions (orange circles) against the baseline city average wage. The blue and orange dashed lines are the (unweighted) fitted lines. The grey line is the empirical (unweighted) fitted line. Panel (b) displays the average skill growth by birthplace. The same nomenclature as in panel (a) applies. The size of the markers is proportional to city size.

inequality. Proposition 2 found that, when learning takes place within cities and individuals learn relatively more from skilled workers, productive cities get bigger as young workers go there to benefit from the local learning opportunities. In addition, these opportunities are more tailored to skilled workers in the presence of strong within-skill learning complementarities, and the spatial concentration of high-skill rises. I find these agglomeration effects to be quantitatively large (Figure F.4): the population of Paris increases from 7% to 14% of the French workforce when workers learn from the individuals around them, and the propensity of workers in the top 10th percentile of the skill distribution to work there triples from 11% to 32%.⁸² The greater agglomeration of skilled workers in a few cities amplifies spatial wage inequality, and the between-city wage variance rises from 0.007 to 0.024.⁸³

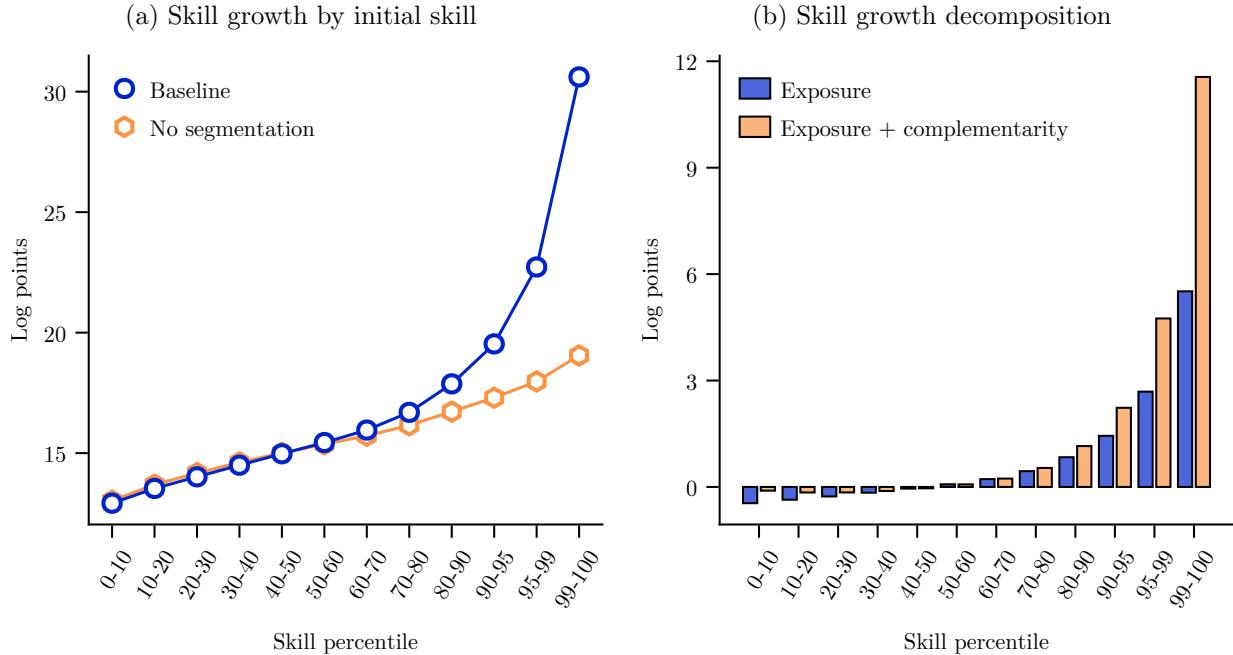
5.2 Local Interactions and Human Capital Accumulation

While the concentration of learning opportunities in space generates spatial inequality, it also boosts substantially aggregate productivity. The average skill of old workers is 1.2% higher when individuals

⁸²In the presence of costly migration, local interactions agglomerate both young and old workers in productive cities, as the majority of old workers stay in the locations where they lived when young (Figure F.5a).

⁸³The change in between-city wage inequality can be decomposed into a TFP effect, a skill disparity effect, and a sorting effect; specifically, $\Delta \text{Var}[\mathbb{E}(\log W_\ell)] = \Delta \text{Var}[\log T_\ell] + \Delta \text{Var}[\log S_\ell] + 2\Delta \text{Cov}[\log T_\ell, \mathbb{E}(\log S_\ell)]$. The TFP effect reflects the greater agglomeration of workers to productive cities and explains only 1% of the total change in between-city wage inequality. The remaining two terms capture the heterogeneity in skill composition across cities, and they explain together the remaining 99%.

Figure 4: The aggregate consequences of local interactions on human capital accumulation



Note: panel (a) displays the average skill growth by young skill in the equilibrium with segmented interactions (blue circles) and in the equilibrium without segmented interactions (orange circles). Panel (b) displays the change in skill growth between the baseline economy and the counterfactual economy across the young skill distribution. The total change is decomposed according to (23). The blue bars plot the “average exposure” effect, and the orange bars plot the total change.

learn within cities, and the average wage rises by by 2.7%.⁸⁴

The spatial segregation of learning opportunities enhances aggregate productivity because it boosts the human capital accumulation of skilled workers without dampening that of other individuals. Figure 4a displays the average lifetime skill growth of workers as a function of their initial skill when opportunities are spatially segmented (blue) and when they are not (orange). When individuals learn from the other workers in their city, workers in the top 1% of the skill distribution see their skill grow by 30 log points, 12 log points more than their lifetime human capital accumulation when interactions are not spatially segmented. At the other end of the distribution, the segmentation of learning opportunities reduces the lifetime skill growth of workers in the bottom 10% of the skill distribution by 0.1 log points. Learning within cities therefore heightens considerably the difference in human capital accumulation between low- and high-skill, a robust pattern documented in the labor literature since at least Mincer (1958).⁸⁵

⁸⁴The average wage increases relatively more than stock of human capital as it also takes into account the greater agglomeration of workers in high-TFP cities. Specifically, the change in the average log wage between the no-segmentation and the segmentation economies can be decomposed into a TFP term and a human capital term, $\mathbb{E}[\log \bar{W}] - \mathbb{E}[\log W] = \sum_\ell \log T_\ell (\bar{N}_\ell - N_\ell) + \mathbb{E}[\log \bar{S}] - \mathbb{E}[\log S]$, where \bar{x} refers to the value of x in the counterfactual economy. In the aggregate, 16% of the wage increase is explained by the larger stock of human capital, and the remaining 84% are due to the greater agglomeration of workers in productive cities.

⁸⁵When interactions are spatially segmented, an increase in initial skill by one standard deviation is associated with a lifetime skill growth 1.6 log points larger. In contrast, this skill learning premium flattens to 0.6 log points when individuals learn from every worker. As a result, the skill variance amongst old workers is 4% larger when interactions are spatially segmented.

Why do high skill workers gain so much from the spatial concentration of learning opportunities? Cities shape skill growth through two channels. First, high skill workers may be agglomerating relatively more to skill-dense cities, and as result, may be more exposed to productive interactions. I refer to this channel as the exposure effect. Second, high skill workers may be better able to capitalize on skilled interactions in the presence of strong within-skill learning complementarities. I coin this force the complementarity effect. Formally, the change in average lifetime skill growth between the baseline and the counterfactual economy can be written

$$\mathbb{E} \left[\log \left(\frac{S^o}{s} \right) | s \right] - \mathbb{E} \left[\log \left(\frac{\bar{S}^o}{s} \right) | s \right] = \underbrace{g_2 \sum_{\ell} \left(\frac{n_{\ell}^y(s)}{n^y(s)} \right) \Delta_{\ell}}_{\text{Exposure}} + \underbrace{g_{12} \log s \sum_{\ell} \left(\frac{n_{\ell}^y(s)}{n^y(s)} \right) \Delta_{\ell},}_{\text{Complementarity}} \quad \forall s, \quad (23)$$

where \bar{x} refers to the value of x when interactions are not spatially segmented, $\mathbb{E}[\log S^o/s | s]$ is the expected lifetime skill growth of young workers endowed with skill s in the baseline economy, and $\Delta_{\ell} \equiv \mathbb{E}[\log S_{\ell}] - \mathbb{E}[\log \bar{S}]$ is the difference between the average skill in city ℓ in the baseline equilibrium and the average aggregate skill in the counterfactual equilibrium.⁸⁶

Learning complementarities are essential in amplifying the learning gains of skilled workers. Figure 4b plots the skill growth decomposition (23). As high-skill agglomerate to the most skill-dense location, they are more likely learn from other skilled workers; this exposure effect accounts for 48% of the faster learning experienced by workers in the top 1% of the skill distribution when interactions are spatially segmented. The remaining 52% of their learning gains are explained by the complementarity effect. Meanwhile, the learning complementarities also minimize the learning losses of workers in the bottom half of the skill distribution.⁸⁷

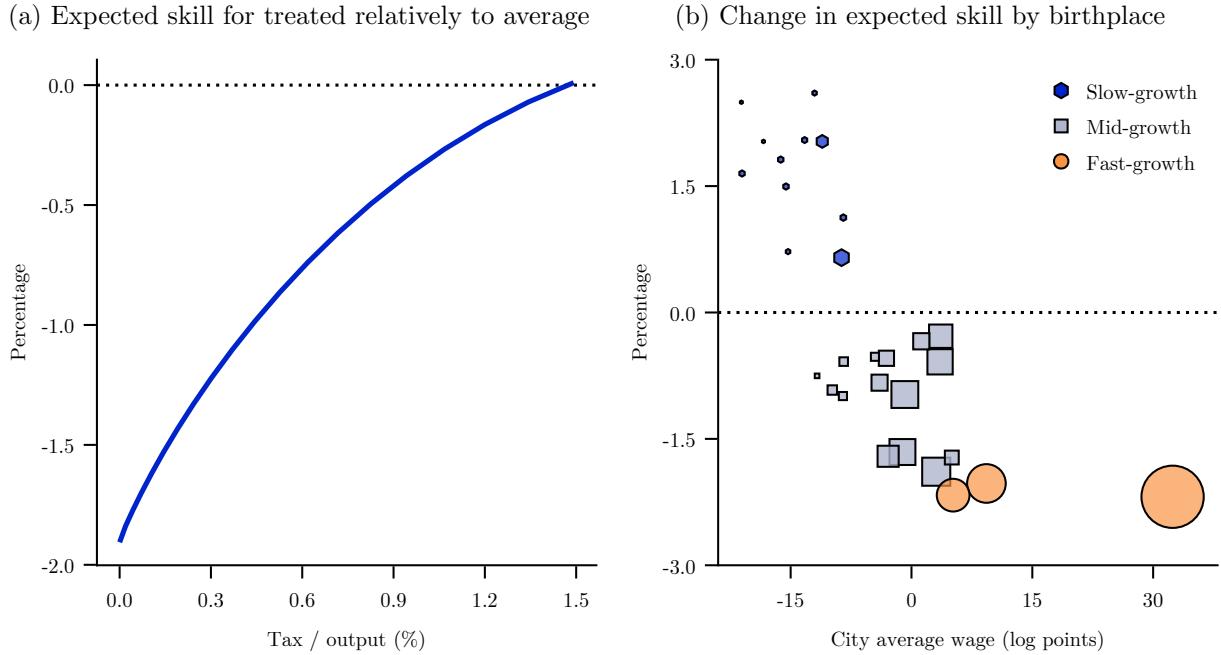
By boosting the learning gains of high-skill and reducing the losses of low-skill, learning complementarities are therefore crucial for the impact of cities on human capital accumulation. Aggregating (23) across workers, I find that these complementarities explain 59% of the aggregate increase in human capital.

This section therefore suggests that governments face an equity-efficiency tradeoff. On the one hand, the spatial segmentation of learning opportunities improves aggregate productivity. On the other hand, it amplifies spatial wage and learning inequality. Policies aimed at reducing the spatial concentration of skills may therefore have detrimental effect on the aggregate stock of human capital. I conclude this paper by quantifying how steep is the equity-efficiency tradeoff.

⁸⁶The change in skill growth can further be decomposed into a partial equilibrium effect that holds the average old skill constant, $\mathbb{E}[\log S] - \sum_{\ell} \left(\frac{n_{\ell}^y(s)}{n^y(s)} \right) \mathbb{E}[\log S_{\ell}]$, and a general equilibrium effect, $\mathbb{E}[\log \bar{S}] - \mathbb{E}[\log S]$. The general equilibrium effects alone are however small (see Figure F.3).

⁸⁷In the baseline equilibrium, relatively low-skill workers do not sort much across space (Section 4.4). As a result, the average learning opportunity they have access to is rather similar to the average nationwide opportunity. This, together with the strong within-skill learning complementarities, explain why these workers do not lose much from the spatial segregation of opportunities.

Figure 5: The consequences of spatial policies on spatial learning inequality



Note: panel (a) displays the expected old skill of workers born in cities in the bottom 25% of the city growth distribution relative to the nationwide expected old skill against the size of the voucher policy. The size of the policy is measured as the aggregate tax used to finance the policy as a fraction of total GDP. Panel (b) plots the change in expected old skill by birthplace between the baseline equilibrium and the policy equilibrium when the policy reaches 1.5% of GDP. The blue hexagons are the cities in the bottom 25% of the city growth distribution. The orange circles are the three largest French cities (Paris, Lyon and Toulouse). The grey rectangles are the remaining cities. The size of the markers is proportional to the baseline city size.

6 The Consequences of Spatial Policies

I study the general equilibrium consequences of a moving voucher policy aimed at offering equal learning opportunities to workers born in remote locations (Chetty et al., 2016).⁸⁸ Specifically, the policy consists of a subsidy granted to young workers born in the bottom 25% of the city-growth distribution conditional on moving to the three largest French cities (Paris, Lyon, and Toulouse). Figure 7a displays the 185 cities that are treated by the policy. The policy is self-financed within skill and age group to focus on spatial redistribution.⁸⁹

6.1 Spatial Inequality

As emphasized in Section 5.1, the spatial concentration of learning opportunities, together with the presence of large migration costs, generate substantial learning inequality. Quantitatively, the average skill obtained by workers born in the bottom 25% of the city-growth distribution at the end of their career is 2% lower than the average French worker, which feeds into 4% lower lifetime

⁸⁸Chetty et al. (2016) evaluates the consequence of the Moving to Opportunity program in the United States, which subsidized children and teenagers born in distressed neighborhoods to move to large, productive places. In my setting, the vouchers are granted to young professionals at the beginning of their career. See Fogli et al. (2023) for a paper that evaluates the general equilibrium consequences of the MTO program.

⁸⁹The financing matters only for the welfare calculation. As long as the financing is through a lump-sum tax that is not place-based, it has no implication on the spatial distribution of economic activity, and therefore on human capital.

income. To what extent can the moving voucher policy reduce these learning inequalities?

Large moving vouchers have the potential to improve the lifetime human capital of workers born in remote locations. Figure 5a plots the average skill of treated workers at the end of their career compared to the average worker as a function of the size of the policy. As the size of the moving voucher increases, it covers a greater share of the migration cost to productive cities. Treated workers have an easier access to the learning opportunities present in these cities, which increases their lifetime accumulation of human capital. When the voucher reaches 1,030€, which covers 80% of the average migration cost and represents 1.5% of GDP, the probability that treated workers migrate to the three largest French cities rises from 7% to 45%. As a result, workers born in the bottom 25% of the city-growth distribution accumulate human capital as much as the average worker.

The policy has heterogeneous treatment effects across workers. Figure 5b plots the change in expected old skill by birthplace between the baseline equilibrium and the equilibrium when the policy reaches 1.5% of GDP. Workers born in treated cities (blue hexagons) all experience on average an increase in their human capital.⁹⁰ The gains are relatively larger for workers born near Lyon, Paris, and Toulouse for whom the take-up rate of the policy is larger (Figure G.1). Similarly, skilled workers are more likely to opt-in the policy (Figure G.3a). Together with their better capacity to capitalize on the learning opportunities present in productive cities, skilled treated workers benefit relatively more from the policy (Figure G.3b).

The learning gains experienced by the treated workers comes at the expense of slower human capital accumulation for the non-treated. The voucher policy indeed reallocates to productive cities workers that are marginally less skilled, and in doing so, worsens the quality of the local opportunities (Figure G.4). As a result, the policy reduces the learning advantage of workers born in Lyon, Paris and Toulouse (orange circles in Figure 5b). However, the policy also affects negatively the human capital accumulation of non-treated individuals born outside the three largest French cities who used to migrate there to work and learn (grey rectangles).⁹¹

The moving voucher policy therefore redistributes learning opportunities across birthplaces. Geographic learning disparities shrink, and the variance of wage growth across birthplaces decreases from 3.6 to 1.9.⁹² The policy is therefore effective at addressing spatial equity concerns.

6.2 Human Capital Accumulation

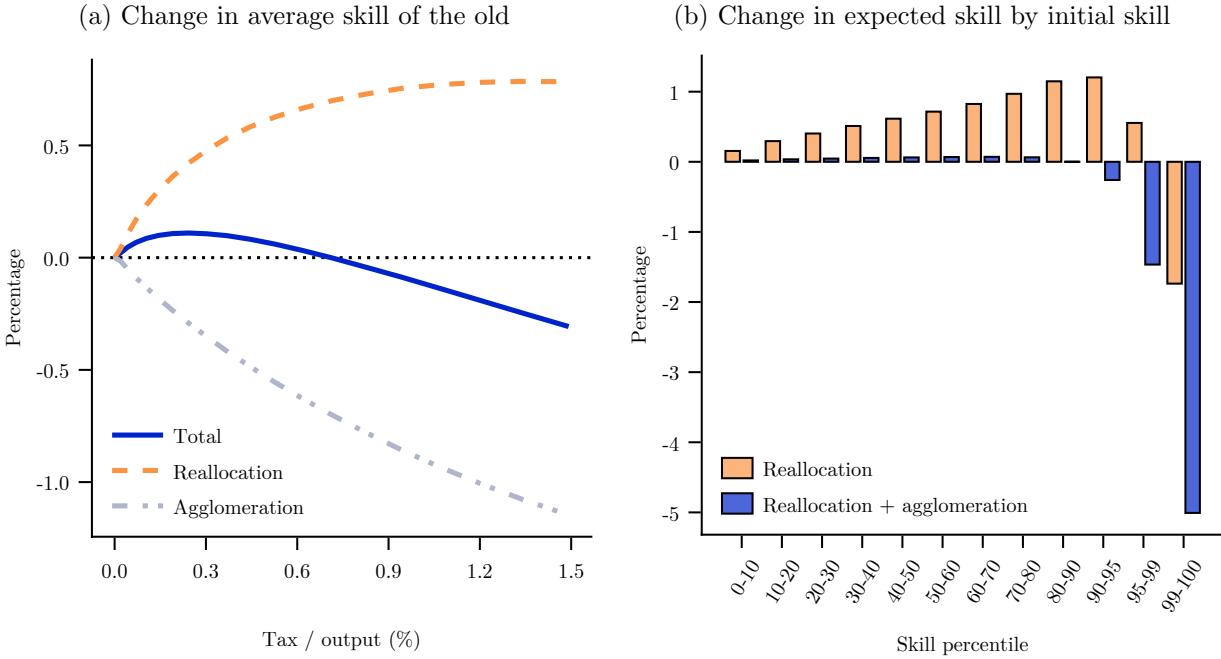
The policy also affects negatively aggregate efficiency. Figure 6a displays the change in the average skill of old workers as a function of the size of the policy. When the policy reaches 1.5% of GDP, the stock of human capital is 0.3% lower than in the baseline equilibrium.

⁹⁰The average skill obtained by treated workers at the end of their career increases by 1.8%. Combined with an easier access to high-productivity jobs, the moving voucher policy boosts their lifetime labor income by 5.7%.

⁹¹The learning losses for the non-treated born outside Lyon, Paris and Toulouse are relatively lower for two reasons. First, not every individuals born outside of these cities migrate there to work. Second, in general equilibrium, some of these mid-productivity cities experience an increase in their skill density as skilled workers have marginally less incentives to agglomerate in productive locations (Figure G.4a). As such, the learning opportunities offered by these places improve.

⁹²The policy also reduces spatial wage inequality by decreasing the spatial concentration of skilled workers. The between-city wage variance shrinks from 0.024 to 0.018 when the policy reaches 1.5% of GDP.

Figure 6: The consequences of local policies on human capital accumulation



Note: panel (a) displays the average old skill against the size of the policy. The blue solid line is the change in average old skill under the voucher policy. The orange dashed line is the change in average old skill under the quasi-optimal policy. The size of the policy is measured as the aggregate tax used to finance the policy as a fraction of total GDP. Panel (b) and (c) plot the change in expected old skill across the skill distribution between the baseline equilibrium and the policy equilibrium when the policy reaches 1.5% of GDP under the moving voucher and the quasi-optimal policy respectively. The blue bars represent the partial equilibrium, reallocation effect. The orange bars display the total change.

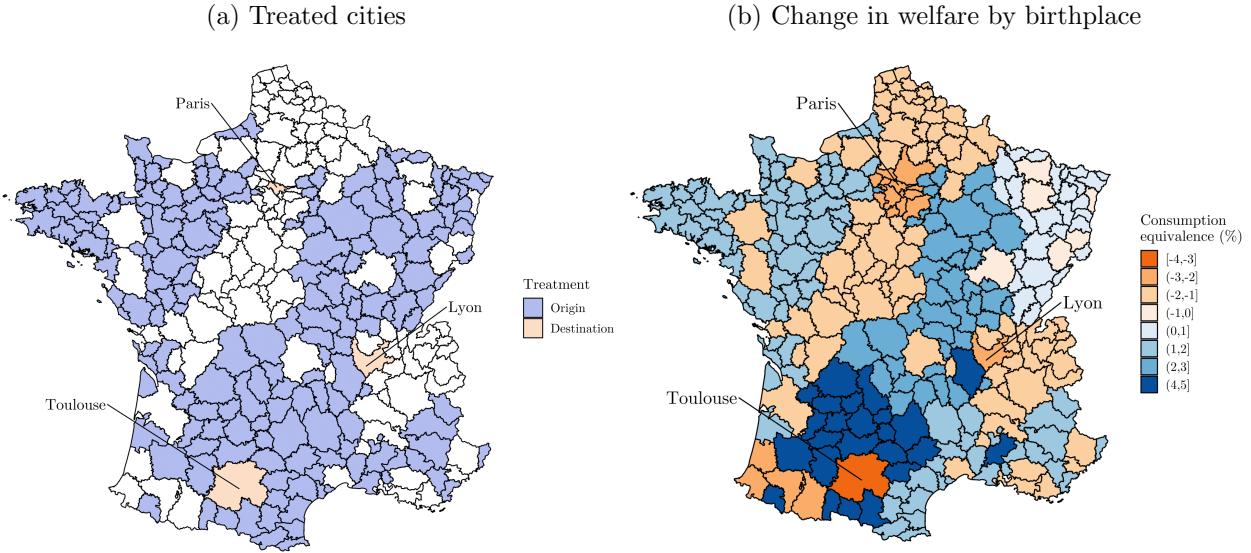
The voucher policy acts negatively on aggregate efficiency because it reduces the spatial segregation of learning opportunities. The impact of the policy on human capital accumulation can be decomposed into two effects. First, holding the quality of the local interactions constant, the vouchers reallocate workers to skill-dense places, and therefore increases the pool of individuals who have access to productive learning opportunities. I refer to this as the reallocation effect. Second, in general equilibrium, the policy affects the spatial distribution of skills, and with that the quality of the local opportunities. I name this channel the composition effect. Formally, the percentage change in the average skill of old workers between the policy and the baseline equilibrium can be decomposed into

$$\frac{\mathbb{E}[\bar{S}^o] - \mathbb{E}[S^o]}{\mathbb{E}[S^o]} = \underbrace{\sum_{\ell} \int \int \left(\frac{\gamma(s, s_p)}{\mathbb{E}[S^o]} \right) \Delta n_{\ell}^y(s) \pi_{\ell}(s_p) ds_p ds}_{\text{Reallocation}} + \underbrace{\sum_{\ell} \int \int \left(\frac{\gamma(s, s_p)}{\mathbb{E}[S^o]} \right) \bar{n}_{\ell}^y(s) \Delta \pi_{\ell}(s_p) ds_p ds}_{\text{Composition}},$$

where \bar{x} refers to variable x in the policy equilibrium and $\Delta x \equiv \bar{x} - x$. The dashed orange line and the dotted grey line in Figure 6a display the reallocation and composition effects. Abstracting from the composition effect, the moving voucher policy would increase aggregate human capital by 1%. However, the composition effect more than offsets the partial equilibrium impact of the policy, and in net, the policy triggers efficiency losses.

The learning losses generated by the policy are fully born by the skilled and very skilled workers.

Figure 7: The consequences of the moving voucher policy on welfare



Note: panel (a) and (b) compares the welfare difference between the baseline equilibrium and the moving voucher equilibrium when the policy reaches 1.5% of GDP. Panel (a) displays the change in average welfare by birthplace assuming equal weights by skill within birthplaces. Panel (b) plots the change in average welfare by birthplace and initial skill, grouping cities into slow-growth cities (treated), middle-growth cities (non-treated), and fast-growth cities (non-treated but targeted by the policy).

Figure 6b plots the change in workers' expected skill at the end of their career expected skill between the policy and the baseline equilibrium across the skill distribution. Holding constant the quality of the local learning opportunities, most workers would on average experience faster human capital accumulation thanks to the policy (orange bars). The gains would be the largest for workers between the 50th and 90th percentile of the skill distribution for whom the enhanced access to interactions with skilled workers is the most beneficial. However, the general equilibrium effect neutralizes those partial equilibrium gains, and the policy neither fosters nor dampens the learning of the bottom 90% of the skill distribution (blue bars). In contrast, the largest fraction of very skilled workers already agglomerate in Lyon, Toulouse and Paris in the absence of moving vouchers. For those workers, the policy only affects negatively the quality of the interactions they experience, thus reducing their lifetime learning.

Learning complementarities are crucial in shaping the efficiency cost of the policy. Were those absent, the learning losses experienced by workers in the top 1% of the skill distribution would be halved (Figure G.2). In the aggregate, learning complementarities explain the entirety of the drop in aggregate human capital.⁹³ Said differently, ignoring learning complementarities would lead to underestimate the consequences of spatial policies on aggregate productivity.

Taking stock, the moving voucher policy reduces spatial learning disparities at the cost of lowered aggregate efficiency, thus facing a substantial equity-efficiency tradeoff. I conclude this section by quantifying the welfare consequences of the policy.

⁹³As in (23), the impact of the policy on the average skill of old workers can be decomposed into an exposure and a complementarity term. Setting $g_{12} = 0$, the average skill of old workers would not be affected by the voucher policy.

6.3 Welfare

I measure welfare through the expected lifetime utility of a cohort. I express welfare changes in terms of consumption equivalence (Lucas, 1987; Alvarez and Jermann, 2004). Appendix G.1 provides more details on how the consumption equivalence is derived and computed, as well as a decomposition that separates the different channels through which the policy affects welfare.

The policy is spatially redistributive: it generates welfare gains for the treated workers, and welfare losses for the non-treated. Figure 7b displays the average welfare effect of the policy by birthplaces.⁹⁴ On the one hand, workers born in treated cities enjoy average welfare gains of 2%. Those gains are relatively larger for workers born near Lyon, Paris, or Toulouse, and they are mainly explained by the faster human capital accumulation these workers experience. On the other hand, workers born in non-treated cities suffer average welfare losses of 2.3%. For workers born outside of Lyon, Paris and Toulouse, these losses are entirely caused by the financial cost of the policy. For the non-treated born in the three largest French cities, the welfare losses are larger, going as high as 3.5% for Toulouse, as the policy affects negatively their lifetime human capital.⁹⁵

In the aggregate, the welfare losses outweigh the gains, and the moving voucher policy generates aggregate welfare losses of 1.3% under a utilitarian social welfare function that places equal weights on skills and cities. Alternatively, a utilitarian planner must put Pareto weights four times larger on the treated workers for the policy to be welfare neutral.

Wrapping up, moving vouchers constitute an effective redistributive policy that reduces substantially spatial learning disparities. However, these vouchers are effective only if they cover a substantial fraction of the migration costs; taking into account the general equilibrium of the policy, moving vouchers reduce aggregate inefficiency and trigger welfare losses on non-treated workers.

7 Conclusion

This paper argues that a tradeoff exists between spatial inequality and human capital accumulation. I have shown theoretically that this tradeoff is shaped by the relative strength of within- and between-skill learning complementarities. I have documented that high-skill workers enjoy disproportionately faster wage growth when working in skill-dense cities or neighborhoods. I have argued that this pattern reveals the presence of strong within-skill learning complementarities. Using the estimated model, I concluded that the spatial segmentation of learning opportunities increases the aggregate stock of human capital at the cost of amplified geographic disparities.

This equity-efficiency tradeoff matters for spatial policies. On the one hand, local interactions engender learning spillovers and spatial misallocation. Place-based policies incentivizing a higher

⁹⁴The average welfare change by birthplaces are computed under a utilitarian social welfare function that places equal weights on every worker within the city (see Appendix G.1 for more details). To complement this analysis, Figure G.5 reports the full distribution of welfare changes.

⁹⁵The welfare gains and losses are relatively homogeneous across the skill distribution within a birthplace (Figure G.3c). A noticeable exception is for the workers born in the 10% of the skill distribution in the three largest French cities. These workers experience welfare losses around 4% due to the strong negative effect of the policy on their lifetime human capital.

spatial concentration of skilled workers may correct the local externalities. On the other hand, the spatial concentration of skills deteriorates the lifetime opportunities of workers born in remote cities. Vouchers that help workers relocate to productive cities have the potential to reduce these inequalities at the cost of aggregate efficiency losses.

Skill complementarities are present everywhere. They shape our productivity. They matter for our preferences for cities. And finally, they define how we learn from each other. All these dimensions are sources of local spillovers. A natural direction along which to expand this research agenda is therefore to study optimal spatial policies in the presence of both static and dynamic complementarities. A second promising avenue for this agenda is to study how firms and space interact in shaping human capital accumulation; while firms may create teams that partially internalize the local learning spillovers, they are also constrained by the pool of workers they have access to.

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A Theory

A.1 Proof of Proposition 1

The problem of the young is decoupled from that of the old. The old allocation in turn depends on the aggregate old skill distribution, which follows from the young's allocation. To prove the existence of an equilibrium, I impose mild conditions on the distribution of the idiosyncratic learning shock.

Assumption 2 (Idiosyncratic learning shocks).

Suppose that (i) the support of F is $\{0\} \cup \mathbb{R}_+$, and (ii) for any function $h : [\underline{x}, \bar{x}] \mapsto \mathbb{R}_+$ such that $h(x) < \infty$ for all $x \in [\underline{x}, \bar{x}]$, then $\int h(ex)dF(e) < \infty$ for all $x \in [\underline{x}, \bar{x}]$.

I start from the young spatial allocation. Existence of a solution to (5) is essentially given by Schauder fixed point theorem. I drop the y superscript for notational simplicity. Let $X \equiv [\underline{s}, \bar{s}]^L \subseteq \mathbb{R}_+^L$. Suppose for simplicity that $\underline{s} > 0$, $\bar{s} < \infty$, and $n(s) < \infty$ for all $s \in X$. Then, X is a compact convex subset of \mathbb{R}_+^L . Define $C_b(X, Y)$ as the set of bounded continuous functions that maps X into $Y \subset \mathbb{R}_+^L$, where $Y = [\underline{n}, \bar{n}]^L$ is also a compact convex subset of \mathbb{R}_+^L with $\underline{n} > 0$ and $\bar{n} < \infty$. When equipped with the sup norm, the vector space $C_b(X, Y)$ is a Banach space. Define the operator $T : C_b(X, Y) \rightarrow Q$ by

$$T[\mathbf{f}](\mathbf{s}) = \left\{ n(s_\ell) \left(\frac{e^{\vartheta(s_\ell T_\ell + \beta O(s_\ell, f_\ell))}}{\sum_{\ell'} e^{\vartheta(s_\ell T_{\ell'} + \beta O(s_\ell, f_{\ell'}))}} \right) \right\}_{\ell=1}^L$$

for $\mathbf{f} \in C_b(X, Y)$, where

$$O(s, f) = \int \left(\int \mathbb{E}(V^o[e\gamma(s, s_p), \boldsymbol{\varepsilon}]) dF(e) \right) \left(\frac{f(s_p)}{\int f(\sigma) d\sigma} \right) ds_p.$$

The second part of Assumption 2 guarantees that $O(s, f)$ exists. For any $\mathbf{f} \in C_b(X, Y)$, we know that

$$n(s) \left(\frac{e^{\vartheta(s T_\ell + \beta O(s, f_\ell))}}{\sum_{\ell'} e^{\vartheta(s T_{\ell'} + \beta O(s, f_{\ell'}))}} \right) \in (0, n(s)),$$

for all $s \in [\underline{s}, \bar{s}]$ and $\ell \in \{1, 2, \dots, L\}$. Furthermore, Assumption 1 implies that $s \rightarrow O(s, n)$ is continuous, and therefore so is the above function. Therefore, $T : C_b(X, Y) \rightarrow C_b(X, Y)$. Finally, $O(s, f)$ is continuous in f since $f_\ell(s) > 0$ and $f_\ell(s) < \infty$ for all $s \in [\underline{s}, \bar{s}]$, all $\ell \in \{1, 2, \dots, L\}$, and any $\mathbf{f} \in C_b(X, Y)$. It automatically follows that T is a continuous operator, and Schauder fixed point theorem implies that there exists at least one $f^* \in C_b(X, Y)$ such that $T[\mathbf{f}^*] = f^*$.

Turning to the old allocation, (4) has a solution for all s as long as $n^o(s)$ has a solution. Using the first part of Assumption 2, the old skill distribution (6) can be rewritten

$$N^o(s^o) = \sum_{\ell} \int \int n_{\ell}^y(s_y) \pi_{\ell}^y(s_p) F\left(\frac{s_o}{\gamma(s_y, s_p)}\right) ds_p ds_y.$$

The two integrals always exist. Furthermore, N^o is continuous differentiable with $\lim_{s \rightarrow 0^+} N^o(s) = 0$ and $\lim_{s \rightarrow \infty} N^o(s) = 1$, and $n^o(s)$ exists.

A.2 Uniqueness and Stability of the Symmetric Equilibrium

Proposition A.1 (Stability and uniqueness).

Suppose that $\mathbf{T} = 1$. Then, a symmetric equilibrium exists. Suppose further that $\gamma(s, s') = \mathcal{F}(s) + \mathcal{G}(s)\mathcal{H}(s')$, for \mathcal{F} , \mathcal{G} and \mathcal{H} some functions. Then, if

$$\vartheta\beta \max_{\ell} \max \{1 - \mathcal{B}_{\ell}^y, \mathcal{B}_{\ell}^y\} |\text{Cov}[\mathcal{G}(S^y), \mathcal{H}(S^y)]| < 1,$$

the symmetric equilibrium is stable. Meanwhile, when L is large and

$$4\vartheta\beta \left(\max_s \mathcal{G}(s) - \min_s \mathcal{G}(s) \right) \left(\max_s \mathcal{H}(s) - \min_s \mathcal{H}(s) \right) < 1,$$

then the symmetric equilibrium is the unique equilibrium.

Proof. For simplicity, I do the proof assuming away the idiosyncratic learning shock. Then, under $\mathbf{T} = 1$, the expected

utility of old workers before realizing their taste shocks is $\mathcal{V}^o(s) = \vartheta^{-1} \log s + c$ for some constant c . Since the rest of the equilibrium is fully determined by the young spatial allocation, I omit the y superscript. Given the old utility, the young expected utility before knowing what interactions they will experience is $O_\ell(s) = \mathcal{F}(s) + \mathcal{G}(s)\mathbb{E}[\mathcal{H}(S_\ell)]$. Let $\mu_\ell \equiv \mathbb{E}[\mathcal{H}(S_\ell)]$ and $\mu \equiv \mathbb{E}[\mathcal{H}(S)]$. The young spatial distribution of economic activity is given by

$$n_\ell(s) = n(s) \left(\frac{e^{\vartheta B_\ell + \vartheta \beta \mathcal{G}(s) \mu_\ell}}{\sum_{\ell'} e^{\vartheta B_{\ell'} + \vartheta \beta \mathcal{G}(s) \mu_{\ell'}}} \right).$$

Note that only the $\boldsymbol{\mu} \equiv \{\mu_\ell\}_\ell$ matters to pin down the young allocation. These local averages are in turn given by

$$\mu_\ell = \frac{\int \mathcal{H}(s) \left(\frac{e^{\vartheta \beta \mathcal{G}(s) \mu_\ell}}{\sum_{\ell'} e^{\vartheta B_{\ell'} + \vartheta \beta \mathcal{G}(s) \mu_{\ell'}}} \right) n(s) ds}{\int \left(\frac{e^{\vartheta \beta \mathcal{G}(s') \mu_\ell}}{\sum_{\ell'} e^{\vartheta B_{\ell'} + \vartheta \beta \mathcal{G}(s') \mu_{\ell'}}} \right) n(s') ds'}$$

Hence, we have reduced the problem to a L -dimensional fixed point. Let T be the operator that maps $\boldsymbol{\mu}$ onto itself as defined by the above L equations. Note that Assumption 1 requires $\mathcal{H}(s)$ to be bounded above and below. Let $\underline{h} \equiv \min_s \mathcal{H}(s)$ and $\bar{h} \equiv \max_s \mathcal{H}(s)$. Then, we know that $T : [\underline{h}, \bar{h}]^L \mapsto [\underline{h}, \bar{h}]^L$. Clearly, $\mu_\ell = \mu$ is a solution to this fixed point. A sufficient condition for the symmetric equilibrium to be stable is $|\partial_{\mu_{\ell'}} T_\ell(\boldsymbol{\mu})| < 1$ for all pair (ℓ, ℓ') and $\boldsymbol{\mu} = \{\mu\}_{\ell=1}^L$. A sufficient condition for the symmetric equilibrium to be unique is $|\partial_{\mu_{\ell'}} T_\ell(\boldsymbol{\mu})| < 1$ for all pair (ℓ, ℓ') and all $\boldsymbol{\mu}$, in which case T is a contraction.⁹⁶ For any $\boldsymbol{\mu}$, the partial derivative of T_ℓ w.r.t. μ_ℓ is

$$\frac{\partial T_\ell(\boldsymbol{\mu})}{\partial \mu_\ell} = \vartheta \beta \int (\mathcal{H}(s) - \mu_\ell) \mathcal{G}(s) \pi_\ell(s) \left(1 - \frac{n_\ell(s)}{n(s)} \right) ds,$$

and, for $\ell \neq \ell'$, it is

$$\frac{\partial T_\ell(\boldsymbol{\mu})}{\partial \mu_{\ell'}} = -\vartheta \beta \int (\mathcal{H}(s) - \mu_\ell) \mathcal{G}(s) \pi_\ell(s) \left(\frac{n_{\ell'}(s)}{n(s)} \right) ds.$$

Stability. When the equilibrium is symmetric, $\boldsymbol{\mu} = \{\mu\}_\ell$. Then, the derivatives simplify to

$$\frac{\partial T_\ell(\boldsymbol{\mu})}{\partial \mu_\ell} = \vartheta \beta (1 - \mathcal{B}_\ell) \int (\mathcal{H}(s) - \mu) \mathcal{G}(s) n(s) ds = \vartheta \beta (1 - \mathcal{B}_\ell) \text{Cov}[\mathcal{G}(S), \mathcal{H}(S)],$$

and

$$\frac{\partial T_\ell(\boldsymbol{\mu})}{\partial \mu_{\ell'}} = -\vartheta \beta \mathcal{B}_{\ell'} \text{Cov}[\mathcal{G}(S), \mathcal{H}(S)]$$

for $\ell' \neq \ell$, where

$$\mathcal{B}_\ell \equiv \frac{e^{\vartheta B_\ell}}{\sum_{\ell'} e^{\vartheta B_{\ell'}}}. \quad (24)$$

Imposing $|\partial_{\mu_{\ell'}} T_\ell(\boldsymbol{\mu})| < 1$ yields the first condition of Proposition A.1.

Uniqueness. For uniqueness, the above condition is necessary but not sufficient. To derive a sufficient condition, suppose that there are many cities. Since \mathcal{S}^y is bounded, we know that $|\mu_\ell - \mu_{\ell'}| \leq \bar{s} - \underline{s} < \infty$ for all (ℓ, ℓ') . That is, no city will ever have learning opportunities so attractive as to capture the entire employment share. As a consequence,

⁹⁶To see this, note that the condition implies $\|DT(\boldsymbol{\mu})\| \leq K < 1$. Then, take two points $\boldsymbol{\mu}$ and $\boldsymbol{\mu}'$ in $[\underline{s}, \bar{s}]^L$. Define $\Delta(\lambda) \equiv \lambda \boldsymbol{\mu} + (1 - \lambda) \boldsymbol{\mu}'$, for $\lambda \in [0, 1]$. Clearly, $\partial_\lambda \Delta(\lambda) = \boldsymbol{\mu} - \boldsymbol{\mu}' \perp \lambda$. Hence, it follows that

$$T(\boldsymbol{\mu}) - T(\boldsymbol{\mu}') = T[\Delta(1)] - T[\Delta(0)] = \int_0^1 \frac{dT[\Delta(\lambda)]}{d\lambda} d\lambda = \int_0^1 dT[\Delta(\lambda)] \frac{\partial \Delta(\lambda)}{\partial \lambda} d\lambda,$$

where the second equality is from the fundamental theorem of calculus and the third from the chain rule. Thus, applying the norm $\|\cdot\|$ on both sides,

$$\|T(\boldsymbol{\mu}) - T(\boldsymbol{\mu}')\| = \left\| \int_0^1 dT[\Delta(\lambda)] \frac{\partial \Delta(\lambda)}{\partial \lambda} d\lambda \right\| \leq \int_0^1 \|dT[\Delta(\lambda)]\| \left\| \frac{\partial \Delta(\lambda)}{\partial \lambda} \right\| d\lambda \leq \int_0^1 K \|\boldsymbol{\mu} - \boldsymbol{\mu}'\| d\lambda = K \|\boldsymbol{\mu} - \boldsymbol{\mu}'\|,$$

where the first inequality is from the triangle inequality. Since $K < 1$, T is a contraction.

if amenities are independent of L , then $\lim_{L \rightarrow \infty} \mathcal{B}_\ell \rightarrow 0^+$ for all ℓ . Hence, for L large, the partial derivatives rewrite

$$\frac{\partial T_\ell(\boldsymbol{\mu})}{\partial \mu_\ell} \approx \vartheta \beta \int (\mathcal{H}(s) - \mu_\ell) \mathcal{G}(s) \pi_\ell(s) ds = \vartheta \beta \text{Cov}[\mathcal{G}(S_\ell), \mathcal{H}(S_\ell)]$$

and $\partial_{\mu_{\ell'}} T_\ell(\boldsymbol{\mu}) \approx 0$. If we knew the local distributions $\{\pi_\ell\}$, then uniqueness would be guaranteed by

$$\vartheta \beta < \frac{1}{|\text{Cov}[\mathcal{G}(S_\ell), \mathcal{H}(S_\ell)]|}.$$

However, the local distributions are themselves a function of $(\vartheta, \beta, \gamma)$. Yet, it is possible to bound the covariance since we know that the $\mathcal{G}(S_\ell)$ and $\mathcal{H}(S_\ell)$ are bounded. This yields the second condition of Proposition A.1. \square

A.3 The Sorting of Old Workers

Proposition A.2 (Sorting).

The old allocation satisfies SPAM.

Proof. For the entire proof I omit the old superscript for notational simplicity. I first derive an expression for the difference in density between ℓ and ℓ' :

$$\pi_\ell(s) - \pi_{\ell'}(s) = \left(\frac{N_{\ell'}}{N_\ell} \right) \pi_{\ell'}(s) e^{\vartheta(A_\ell - A_{\ell'})} \left(e^{\vartheta s(T_\ell - T_{\ell'})} - \mathbb{E} \left[e^{\vartheta S_{\ell'}(T_\ell - T_{\ell'})} \right] \right). \quad (25)$$

This follows from the definition of $\pi_\ell(s)$, N_ℓ and (4). Let $f : \mathcal{S}^o \mapsto \mathbb{R}$ be any measurable function. Using (25), the difference in the f -transformed mean skill between city ℓ and ℓ' is

$$\mathbb{E}[f(S_\ell)] - \mathbb{E}[f(S_{\ell'})] = \left(\frac{N_{\ell'}^o}{N_\ell^o} \right) e^{\vartheta(A_\ell - A_{\ell'})} \text{Cov} \left(f(S_{\ell'}), e^{\vartheta S_{\ell'}(T_\ell - T_{\ell'})} \right).$$

Take any non-decreasing function f . Then, the above expression implies $\mathbb{E}[f(S_\ell)] > \mathbb{E}[f(S_{\ell'})]$ iff $T_\ell > T_{\ell'}$. That is, the local skill densities of old workers can be FOSD-ordered by T_ℓ . \square

A.4 The First Order Approximation

A.4.1 The general learning technology

Old workers Linearizing the old allocation is straightforward. From (4), we know that

$$\frac{\partial n_\ell^o(s)}{\partial T_{\ell'}} \Big|_{\mathbf{T}=1} = \mathcal{B}_\ell^o \left(\frac{\partial n^o(s)}{\partial T_{\ell'}} + \vartheta n^o(s) I_{\ell\ell'} \right),$$

for $I_{\ell\ell'} \equiv \mathbb{1}\{\ell' = \ell\} - \mathcal{B}_{\ell'}^o$ and \mathcal{B}_ℓ^o defined in (24). The first term is the GE effect of increasing the TFP of city ℓ' on the density of skill s . This term will be nil in equilibrium (see (32)). The second term is the reallocation of workers over space. Hence, to a first order, the spatial allocation of old workers is

$$n_\ell^o(s) \approx n^o(s) \mathcal{B}_\ell^o + \vartheta n^o(s) \mathcal{B}_\ell^o \mathcal{T}_\ell^o s, \quad (26)$$

where $\mathcal{T}_\ell^o \equiv T_\ell - \sum_{\ell'} \mathcal{B}_{\ell'}^o T_{\ell'}$.

Young workers For the young, given (5), we have

$$\frac{\partial n_\ell^y(s)}{\partial T_{\ell'}} \Big|_{\mathbf{T}=1} = \vartheta \mathcal{B}_\ell^y n^y(s) \left[s I_{\ell\ell'} + \beta \left(\frac{\partial O_\ell}{\partial T_{\ell'}} - \sum_l \mathcal{B}_l^y \frac{\partial O_l(s)}{\partial T_{\ell'}} \right) \right].$$

The first term is identical to the old allocation. The second term captures how the local learning varies with \mathbf{T} . Recall that

$$O_\ell(s) = \int \int \mathcal{V}^o[e\gamma(s, s_p)] \pi_\ell^y(s_p) dF(e) ds_p.$$

When $\mathbf{T} = 1$, $\mathcal{V}^o(s) = s + c$ for some constant c . In addition, $\partial_{T_\ell} \mathcal{V}^o(s) = s \mathcal{B}_\ell^o$. Hence,

$$\frac{\partial O_\ell(s)}{\partial T_{\ell'}} \Big|_{\mathbf{T}=1} = \mu_e \mathcal{B}_{\ell'}^o \int \gamma(s, s_p) n^y(s_p) ds_p + \mu_e \int \gamma(s, s_p) \partial_{T_{\ell'}} \pi_\ell^y(s_p) ds_p + c,$$

where μ_e is the mean of the learning shock, $\mu_e \equiv \int e dF(e)$. Using $\sum_l n_\ell^y(s) = n^y(s)$ for all \mathbf{T} , it follows that

$$\frac{\partial O_\ell}{\partial T_{\ell'}} - \sum_l \mathcal{B}_l^y \frac{\partial O_l}{\partial T_{\ell'}} = \int \frac{\partial \pi_\ell^y(s_p)}{\partial T_{\ell'}} \gamma(s, s_p) ds_p = \frac{1}{\mathcal{B}_\ell^y} \int \frac{\partial n_\ell^y(s_p)}{\partial T_{\ell'}} (\gamma(s, s_p) - \mathbb{E}[\gamma(s, S^y)]) ds_p,$$

where the second equality follows from the expression for $\partial_{T_{\ell'}} \pi_\ell^y(s_p)$ and I have redefined $\gamma = \mu_e \gamma$ wlog.⁹⁷ Plugged in the initial expression, we can conclude that

$$\frac{\partial n_\ell^y(s)}{\partial T_{\ell'}} \Big|_{\mathbf{T}=1} = \vartheta n^y(s) \left(\mathcal{B}_\ell^y s I_{\ell\ell'} + \beta \int \frac{\partial n_\ell^y(s_p)}{\partial T_{\ell'}} (\gamma(s, s_p) - \mathbb{E}[\gamma(s, S^y)]) ds_p \right).$$

The above expression constitutes a fixed point over the functions $\partial_{T_{\ell'}} n_\ell^y(s)$. I solve this fixed point in two steps. First, I guess and verify the general form of the solution:

$$\frac{\partial n_\ell^y(s)}{\partial T_{\ell'}} = \vartheta n^y(s) \mathcal{B}_\ell^y I_{\ell\ell'} \eta(s), \quad (27)$$

for η some city-independent function. From this guess, we also know that the partial derivative of the local skill density is

$$\frac{\partial \pi_\ell^y(s)}{\partial T_{\ell'}} = \vartheta n^y(s) I_{\ell\ell'} (\eta(s) - \mathbb{E}[\eta(S^y)]). \quad (28)$$

Second, plugging the guess in the expression for $\partial_{T_{\ell'}} n_\ell^y(s)$ verifies it and yields the implicit expression for η :

$$\eta(s) = s + \vartheta \beta \int (\gamma(s, s_p) - \mathbb{E}[\gamma(s, S^y)]) n^y(s_p) \eta(s_p) ds_p = s + \vartheta \beta \Theta(s),$$

where $\Theta(s)$ is defined in (7). The above expression is a Fredholm integral equation of the second type. Standard results can be used to show that a solution exists when the dispersion forces, summarized here by ϑ , are large enough.

Lemma A.1 (Existence).

Suppose that

$$\vartheta \beta \left(\int \int |\gamma(s, s_p) - \mathbb{E}[\gamma(s, S)]|^2 dN(s_p) dN(s) \right)^{1/2} < 1.$$

Then, a solution to (7) exists, is unique, and is continuous and bounded in $[\underline{s}, \bar{s}]$.

Proof. I omit the y superscript for simplicity. Define $K(s, s_p) \equiv \gamma(s, s_p) - \mathbb{E}[\gamma(s, S)]$ so as to rewrite (7) as

$$\eta(s) = s + \vartheta \beta \int K(s, s_p) \eta(s_p) dN(s).$$

This constitutes a Fredholm equation of the second kind. I restrict my attention to solutions to (7) that belong to $L_2(dN, [\underline{s}, \bar{s}])$. Under Assumption 1 and $\bar{s} < \infty$, we have⁹⁸

$$\int |K(s, s_p)|^2 dN(s_p) \leq C \quad \text{and} \quad \int |s|^2 dN(s) < \infty,$$

for C some constant. In addition, K is globally continuous with respect to x . It follows that any solution to (7) is bounded and continuous in $[\underline{s}, \bar{s}]$ (Zabreiko, 1975, Chapter 2, Theorems 1.7 and 1.8).

Uniqueness of a solution to (7) implies existence (Zabreiko, 1975, Theorem 1.2). Equation (7) has a unique solution when $\vartheta \beta < |\bar{\lambda}|$, where $\bar{\lambda}$ is the characteristic value of K with smallest magnitude. This characteristic value can be solved for when imposing a separability condition on γ (see Section A.4.2). Without this restriction, solving

⁹⁷Clearly the mean of the learning shock and the average learning γ cannot be separately identified from this theory. From the estimation, I assume that e is log-normally distributed and I normalize the mean of e to zero.

⁹⁸As mentioned in the main text, $\bar{s} = \infty$ is possible as long as $\int |s|^2 dN(s) < \infty$ is satisfied.

for $|\bar{\lambda}|$ is non-trivial. However, if the Neumann series

$$\eta^f(s) = f(s) + \sum_{j=1}^{\infty} (\vartheta\beta)^j \int K_j(x, t) tdN(t) \quad (29)$$

converges for any function f satisfying $\int |f(s)|^2 dN(s) < \infty$, where K_j is the j -th iterated kernel of K , then $\vartheta\beta < |\bar{\lambda}|$ (e.g. Zabreiko, 1975, Chapter 2 §2). The inequality $\vartheta\beta\|K\| < 1$ provides a sufficient condition for (29) to converge. \square

From there, the young spatial allocation is given to a first order by

$$n_\ell^y(s) \approx n^y(s)\mathcal{B}_\ell^y + \vartheta n^y(s)\mathcal{B}_\ell^y\mathcal{T}_\ell^y s + \vartheta^2\beta n^y(s)\mathcal{B}_\ell^y\mathcal{T}_\ell^y\Theta(s). \quad (30)$$

The within-city young skill distribution is

$$\pi_\ell^y(s) \approx n^y(s) + \vartheta n^y(s)\mathcal{T}_\ell^y(s - \mathbb{E}[S^y]) + \vartheta^2\beta n^y(s)\mathcal{T}_\ell^y(\Theta(s) - \mathbb{E}[\Theta(S^y)]). \quad (31)$$

Accordingly, the young average skill in city ℓ is

$$\mathbb{E}[\mathcal{W}^y] \approx T_\ell \mathbb{E}[S^y] + \vartheta \mathcal{T}_\ell^y \text{Var}[S^y] + \vartheta^2\beta \mathcal{T}_\ell^y \text{Cov}[S^y, \Theta(S^y)].$$

Aggregates I have argued earlier that, to a first order, there is no aggregate effect of cities on the old skill distribution, $\partial_{T_\ell} N^o(s) = 0$. Differentiating (6) w.r.t. $T_{\ell'}$ yields

$$\frac{\partial N^o(s_o)}{\partial T_{\ell'}} \Big|_{\mathbf{T}=1} = \sum_{\ell} \mathcal{B}_{\ell'}^y \int \int \frac{\partial \pi_{\ell'}^y(s_p)}{\partial T_{\ell'}} n^y(s_y) F\left(\frac{s_o}{\gamma(s_y, s_p)}\right) ds_p ds_y + \sum_{\ell} \int \int n^y(s_p) \frac{\partial n_{\ell'}^y(s_y)}{\partial T_{\ell'}} F\left(\frac{s_o}{\gamma(s_y, s_p)}\right) ds_p ds_y.$$

Using the expression for $\partial_{T_{\ell'}} \pi_{\ell'}^y$ and $\partial_{T_{\ell'}} n_{\ell'}^y$, this turns into

$$\begin{aligned} \frac{\partial N^o(s_o)}{\partial T_{\ell'}} \Big|_{\mathbf{T}=1} &= \vartheta \sum_{\ell} \mathcal{B}_{\ell'}^y I_{\ell\ell'} \int \int (\eta(s_p) - \mathbb{E}[\eta(S_p)]) F\left(\frac{s_o}{\gamma(s_y, s_p)}\right) dN^y(s_p) dN^y(s) + \\ &\quad \vartheta \sum_{\ell} \mathcal{B}_{\ell'}^y I_{\ell\ell'} \int \int \eta(s_y) F\left(\frac{s_o}{\gamma(s_y, s_p)}\right) dN^y(s_p) dN^y(s_y). \end{aligned} \quad (32)$$

However, $\sum_{\ell} \mathcal{B}_{\ell'}^y I_{\ell\ell'} = 0$, and therefore $\partial_{T_{\ell'}} N^o(s_o) = 0$.

A.4.2 An example

Suppose that the learning technology reads:

$$\gamma(s, s_p) = \mathcal{F}(s) + \mathcal{G}(s)\mathcal{H}(s_p),$$

for \mathcal{F} , \mathcal{G} and \mathcal{H} functions that satisfy Assumption 1. This class of learning technology contains (1), e.g. with $\mathcal{F}(s) = g_0 + g_1 s$, $\mathcal{G}(s) = g_2 + g_{12} s$ and $\mathcal{H}(s_p) = s_p$, but also many more. Then, the integral equation simplifies to

$$\eta(s) = s + \vartheta\beta\mathcal{G}(s) \int (\mathcal{H}(s_p) - \mathbb{E}[\mathcal{H}(S^p)]) n^y(s_p) \eta(s_p) ds_p. \quad (33)$$

Solving for this fixed point amounts to solving for the integral on the right-hand side. Multiplying both sides by $(\mathcal{H}(s) - \mathbb{E}[\mathcal{H}(s)])n^y(s)$, integrating over s and re-arranging, we get

$$(1 - \vartheta\beta\text{Cov}[\mathcal{G}(S^y), \mathcal{H}(S^y)]) \int (\mathcal{H}(s) - \mathbb{E}[\mathcal{H}(S^y)]) n^y(s) \eta(s) ds = \text{Cov}[S^y, \mathcal{H}(S^y)].$$

From here, it is easy to show that the characteristic root of (33) is $|\bar{\lambda}| = |1/\text{Cov}[\mathcal{G}(S^y), \mathcal{H}(S^y)]|$. Hence, a solution to (33) exists and is unique when $\vartheta\beta|\text{Cov}[\mathcal{G}(S^y), \mathcal{H}(S^y)]| \leq 1$. This condition is tighter than the one laid out in Lemma A.1. When it is satisfied, we can plug back the expression for the integral into (33) to obtain a closed-form expression for Θ :

$$\Theta(s) = \mathcal{G}(s) \left(\frac{\text{Cov}[S^y, \mathcal{H}(S^y)]}{1 - \vartheta\beta\text{Cov}[\mathcal{G}(S^y), \mathcal{H}(S^y)]} \right).$$

If the covariance between S^y and $\mathcal{H}(S^y)$ is positive, so that, on average, workers learn more from skilled individuals, then Θ inherits the property of $\mathcal{G}(s)$. If $\mathcal{G}(s) > 0$, then worker s learns more from skilled partner, and $\Theta(s) > 0$. If

$\mathcal{G}'(s) > 0$, then so is $\Theta(s)$. Furthermore, Θ is independent from $\mathcal{F}(s)$. Using $\mathcal{G}(s) = g_2 + g_{12}s$ and $\mathcal{H}(s_p) = s_p$ yields

$$\Theta(s) = \theta(g_2 + g_{12}s) \quad \text{where} \quad \theta = \frac{\text{Var}[S^y]}{1 - \vartheta\beta g_{12}\text{Var}[S^y]},$$

as claimed in the main text.

A.5 The Second Order Approximation

The second order approximations are implemented assuming identical amenities over space.⁹⁹

Old skill The expected old skill of a worker with initial skill s reads

$$\mathbb{E}[S^o | s] = \sum_{\ell} \left(\frac{n_{\ell}^y(s)}{n^y(s)} \right) \mathbb{E}_{\ell}[S^o | s] = \sum_{\ell} \left(\frac{n_{\ell}^y(s)}{n^y(s)} \right) \int \gamma(s_y, s_p) \pi_{\ell}^y(s_p) ds_p,$$

while the average skill of old workers is

$$\mathbb{E}[S^o] = \int \mathbb{E}[S^o | s] dN^y(s).$$

In both expressions I have subsumed the expected learning shock $\mu_e = \int e dF(e)$ in γ wlog. The partial derivative of the expected skill for workers with skill s w.r.t. the TFP of city ℓ is

$$\frac{\partial \mathbb{E}[S^o | s]}{\partial T_l} = \frac{1}{n^y(s)} \left(\sum_{\ell} \int \gamma(s, s') \left(\frac{\partial n_{\ell}^y(s)}{\partial T_l} \right) \pi_{\ell}^y(s') ds' + \sum_{\ell} \int \gamma(s, s') n_{\ell}^y(s) \left(\frac{\partial \pi_{\ell}^y(s')}{\partial T_l} \right) ds' \right).$$

By a similar argument as in (32), there is no aggregate effect of local interactions on workers' expected skill at the first order. Hence, moving to the second order, differentiate the above expression w.r.t. $T_{l'}$ to get

$$\begin{aligned} \frac{\partial^2 \mathbb{E}[S^o | s]}{\partial l \partial l'} \Big|_{\mathbf{T}=1} &= \frac{1}{n^y(s)} \left(\underbrace{\int \gamma(s, s') \left(\sum_{\ell} \partial_{ll'}^2 n_{\ell}^y(s) \right) n^y(s') ds'}_{=0} + \frac{1}{L} \int \gamma(s, s') n^y(s) \left(\sum_{\ell} \partial_{ll'}^2 \pi_{\ell}^y(s') \right) ds' \right) + \\ &\quad \frac{1}{n^y(s)} \left(\int \gamma(s, s') \left(\sum_{\ell} \partial_l n_{\ell}^y(s) \partial_{l'} \pi_{\ell}^y(s') \right) ds' + \int \gamma(s, s') \left(\sum_{\ell} \partial_{l'} n_{\ell}^y(s) \partial_l \pi_{\ell}^y(s') \right) ds' \right), \end{aligned}$$

where the equality on the first line follows from the fixed supply of young skill. Meanwhile, the second-order change in $\pi_{\ell}^y(s)$ reads

$$\frac{\partial^2 \pi_{\ell}^y(s)}{\partial T_l \partial T_{l'}} = \frac{1}{N_{\ell}} \left\{ \frac{\partial^2 n_{\ell}^y(s)}{\partial T_l \partial T_{l'}} - \frac{\partial n_{\ell}^y(s)}{\partial T_l} \frac{\partial \log N_{\ell}}{\partial T_{l'}} - \frac{\partial n_{\ell}^y(s)}{\partial T_{l'}} \frac{\partial \log N_{\ell}}{\partial T_l} + 2n_{\ell}^y(s) \frac{\partial \log N_{\ell}}{\partial T_{l'}} \frac{\partial \log N_{\ell}}{\partial T_l} - \pi_{\ell}^y(s) \frac{\partial^2 N_{\ell}}{\partial T_l \partial T_{l'}} \right\}.$$

Hence, when evaluated at $\mathbf{T} = 1$ and summed across ℓ , we end up with

$$\sum_{\ell} \frac{\partial^2 \pi_{\ell}^y(s)}{\partial T_l \partial T_{l'}} \Big|_{\mathbf{T}=1} = -L \sum_{\ell} \left(\frac{\partial \pi_{\ell}^y(s)}{\partial T_l} \frac{\partial N_{\ell}}{\partial T_{l'}} + \frac{\partial \pi_{\ell}^y(s)}{\partial T_{l'}} \frac{\partial N_{\ell}}{\partial T_l} \right),$$

since $\partial_l \pi_{\ell}^y(s)|_{\mathbf{T}=1} = L(\partial_l n_{\ell}^y(s) - n^y(s) \partial_l N_{\ell})$. Plugged in the expression for the aggregate change in old skill, we therefore obtain

$$\frac{\partial^2 \mathbb{E}[S^o | s]}{\partial T_l \partial T_{l'}} \Big|_{\mathbf{T}=1} = \frac{1}{n^y(s)L} \int \gamma(s, s') \sum_{\ell} \left(\frac{\partial \pi_{\ell}^y(s)}{\partial T_l} \frac{\partial \pi_{\ell}^y(s')}{\partial T_{l'}} + \frac{\partial \pi_{\ell}^y(s)}{\partial T_{l'}} \frac{\partial \pi_{\ell}^y(s')}{\partial T_l} \right) ds',$$

which follows again from $\partial_l \pi_{\ell}^y(s)|_{\mathbf{T}=1} = L(\partial_l n_{\ell}^y(s) - n^y(s) \partial_l N_{\ell})$. This expression relies entirely on first order micro term which we have derived in Section A.4.1. Using (28), we get

$$\sum_{\ell} \frac{\partial \pi_{\ell}^y(s)}{\partial T_l} \frac{\partial \pi_{\ell}^y(s')}{\partial T_{l'}} = \vartheta^2 I_{ll'} (\eta(s) - \mathbb{E}[\eta(S^y)]) (\eta(s') - \mathbb{E}[\eta(S^y)]) n^y(s') n^y(s),$$

⁹⁹The aggregate effects on productivity are due to the spatial variations in local skill density, see (31). The local skill densities are independent of city amenity. Adding city amenity would therefore not change the conclusion.

which follows from $\sum_\ell I_{\ell l} I_{\ell l'} = I_{ll'}$. But I is symmetric function, $I_{ll'} = I_{l'l}$. Hence, $\sum_\ell \partial_l \pi_\ell^y(s) \partial_{l'} \pi_\ell^y(s') = \sum_\ell \partial_{l'} \pi_\ell^y(s) \partial_l \pi_\ell^y(s')$, and we end up with

$$\frac{\partial^2 \mathbb{E}[S^o | s]}{\partial T_l \partial T_{l'}} \Big|_{\mathbf{T}=\mathbf{1}} = \frac{2}{L} \vartheta^2 I_{ll'} \int \gamma(s, s') (\eta(s) - \mathbb{E}[\eta(S^y)]) (\eta(s') - \mathbb{E}[\eta(S^y)]) dN^y(s').$$

We can therefore conclude that, to a second-order, the expected old skill workers with young skill s is

$$\mathbb{E}[S^o | s] \approx \mathbb{E}[S^o | s] + \frac{1}{2} \sum_l \sum_{l'} (T_l - 1) (T_{l'} - 1) \frac{\partial^2 \mathbb{E}[S^o | s]}{\partial T_l \partial T_{l'}} = \mathbb{E}[S^o | s] + \vartheta^2 \text{Var}[T] \Omega(s),$$

where

$$\Omega(s) \equiv (\eta(s) - \mathbb{E}[\eta(S^y)]) \int \gamma(s, s') (\eta(s') - \mathbb{E}[\eta(S^y)]) dN^y(s'). \quad (34)$$

Accordingly, to a second order, the average skill of old workers is

$$\mathbb{E}[S^o] \approx \mathbb{E}[S^o] + \vartheta^2 \text{Var}[T] \int \Omega(s) dN^y(s). \quad (35)$$

Between-city wage inequality Let $\bar{W}_\ell^y \equiv \mathbb{E}[W_\ell^y]$ be the average wage in city ℓ . The between-city wage inequality is

$$\text{Var}[\bar{W}_\ell^y] = \sum_\ell (\bar{W}_\ell^y - \bar{W}^y)^2 N_\ell^y,$$

for $\bar{W}^y \equiv \mathbb{E}[W^y]$ the aggregate average wage. As expected, there is no first order effect on the variance. The partial derivative of $\text{Var}[\bar{W}_\ell^y]$ w.r.t. T_l reads

$$\partial_l \text{Var}[\bar{W}_\ell^y] = 2 \sum_\ell (\bar{W}_\ell^y - \bar{W}^y) (\partial_l \bar{W}_\ell^y - \partial_l \bar{W}^y) N_\ell^y + \sum_\ell (\bar{W}_\ell^y - \bar{W}^y)^2 \partial_l N_\ell^y,$$

which, when evaluated at $\mathbf{T} = \bar{\mathbf{T}}$, simplifies to $\partial_l \text{Var}[\bar{W}_\ell^y] = 0$. Hence, turning to the second order effect, we have that the second order partial derivative of $\text{Var}[\bar{W}_\ell^y]$ w.r.t. $(T_l, T_{l'})$ evaluated at $\mathbf{T} = \bar{\mathbf{T}}$ is

$$\partial_{ll'}^2 \text{Var}[\bar{W}_\ell^y] = \frac{2}{L} \sum_\ell (\partial_{l'} \bar{W}_\ell^y - \partial_{l'} \bar{W}^y) (\partial_l \bar{W}_\ell^y - \partial_l \bar{W}^y). \quad (36)$$

All that is required is therefore the marginal, first order effect of cities' TFP on the cities' average wages and the aggregate average wage. Using (28), the first marginal effect reads

$$\partial_l \bar{W}_\ell^y = \mathbb{1}\{\ell = l\} \mathbb{E}[S^y] + \vartheta I_{ll} \bar{T} \text{Cov}[S^y, \eta(S^y)].$$

Using (27), the second marginal effect is

$$\partial_l \bar{W}^y = \frac{1}{L} \mathbb{E}[S^y].$$

Combined, (36) rewrites

$$\partial_{ll'}^2 \text{Var}[\bar{W}_\ell^y] = \frac{2}{L} I_{ll'} (\mathbb{E}[S^y] + \vartheta \bar{T} \text{Cov}[S^y, \eta(S^y)])^2,$$

where I have used $\sum_\ell I_{l'\ell} I_{l\ell} = I_{ll'}$. I therefore conclude that, to a second order, the between-city variance of wages is

$$\text{Var}[\bar{W}_\ell^y] \approx \text{Var}[T_\ell] (\mathbb{E}[S^y] + \vartheta \bar{T} \text{Var}[S^y] + \vartheta^2 \beta \bar{T} \text{Cov}[S^y, \Theta(S^y)])^2 \quad (37)$$

since the between-city variance of wages is nil when city TFPs are homogeneous.

A.6 Proof of Lemma 1

Suppose that the learning technology is either supermodular or submodular, $\gamma_{12}(s, s_p) > 0$ or $\gamma_{12}(s, s_p) < 0$ a.e. I then guess and verify that $\text{Cov}[\gamma_1(s, S^y), S^y] \geq -1$ implies $\eta'(s) \geq 0$. So guess that $\eta'(s) > 0$. I first sign Θ' under this guess. Note from (7) that Θ can be written $\Theta(s) = \text{Cov}[\gamma(s, S^y), \eta(S^y)]$. Differentiate Θ to obtain $\Theta'(s) = \text{Cov}[\gamma'_1(s, S), \eta(S)]$.

The covariance of two increasing function is positive while the covariance of an increasing and a decreasing function is negative. Hence, since $\eta' > 0$, we have that $\gamma_{12} > 0$ implies $\Theta'(s) > 0$ while $\gamma_{12} < 0$ implies $\Theta'(s) < 0$. We can now verify the guess. Differentiate η and plug in the expression for η in Θ to find

$$\eta'(s) = 1 + \vartheta\beta\text{Cov}[\gamma_1(s, S^y), S^y] + (\vartheta\beta)^2\text{Cov}[\gamma_1(s, S^y), \Theta(S^y)].$$

I distinguish between two cases. First, suppose that $\gamma_{12} > 0$. Then, $\text{Cov}[\gamma_1(s, S^y), S^y] > 0$. Furthermore, since $\Theta' > 0$, we also have $\text{Cov}[\gamma_1(s, S^y), \Theta(S^y)] > 0$. Hence, $\eta' > 0$. Second, suppose that $\sigma_{12} < 0$. Then, $\text{Cov}[\gamma_1(s, S^y), S^y] < 0$. Second, since $\Theta' < 0$ and the covariance of two decreasing functions is positive, we have $\text{Cov}[\gamma_1(s, S^y), \Theta(S^y)] > 0$. Hence, $\eta'(s) > 1 + \vartheta\beta\text{Cov}[\gamma_1(s, S^y), S^y] \geq 0$, where the second inequality is from the assumption on γ . This verifies our guess.

A.7 Proof of Proposition 2

Proposition 2.1 To a first order, (30) and (26) implies that the size of city ℓ is

$$N_\ell \approx \mathcal{B}_\ell^y + \mathcal{B}_\ell^o + \vartheta(\mathcal{B}_\ell^y \mathcal{T}_\ell^y \mathbb{E}[S^y] + \mathcal{B}_\ell^o \mathcal{T}_\ell^o \mathbb{E}[S^o]) + \vartheta^2 \beta \mathcal{B}_\ell^y \mathcal{T}_\ell^y \mathbb{E}[\Theta(S^y)].$$

Meanwhile, if interactions are not spatially segmented, then

$$N_\ell^C \approx \mathcal{B}_\ell^y + \mathcal{B}_\ell^o + \vartheta(\mathcal{B}_\ell^y \mathcal{T}_\ell^y \mathbb{E}[S^y] + \mathcal{B}_\ell^o \mathcal{T}_\ell^o \mathbb{E}[S^o]).$$

When $\mathbf{T} \approx \bar{\mathbf{T}}$, we thus have that for any ℓ such that $\mathcal{T}_\ell^y > 0$, then $N_\ell > N_\ell^C \iff \mathbb{E}[\Theta(S^y)] > 0$. Under Lemma 1, η is an increasing function. Hence, $\gamma(s, \cdot)$ increasing implies $\Theta(s) = \text{Cov}[\gamma(s, S^y), \eta(S^y)] > 0$. Conversely, $\gamma(s, \cdot)$ decreasing implies $\Theta(s) < 0$. When amenities are the same everywhere, $\mathcal{T}_\ell^y > 0 \iff T_\ell > \bar{T}$, which yields Proposition 2.1. \square

Proposition 2.2 The between-city wage standard deviation for young workers is given by taking the square root of (37). When interactions are not spatially segmented, it is

$$\text{Sd}[\mathbb{E}(W_\ell^{yC})] \approx \mathbb{E}[S^y] \text{Sd}[T_\ell] + \vartheta \text{Var}[S^y] \text{Sd}[T_\ell].$$

Therefore, $\text{Sd}[\mathbb{E}(W_\ell^y)] > \text{Sd}[\mathbb{E}(W_\ell^{yC})] \iff \text{Cov}[S^y, \Theta(S^y)] > 0$. If γ is supermodular, then $\gamma_1(s, \cdot)$ is increasing. Hence $\Theta'(s) = \text{Cov}[\gamma_1(s, S^y), \eta(S^y)] > 0$, and $\text{Cov}[S^y, \Theta(S^y)] > 0$. Conversely, $\gamma_1(s, \cdot)$ is decreasing under γ , and $\text{Cov}[S^y, \Theta(S^y)] < 0$. \square

A.8 Proof of Proposition 3

The second order approximation of $\mathbb{E}[S^o]$ is derived in (35). Let $\Omega = \int \Omega(s) dN^y(s)$ where $\Omega(s)$ is given by (34). Define $\chi(s) \equiv \eta(s) - \mathbb{E}[\eta(S^y)]$. From the fundamental theorem of calculus,

$$\gamma(s, s') = \int_{\underline{s}}^s \int_{\underline{s}}^{s'} \gamma_{12}(x, y) dy dx + \gamma(s, \underline{s}) - \gamma(\underline{s}, \underline{s}) + \gamma(\underline{s}, s').$$

From the definition of χ , we know that $\int \gamma(s, \underline{s}) \chi(s) ds = \int \gamma(\underline{s}, s') \chi(s') ds' = \int \gamma(\underline{s}, \underline{s}) \chi(s) ds = 0$. Therefore, Ω can be rewritten

$$\Omega = \int \int \int_{\underline{s}}^s \int_{\underline{s}}^{s'} \gamma_{12}(x, y) \chi(s) \chi(s') dy dx dN^y(s') dN^y(s) = \int \int \gamma_{12}(x, y) \Psi(x) \Psi(y) dx dy,$$

where $\Psi(x) \equiv \int_x \chi(s) dN^y(s)$ and the second equality follows from Fubini's. Note that Ψ rewrites $\Psi(x) = (1 - N(x))(\mathbb{E}[\eta(S^y) | S^y \geq x] - \mathbb{E}[\eta(S^y)])$. Hence, $\Psi(x) > 0$ iff $\mathbb{E}[\eta(S^y) | S^y \geq x] > \mathbb{E}[\eta(S^y)]$. But Lemma 1 guarantees that η is an increasing function. It follows that $s \rightarrow \mathbb{E}[\eta(S^y) | S^y \geq s]$ is increasing, and $\mathbb{E}[\eta(S^y) | S^y \geq s] \geq \mathbb{E}[\eta(S^y) | S^y \geq \underline{s}] = \mathbb{E}[\eta(S^y)]$. Hence, $\Psi(x)\Psi(y) > 0$ and Ω preserves the sign of γ_{12} .

A.9 The Learning Consequences of Local Interactions across Skills

In a similar fashion as 10, the expected old skill of workers endowed with an initial skill s is, to a second order, given by (see Section A.5)

$$\mathbb{E}[S^o | s] \approx \mathbb{E}[\bar{S}^o | s] + \vartheta^2 \text{Var}[T] \Omega(s),$$

where

$$\Omega(s) = (\eta(s) - \mathbb{E}[\eta(S^y)]) \int \gamma(s, s_p) (\eta(s_p) - \mathbb{E}[\eta(S^y)]) dN^y(s_p).$$

The term $\Omega(s)$ has a similar interpretation as Ω but at the skill level. If $\Omega(s) > 0$, the spatial segmentation of learning interactions boost the average learning of workers initially endowed with a skill s . The converse happen if $\Omega(s) < 0$. The following proposition characterizes $\Omega(s)$ as a function of the learning technology.

Proposition A.3 (Learning inequality).

Define s^* as the skill with the average willingness to sort, $\eta(s^*) \equiv \mathbb{E}[\eta(S^y)]$.

1. If $\gamma(s, \cdot)$ is increasing for all s , then $\Omega(s) > 0$ if and only if $s > s^*$;
2. If $\gamma(s, \cdot)$ is decreasing for all s , then $\Omega(s) > 0$ if and only if $s < s^*$.

Proof. I use similar notation as for the proof of Proposition 3. From the fundamental theorem of calculus, $\Omega(s)$ can be rewritten

$$\gamma(s, s') = \int_{\underline{s}}^{s'} \gamma_2(s, y) dy dx + \gamma(s, \underline{s}).$$

From the definition of χ , we know that $\int \gamma(s, \underline{s}) \chi(s) ds' = 0$, and therefore $\Omega(s)$ reads

$$\Omega(s) = \chi(s) \int_{\underline{s}}^{s'} \gamma_2(s, y) dy \chi(s') dN^y(s') = \chi(s) \int \gamma_2(s, y) \Psi(y) dy.$$

The proof of Proposition 3 has shown that $\Psi(y) > 0$. The sign of $\Omega(s)$ therefore depends on the product between the sign of $\chi(s)$ and that of γ_2 . Let s^* be such that $\eta(s^*) = \mathbb{E}[\eta(S^y)]$ and $\eta(s) > \mathbb{E}[\eta(S^y)]$ iff $s > s^*$. Lemma 1 guarantees that such s^* exists. For $s > s^*$, if $\gamma_2 > 0$ for all y , then $\Omega(s) > 0$; if $\gamma_2 < 0$ for all y , then $\Omega(s) < 0$. Opposite equality exists for $s < s^*$. \square

In particular, when every worker learns relatively more from skilled interactions, Proposition A.3 implies that the segmentation of learning interactions boost the learning of relatively skilled workers and dampens that of relatively low-skill individuals. That is, local interactions spur learning inequality across skills.

B Efficiency

B.1 Planner's problem

Suppose that the planner is utilitarian. The planner places unitary weights on skill and cities and discounts the future of future generations at rate β_S . Let $\mathbb{E}_\ell[V_t^{y*}(s, \boldsymbol{\varepsilon}) | s]$ denote the expected utility of young workers with skill s working in city ℓ at time t , where the expectation is taken across the unobserved idiosyncratic preferences $\boldsymbol{\varepsilon}$. Define $\mathbb{E}_\ell[V_t^{o*}(s, \boldsymbol{\varepsilon}) | s]$ for old workers. The planner's social welfare function,

$$\int \sum_\ell \mathbb{E}_\ell[V_0^{o*}(s, \boldsymbol{\varepsilon}) | s] n_{0\ell}^{o*}(s) ds + \sum_{t>0} \beta_S^t \int \sum_\ell \mathbb{E}_\ell[V_t^{y*}(s, \boldsymbol{\varepsilon}) | s] n_{t\ell}^{y*}(s) ds.$$

The expected utility of workers must be consistent with workers' location choices. By the property of extreme-value type one distribution, the expected utility of old workers working in city ℓ is identical to the *ex-ante* expected utility:

$$\begin{aligned} \mathbb{E}_\ell[V_t^{o*}(s, \boldsymbol{\varepsilon}) | s] &= \mathbb{E}[V_t^{o*}(s, \boldsymbol{\varepsilon}) | s] \\ &= \frac{1}{\vartheta} \log \left(\sum_{\ell'} e^{\vartheta c_{t\ell'}^{o*}(s)} \right) \equiv \mathcal{V}_t^{o*}(s). \end{aligned}$$

Similarly for the young,

$$\mathcal{V}_t^{y*}(s) = \frac{1}{\vartheta} \log \left(\sum_\ell e^{\vartheta (c_\ell^{y*}(s) + \beta O_\ell^*(s))} \right),$$

where

$$O_\ell^*(s) = \int \int \mathcal{V}^{o*}[e\gamma(s, s_p)] dF(e) \pi_{t\ell}^{y*}(s_p) ds_p.$$

Hence, the social welfare function simplifies to

$$\int \mathcal{V}_0^{o*}(s) \sum_\ell n_{0\ell}^{o*}(s) ds + \sum_{t>0} \beta_S^t \int \mathcal{V}_t^{y*}(s) \sum_\ell n_{t\ell}^{y*}(s) ds.$$

The problem of the planner is to maximize this objective function by choosing a sequence $\{\mathbf{c}_t^{y*}, \mathbf{c}_t^{o*}, \mathbf{n}_t^{y*}, \mathbf{n}_t^{o*}, n_t^*\}_{t=0}^\infty$.

Next, I note that between-skill transfers are not pinned down. Intuitively, workers' utility is linear in income. The idiosyncratic location preferences generate some concavity across cities but not across skills. Hence, any between-skill transfer can be sustained to the extent that these transfers are feasible. To see this, suppose that the planner considers two consumption plans at time t for young workers: \mathbf{c}_t^y on the one hand, and $\tilde{\mathbf{c}}_t^y$ on the other hand. The two plans differ in that $\tilde{c}_{t\ell}^{y*}(s) = c_{t\ell}^{y*}(s) + q(s)$ for some function q . Since q is not city-specific, it does not affect the spatial allocation, and the learning value of cities is the same in the two plans. Similarly, total output is constant. Hence, these two plans are jointly feasible if $\int q(s) dN^y(s) ds = 0$. Meanwhile, the difference in the aggregate utility of cohort t between the two consumption plans is

$$\frac{1}{\vartheta} \int \left(\log \left(\sum_\ell e^{\vartheta(c_{t\ell}^{y*}(s) + \beta O_\ell^*(s))} \right) - \log \left(\sum_\ell e^{\vartheta(\tilde{c}_{t\ell}^{y*}(s) + \beta O_\ell^*(s))} \right) \right) n^y(s) ds = \int q(s) n^y(s) ds = 0.$$

That is, any function q yields the same aggregate welfare, and between-skill transfers are not determinate. I therefore suppose that between-skill transfers are not allowed. This restriction is without loss of generality for the optimal spatial allocation since between-skill transfers do not distort workers' incentives to live in particular cities. I also suppose that between-age transfers are not allowed to focus on the learning externalities.

The planner thus faces the following conditions:

1. Young and old consumption feasibility, $\kappa_t^y(s)$ and $\kappa_t^o(s)$ respectively:

$$\sum_\ell c_{t\ell}^{y*}(s) n_{t\ell}^{y*}(s) \leq \sum_\ell T_\ell s n_{t\ell}^{y*}(s), \quad \text{and} \quad \sum_\ell c_{t\ell}^{o*}(s) n_{t\ell}^{o*}(s) \leq \sum_\ell T_\ell s n_{t\ell}^{o*}(s), \quad \forall(s, t)$$

2. Young labor mobility conditional on workers' unobserved idiosyncratic preferences, $\lambda_{t\ell}^y(s)$:

$$n_{t\ell}^{y*}(s) \leq n^y(s) \left(\frac{e^{\vartheta(c_{t\ell}^{y*}(s) + \beta O_{t\ell}^*(s))}}{\sum_{\ell'} e^{\vartheta(c_{t\ell'}^{y*}(s) + \beta O_{t\ell'}^*(s))}} \right), \quad \forall(s, t, \ell).$$

3. Old labor mobility conditional on workers' (unobserved) idiosyncratic preferences, $\lambda_{t\ell}^o(s)$:

$$n_{t\ell}^{o*}(s) \leq n_t^{o*}(s) \left(\frac{e^{\vartheta c_{t\ell}^{o*}(s)}}{\sum_{\ell'} e^{\vartheta c_{t\ell'}^{o*}(s)}} \right), \quad \forall(s, t, \ell).$$

4. The aggregate old skill law of motion, $\nu_t(s)$:

$$n_{t+1}^{o*}(s_o) = \sum_\ell \int \int \frac{1}{\gamma(s_y, s_p)} f\left(\frac{s_o}{\gamma(s_y, s_p)}\right) n_{t\ell}^{y*}(s_y) \pi_{t\ell}^{y*}(s_p) ds_p ds_y, \quad \forall(s, t).$$

Given these preliminary remarks, the Lagrangian of the planner's problem reads

$$\begin{aligned}
\mathcal{L} = & \frac{1}{\vartheta} \int \log \left(\sum_{\ell} e^{\vartheta c_{0\ell}^{o*}(s)} \right) \sum_{\ell} n_{0\ell}^{o*}(s) ds + \frac{1}{\vartheta} \sum_{t>0} \beta_S^t \int \log \left(\sum_{\ell} e^{\vartheta(c_{t\ell}^{y*}(s) + \beta O_{t\ell}^{*}(s))} \right) \sum_{\ell} n_{t\ell}^{y*}(s) ds - \\
& \sum_t \sum_{\ell} \int \lambda_{t\ell}^y(s) \left(n_{t\ell}^{y*}(s) - n^y(s) \left(\frac{e^{\vartheta(c_{t\ell}^{y*}(s) + \beta O_{t\ell}^{*}(s))}}{\sum_{\ell'} e^{\vartheta(c_{t\ell'}^{y*}(s) + \beta O_{t\ell'}^{*}(s))}} \right) \right) ds - \\
& \sum_t \sum_{\ell} \int \lambda_{t\ell}^o(s) \left(n_{t\ell}^{o*}(s) - n_t^{o*}(s) \left(\frac{e^{\vartheta c_{t\ell}^{o*}(s)}}{\sum_{\ell'} e^{\vartheta c_{t\ell'}^{o*}(s)}} \right) \right) ds - \\
& \sum_t \int \nu_t(s_o) \left(n_{t+1}^{o*}(s_o) - \sum_{\ell} \int \int \frac{1}{\gamma(s_y, s_p)} f \left(\frac{s_o}{\gamma(s_y, s_p)} \right) n_{t\ell}^{y*}(s_y) \pi_{t\ell}^{y*}(s_p) ds_p ds_y \right) ds_o - \\
& \sum_t \int \kappa_t^y(s) \sum_{\ell} (c_{t\ell}^{y*}(s) - T_{t\ell}s) n_{t\ell}^{y*}(s) ds + \sum_t \int \kappa_t^o(s) \sum_{\ell} (c_{t\ell}^{o*}(s) - T_{t\ell}s) n_{t\ell}^{o*}(s) ds,
\end{aligned}$$

where I have kept implicit that

$$O_{t\ell}^*(s) = \frac{1}{\vartheta} \int \int \log \left(\sum_{\ell'} e^{\vartheta c_{t+1\ell'}^{o*}[e\gamma(s, s_p)]} \right) dF(e) \pi_{t\ell}^{y*}(s_p) ds_p.$$

B.2 Non-linear optimal allocation

Solving this maximization problem consists of finding the function $s \rightarrow c_{t\ell}^{y*}(s)$, $s \rightarrow c_{t\ell}^{o*}(s)$, $s \rightarrow n_{t\ell}^{y*}(s)$, $s \rightarrow n_{t\ell}^{o*}(s)$, and $s \rightarrow n_t^{o*}(s)$, for each $\ell \in \{1, 2, \dots, L\}$ and $t \in \{0, 1, 2, \dots\}$. This is an infinite-dimensional maximization problem that is solved using functional derivatives. I lay down the complete argument for the optimality condition regarding the initial old allocation, $c_{0\ell}^{o*}$ and $n_{0\ell}^{o*}(s)$. I then present more succinct derivations for the remaining optimality conditions. For the remaining of the derivation, I drop the star superscript for notation simplicity.

Initial old Suppose the planner contemplates an alternative consumption plan given by $\tilde{c}_{0l}^o(s) = c_{0l}^o(s) + \varepsilon \eta(s)$ for some l and some arbitrary function $\eta(s)$, while $\tilde{c}_{0\ell}^o(s) = c_{0\ell}^o(s)$ for $\ell \neq l$. Optimality requires that $d\mathcal{L}/d\varepsilon = 0$ at $\varepsilon = 0$, or

$$\int \eta(s) n_{0l}^o(s) ds + \vartheta \int \eta(s) n_{0l}^o(s) \left(\lambda_{0l}^o(s) - \sum_{\ell} \lambda_{0\ell}^o(s) \frac{n_{0\ell}^o(s)}{n_0^o(s)} \right) ds - \int \kappa_0^o(s) \eta(s) n_{0l}^o(s) ds = 0,$$

where I have already imposed that $\sum_{\ell} n_{0\ell}^o(s) = n_0^o(s)$. Optimality requires that this hold for any function $\eta(s)$. In particular, letting $\eta(s) = \delta_x(s) = \delta(s-x)$, where δ is the Dirac delta function, the above optimality condition simplifies to

$$1 + \vartheta \left(\lambda_{0l}^o(x) - \sum_{\ell} \lambda_{0\ell}^o(x) \frac{n_{0\ell}^o(x)}{n_0^o(x)} \right) = \kappa_0^o(x),$$

where I have also used that the idiosyncratic location preferences guarantee an interior allocation to simplify the $n_{0l}^o(x)$. In the above expression, the only l specific term is the KKT multiplier $\lambda_{0l}^o(x)$. Hence, $\lambda_{0l}^o(x) = \lambda_0^o(x)$ for all l , and we can conclude that $\kappa_0^o(x) = 1$.

Proceeding in a similar fashion for the optimality condition regarding $n_{0l}^o(s)$ and using $\kappa_0^o(x) = 1$, we have

$$\mathcal{V}_0^o(x) - (c_{0l}^o(x) - T_l x) = \lambda_0^o(x).$$

Multiplying by $n_{0l}^o(x)$, summing across l and using the age-skill specific feasibility condition yields $\lambda_0^o(x) = \mathcal{V}_0^o(x)$ and therefore $c_{0l}^o(x) = T_l x$.

Old workers I now derive the optimality conditions for $(\mathbf{n}_t^o, \mathbf{n}_{tl}^o, \mathbf{c}_{tl}^o)$ for $t \geq 1$. Regarding \mathbf{c}_{tl}^o , we have

$$\begin{aligned} \int \kappa_t^o(s) n_{tl}^o(s) \eta(s) ds &= \beta_S^{t-1} \beta \int \sum_\ell n_{t-1\ell}^y(s) \delta_{c_{tl}^o} O_{t-1\ell}(s) ds + \\ &\quad \vartheta \beta \sum_\ell \int \lambda_{t-1\ell}^y(s) n_{t\ell}^y(s) \left(\delta_{c_{tl}^o} O_{t-1\ell}(s) - \sum_{\ell'} \frac{n_{t-1\ell'}^y(s)}{n_t^y(s)} \delta_{c_{tl}^o} O_{t-1\ell'}(s) \right) ds + \\ &\quad \vartheta \int n_{tl}^o(s) \eta(s) \left(\lambda_{tl}^o(s) - \sum_\ell \lambda_{t\ell}^o(s) \frac{n_{t\ell}^o(s)}{n_t^o(s)} \right) ds, \end{aligned}$$

for any η function, where $\delta_x F$ denote the functional derivative of F w.r.t. x . I anticipate that, at the optimum, it must be that $\lambda_{t-1\ell}^y(s) \equiv \lambda_{t-1}^y(s)$ for all ℓ and t . Hence, the second line is equal to zero. From the expression for $O_{t\ell}$, we further know that

$$\delta_{c_{tl}^o} O_{t-1\ell}(s) = \int \int \eta[e\gamma(s, s_p)] \frac{n_{tl}^o[e\gamma(s, s_p)]}{n_t^o[e\gamma(s, s_p)]} dF(e) \pi_{t-1\ell}^y(s_p) ds_p.$$

Hence, the optimality condition turns into

$$\begin{aligned} \int \kappa_t^o(s) n_{tl}^o(s) \eta(s) ds &= \beta_S^{t-1} \beta \int \eta(q) \frac{n_{tl}^o(q)}{n_t^o(q)} \sum_\ell \int \int \frac{1}{\gamma(s, s_p)} f\left(\frac{q}{\gamma(s, s_p)}\right) n_{t-1\ell}^y(s) \pi_{t-1\ell}^y(s_p) ds_p ds dq + \\ &\quad \vartheta \int n_{tl}^o(s) \eta(s) \left(\lambda_{tl}^o(s) - \sum_\ell \lambda_{t\ell}^o(s) \frac{n_{t\ell}^o(s)}{n_t^o(s)} \right) ds, \end{aligned}$$

where I have used the change of variable $e\gamma(s, s_p) \rightarrow q$ to rewrite the integral on the first line. Using the law of motion for the aggregate old skill distribution, the two inner most integrals on the first line cancel out with $n_t^o(q)$. Setting $\eta(s) = \delta_x(s)$, we then obtain

$$\kappa_t^o(x) = \beta_S^{t-1} \beta + \vartheta \left(\lambda_{tl}^o(x) - \sum_\ell \lambda_{t\ell}^o(x) \frac{n_{t\ell}^o(x)}{n_t^o(x)} \right),$$

where both sides have been divided by $n_{tl}^o(x)$. As for the initial old consumption allocation, there is no l -specific term in the above expression, and $\lambda_{tl}^o(x) = \lambda_t^o(x)$. Hence, $\kappa_t^o(x) = \beta_S^{t-1} \beta \equiv \kappa_t^o$ for $t \geq 1$. Setting $\beta_S = \beta$, then $\kappa_t^o = \beta^t$ for $t \geq 0$.

Turning to the optimality condition w.r.t. n_{tl}^o , note that $O_{t\ell}(s)$ is independent of n_{tl}^o . Hence, after using $\lambda_{tl}^o(x) = \lambda_t^o(x)$ and $\kappa_t^o = \beta_S^{t-1} \beta$, the optimality condition reads

$$\lambda_t^o(x) = \beta_S^{t-1} \beta (T_l s - c_{tl}^o(x)).$$

Multiplying by $n_{tl}^o(x)$, summing across l and using the feasibility condition, this implies $\lambda_t^o(x) = 0$ for all $t \geq 1$, and therefore $c_{tl}^o(x) = T_l s$.¹⁰⁰

Finally, there remains the optimality condition w.r.t. n_t^o . There, we have

$$\sum_\ell \int \lambda_{t\ell}^o(s) \eta(s) \frac{n_{t\ell}^o(s)}{n_t^o(s)} ds - \int \nu_{t-1}(s) \eta(s) ds = \int \lambda_t^o(s) \eta(s) ds - \int \nu_{t-1}(s) \eta(s) ds = 0,$$

for $t \geq 1$, where the first equality follows from $\lambda_{t\ell}^o(x) = \lambda_t^o(x)$. Setting $\eta = \delta_x(s)$, we obtain the optimality condition $\nu_{t-1}(x) = \lambda_t^o(x) = 0$.

Young workers I finally derive the optimality conditions for $(\mathbf{n}_t^y, \mathbf{n}_{t\ell}^y, \mathbf{c}_{t\ell}^y)$ for $t \geq 0$. For consumption, note that the learning value of cities is independent of $c_{t\ell}^y$. Hence, the optimality condition w.r.t. $c_{t\ell}^y$ is

$$\beta_S^t + \vartheta \left(\lambda_{tl}^y(x) - \sum_\ell \lambda_{t\ell}^y(x) \frac{n_{t\ell}^y(x)}{n_t^y(x)} \right) = \kappa_t^y(x).$$

¹⁰⁰The same would hold if we were to allow for transfers within age across skills. Then, feasibility would require $\int \lambda_t^o(x) n_t^o(x) dx = \beta_S^{t-1} \beta \sum_l \int n_{tl}^o(x) (T_l s - c_{tl}^o(x)) dx = 0$. But $\lambda_t^o(x) \geq 0$ since it is a KKT multiplier, and therefore $\lambda_t^o(x) = 0$ for all x . Hence, on the contrary of the young allocation, the old allocation is uniquely pin down even with across-skill transfers. Why? Between-skill transfers for old workers affect the incentives to learn, and thus the spatial allocation of workers.

Hence, here as well, this implies $\lambda_{lt}^y(x) \equiv \lambda_t^y(x)$ and $\kappa_t^y(x) = \beta_S^t \equiv \kappa_t^o$. When $\beta_S = \beta$, then $\kappa_t^y = \kappa_t^o$.

I conclude with the optimality condition for n_{tl}^y . There, and crucially, n_{tl}^y affects O_{tl} . The optimality condition is

$$0 = \beta_S^t \beta \int \sum_{\ell} n_{tl}^y(s) \delta_{n_{tl}^y} O_{t\ell}(s) ds + \beta_S^t \int \mathcal{V}_t^y(s) \eta(s) ds -$$

$$\int \left(\lambda_{tl}^y(s) \eta(s) - \vartheta \beta \sum_{\ell} \lambda_{t\ell}^y(s) n_{t\ell}^y(s) \left[\delta_{n_{tl}^y} O_{t\ell}(s) - \sum_{\ell'} \frac{n_{t\ell'}^y(s)}{n^y(s)} \delta_{n_{tl}^y} O_{t\ell'}(s) \right] \right) ds +$$

$$\int \nu_t(s_o) \int \int \frac{1}{\gamma(s_y, s_p)} f\left(\frac{s_o}{\gamma(s_y, s_p)}\right) \left(\eta(s_y) \pi_{tl}^y(s_p) + \pi_{tl}^y(s_y) \left[\eta(s_p) - \pi_{tl}^y(s_p) \int \eta(\sigma) d\sigma \right] \right) ds_p ds_y ds_o -$$

$$\int \kappa_t^y(s) [c_{tl}^y(s) - sT_l] \eta(s) ds.$$

where I have already imposed on the first line that $\sum_{\ell} \phi_{\ell}(x) \frac{n_{t\ell}^y(x)}{n^y(x)} = 1$ by setting $\phi_{\ell}(s) = 1$. Using the spatial equalization of λ_{lt}^y , the second line boils down to $\int \lambda_t^y(s) \eta(s) ds$. Using $\nu_t^o(s) = 0$, the third line vanishes. Finally, from the expression for $O_{tl}(s)$, we have

$$\delta_{n_{tl}^y} O_{t\ell}(s) = \frac{1}{N_{tl}^y} \mathbb{1}\{\ell = l\} \left(\int \int \mathcal{V}^o[e\gamma(s, s_p)] dF(e) \eta(s_p) ds_p - O_{tl}(s) \int \eta(\sigma) d\sigma \right).$$

Using $\eta(s) = \delta_x(s)$ and $\int \delta_x(s) ds = 1$, this simplifies to

$$\partial_{n_{tl}(x)^y} O_{t\ell}(s) = \frac{1}{N_{tl}^y} \mathbb{1}\{\ell = l\} \left(\int \mathcal{V}^o[e\gamma(s, x)] dF(e) - O_{tl}(s) \right).$$

When the planner increases the measure of workers x in ℓ , it has two effects on the opportunities of the city. On the one hand, it increases the likelihood of interactions with x . The gains from these extra interactions are captured by the first term. On the other hand, it decreases the likelihood of interactions with every other workers in the city. When there are a continuum of skills, this congestion cost is captured by the average value of interactions in l , which is the second term. Combining this expression in the optimality condition, and setting $\kappa_t^y = \beta_S^t$, we obtain

$$c_{tl}^y(x) = xT_l + \beta \int \left(\int \mathcal{V}^o[e\gamma(s, x)] dF(e) - O_{tl}(s) \right) \pi_{tl}^y(s) ds + \mathcal{V}_t^y(x) - \lambda_t^y(x)/\beta_S^t.$$

In steady state, it must be that $\lambda_t^y(s)/\beta_S^t \equiv \lambda^y(s)$ is constant over time. Then, the optimal allocation is given by

$$c_l^y(x) = xT_l + \tau_l(x) + \mathcal{V}^y(x) - \lambda^y(x),$$

for

$$\tau_l(x) \equiv \beta \int \int (\mathcal{V}^o[e\gamma(s, x)] - \mathbb{E}[\mathcal{V}^o[e\gamma(s, S_{\ell}^y)]]) dF(e) \pi_l^y(s) ds$$

after substituting the expression for $O_l(s)$. This expression corresponds to (13) in the main text. Using the feasibility condition, it must be that $\mathcal{V}^y(x) - \lambda^y(x) = -\sum_l n_l^y(x)/n^y(x)\tau_l(x)$, and we conclude that¹⁰¹

$$c_l^y(x) = xT_l + \tau_l(x) - \sum_{\ell} \left(\frac{n_{\ell}^y(x)}{n^y(x)} \right) \tau_{\ell}(x). \quad (38)$$

In the competitive equilibrium, workers' consumption equate their wage, i.e. $c_l^y(x) = xT_l$. (38) thus yields (12) in the main text. Alternatively, (38) can be rewritten

$$c_l^y(x) = w_l(x) + t_l(x),$$

where $t_l(x) \equiv \tau_l(x) - \sum_{\ell} \left(\frac{n_{\ell}^y(x)}{n^y(x)} \right) \tau_{\ell}(x)$. Hence, the optimal allocation can be decentralized through the transfers $t_l(x)$.

¹⁰¹If we were to allow for transfers across skill within the young, then the optimal allocation would be $c_l^y(x) = xT_l + \tau_l(x) + t(x)$, for any function $t(x)$ that satisfies $\int t(x)n^y(x)dx = -\int \sum_l n_l^y(x)\tau_l(x)dx$.

B.3 Linearizing the social optimum

The social optimum is given by the spatial consumption allocation (38) and the young spatial allocation

$$n_\ell^{y*}(s) = n^y(s) \left(\frac{e^{\vartheta(c_\ell^{y*}(s) + \beta O_\ell^*(s))}}{\sum_{\ell'} e^{\vartheta(c_{\ell'}^{y*}(s) + \beta O_{\ell'}^*(s))}} \right). \quad (39)$$

Solving for the perturbed equilibrium around $\mathbf{T} \approx T$ requires to solve for the joint approximation of (38) and (39). I drop the star superscript for notational simplicity. When $\mathbf{T} = T$, (38) implies that $c_l^y(x) = x\bar{T}$ and $n_l^y(x) = n^y(x)/L$, as in the decentralized equilibrium.

Spatial allocation From (39), we have

$$\frac{\partial n_\ell^y(s)}{\partial T_l} \Big|_{\mathbf{T}=T} = \vartheta \left(\frac{n^y(s)}{L} \right) \left\{ \frac{\partial c_\ell^y(s)}{\partial T_l} + \beta \frac{\partial O_\ell(s)}{\partial T_l} - \frac{1}{L} \sum_{\ell'} \left(\frac{\partial c_{\ell'}^y(s)}{\partial T_l} + \beta \frac{\partial O_{\ell'}(s)}{\partial T_l} \right) \right\} \Big|_{\mathbf{T}=1}.$$

Following similar steps as in Section A.4.1, the change in the city option value is

$$\frac{\partial O_\ell(s)}{\partial T_l} - \frac{1}{L} \sum_{\ell'} \frac{\partial O_{\ell'}(s)}{\partial T_l} = L \int \frac{\partial n_\ell^y(s_p)}{\partial T_l} (\gamma(s, s_p) - \mathbb{E}[\gamma(s, S^y)]) ds_p.$$

Consumption allocation To continue, we need to derive the consumption perturbation. From (38), the perturbed transfers read

$$\partial_t \tau_\ell(x) = \beta \int \left(\partial_t \pi_\ell^y(s) + \frac{n^y(s)}{L} \right) (\gamma(s, x) - \mathbb{E}[\gamma(s, S^y)]) ds - \beta \int \mathbb{E}[\gamma(S^y, s_p)] \partial_t \pi_\ell^y(s_p) ds_p.$$

Hence,

$$\partial_t (\tau_\ell(x) - t(x)) = \beta \int \partial_t \pi_\ell^y(s) (\gamma(s, x) - \mathbb{E}[\gamma(s, S^y)]) ds - \beta \int \mathbb{E}[\gamma(S^y, s_p)] \partial_t \pi_\ell^y(s_p) ds_p.$$

where I have used $\tau_\ell(s) = 0$ when $\mathbf{T} = T$ and $\sum_\ell \partial_t \pi_\ell(s) = 0$. It follows that the perturbed consumption allocation is

$$\partial_t c_\ell^y(x) = x \mathbb{1}\{l = \ell\} + \beta \int \partial_t \pi_\ell^y(s) (\gamma(s, x) - \mathbb{E}[\gamma(s, S^y)]) ds - \beta \int \mathbb{E}[\gamma(S^y, s_p)] \partial_t \pi_\ell^y(s_p) ds_p. \quad (40)$$

Using $\sum_\ell \partial_t c_\ell^y(x) = x$ and the expression for $\partial_t \pi_\ell^y(s)$ returns

$$\begin{aligned} \partial_t c_\ell^y(x) - \frac{1}{L} \sum_\ell \partial_t c_\ell^y(x) &= x I_{\ell l} + \beta L \int \left(\partial_t n_\ell^y(s) - n(s) \int \partial_t n_\ell^y(q) dq \right) (\gamma(s, x) - \mathbb{E}[\gamma(s, S^y)]) ds - \\ &\quad \beta L \int \left(\partial_t n_\ell^y(s_p) - n(s_p) \int \partial_t n_\ell^y(q) dq \right) \mathbb{E}[\gamma(S^y, s_p)] ds_p. \end{aligned}$$

Optimal integral equation Combining the expression for $O_\ell(s)$ and $c_\ell(s)$, we obtain

$$\begin{aligned} \partial_t \partial n_\ell^y(x) &= \vartheta n^y(x) \left\{ \frac{x I_{\ell l}}{L} + \right. \\ &\quad \beta \int \left(\partial_t n_\ell^y(s) - n(s) \int \partial_t n_\ell^y(q) dq \right) (\gamma(s, x) - \mathbb{E}[\gamma(s, S^y)]) ds - \\ &\quad \beta \int \left(\partial_t n_\ell^y(s_p) - n(s_p) \int \partial_t n_\ell^y(q) dq \right) \mathbb{E}[\gamma(S^y, s_p)] ds_p + \\ &\quad \left. \beta \int \partial_t n_\ell^y(s_p) (\gamma(x, s_p) - \mathbb{E}[\gamma(x, S^y)]) ds_p \right\}. \end{aligned}$$

Guessing and verifying the form of the solution,

$$\partial_t n^y(s) = \vartheta n^y(s) \left(\frac{I_{\ell l}}{L} \right) \eta^*(s),$$

we end up with the optimal integral equation

$$\begin{aligned}\eta^*(x) = x + \vartheta\beta \int (\{\gamma(x, s) - \mathbb{E}[\gamma(x, S^y)]\} - \{\mathbb{E}[\gamma(S^y, s)] - \mathbb{E}[\gamma(S^y, S^y)]\}) \eta^*(s) n^y(s) ds + \\ \vartheta\beta \int (\{\gamma(s, x) - \mathbb{E}[\gamma(S^y, x)]\} - \{\mathbb{E}[\gamma(s, S^y)] - \mathbb{E}[\gamma(S^y, S^y)]\}) \eta^*(s) n^y(s) ds.\end{aligned}\tag{41}$$

Finally, using (40) and the fact that $\partial_t \pi_\ell^y(s) = \vartheta n^y(s) I_{t\ell}(\eta^*(s) - \mathbb{E}[\eta^*(S^y)])$, the skill-by-city transfers $t_\ell(x)$ can be decomposed into a city-specific tax, T , and additional skill-by-city subsidies, $d_\ell(x)$. Specifically,

$$t_\ell^y(x) \approx T + d_\ell^y(x),\tag{42}$$

where

$$T_\ell = -\vartheta\beta (T_\ell - \bar{T}) \int \mathbb{E}[\gamma(S^y, s_p)] (\eta^*(s_p) - \mathbb{E}[\eta^*(S^y)]) dN^y(s_p)$$

and

$$d_\ell(x) = \vartheta\beta (T_\ell - \bar{T}) \int (\eta^*(s) - \mathbb{E}[\eta^*(S^y)]) (\gamma(s, x) - \mathbb{E}[\gamma(s, S^y)]) dN^y(s).$$

B.4 Proof of Proposition 5

Using covariance, (41) rewrites

$$\begin{aligned}\eta^*(x) = x + \vartheta\beta \text{Cov}[\gamma(x, S^y), \eta^*(S^y)] + \vartheta\beta \text{Cov}[\gamma(S^y, x), \eta^*(S^y)] - \\ \vartheta\beta \text{Cov}[\mathbb{E}[\gamma(s, S^y) | s], \eta^*(s)] - \vartheta\beta \text{Cov}[\mathbb{E}[\gamma(S^y, s) | s], \eta^*(s)].\end{aligned}$$

The next lemma provides condition to ensure positive SPAM in the social optimum.

Lemma B.1 (Positive sorting).

Suppose that γ is either (weakly) supermodular or submodular. If

$$\vartheta\beta (\text{Cov}[\gamma_1(x, S^y), S^y] + \text{Cov}[\gamma_2(S^y, x), S^y]) > -1,$$

then $\eta'^*(x) > 0$.

Proof. For notational simplicity, define $\tilde{\Theta}^*(s) \equiv \text{Cov}[\gamma(s, S^y), \eta^*(S^y)]$ and $\tilde{\Upsilon}^*(s) \equiv \text{Cov}[\gamma(S^y, x), \eta^*(S^y)]$, so that the expression for η^* reads

$$\eta^*(x) = x + \vartheta\beta \tilde{\Theta}^*(x) + \vartheta\beta \tilde{\Upsilon}^*(x) - \vartheta\beta \text{Cov}[\mathbb{E}[\gamma(s, S^y) | s], \eta^*(s)] - \vartheta\beta \text{Cov}[\mathbb{E}[\gamma(S^y, s) | s], \eta^*(s)]$$

Differentiate w.r.t. x and use the expression for $\tilde{\Theta}$ and $\tilde{\Upsilon}$ to obtain

$$\eta'^*(x) = 1 + \vartheta\beta \text{Cov}[\gamma_1(x, S^y), \eta^*(S^y)] + \vartheta\beta \text{Cov}[\gamma_2(S^y, x), \eta^*(S^y)].$$

Plug the expressions for $\eta^*(x)$ back in the above,

$$\begin{aligned}\eta'^*(x) = 1 + \vartheta\beta \text{Cov}[\gamma_1(x, S^y), S^y] + (\vartheta\beta)^2 \text{Cov}[\gamma_1(x, S^y), \tilde{\Theta}^*(S^y)] + (\vartheta\beta)^2 \text{Cov}[\gamma_1(x, S^y), \tilde{\Upsilon}^*(S^y)] + \\ \vartheta\beta \text{Cov}[\gamma_2(S^y, x), S^y] + (\vartheta\beta)^2 \text{Cov}[\gamma_2(S^y, x), \tilde{\Theta}^*(S^y)] + (\vartheta\beta)^2 \text{Cov}[\gamma_2(S^y, x), \tilde{\Upsilon}^*(S^y)].\end{aligned}$$

Now, guess that η is increasing. From the expression for $\tilde{\Theta}$ and $\tilde{\Upsilon}$, if γ is supermodular (submodular), then $\tilde{\Theta}$ and $\tilde{\Upsilon}$ are increasing. Hence, if γ is supermodular, then all the covariances in the expression above are positive, and $\eta'^*(x) > 1 > 0$, which verifies the guess. Suppose now that γ is submodular. Then, the covariances between γ_1 , γ_2 , $\tilde{\Theta}$ and $\tilde{\Upsilon}$ are positive since the covariance between two decreasing function is positive. Hence,

$$\eta'^*(x) > 1 + \vartheta\beta \text{Cov}[\gamma_1(x, S^y), S^y] + \vartheta\beta \text{Cov}[\gamma_2(S^y, x), S^y].$$

It follows that $\vartheta\beta (\text{Cov}[\gamma_1(x, S^y), S^y] + \text{Cov}[\gamma_2(S^y, x), S^y]) > -1$ implies $\eta'^*(x) > 0$. \square

This lemma is sufficient to prove the two elements of Proposition 5.

Proposition 5.1 The optimal spatial allocation solves

$$n_\ell^{y*}(s) \approx \frac{n^y(s)}{L} + \vartheta \left(\frac{n^y(s)}{L} \right) \mathcal{T}_\ell \eta^*(s).$$

Note that $\mathbb{E}[\eta^*(S^y)] = \int \eta^*(x)n^y(x)dx = \mathbb{E}[S^y]$. Hence, the optimal city sizes are

$$N_\ell^* \approx \frac{1}{L} + \frac{1}{L} \vartheta \mathcal{T}_\ell \int \eta^*(s)n^y(s)ds = \frac{1}{L} + \frac{1}{L} \vartheta \mathcal{T}_\ell \mathbb{E}[S^y].$$

In the decentralized equilibrium, city size was given by

$$N_\ell \approx \frac{1}{L} + \vartheta \frac{1}{L} \mathcal{T}_\ell \mathbb{E}[S^y] + \vartheta^2 \beta \frac{1}{L} \mathcal{T}_\ell \mathbb{E}[\Theta(S^y)].$$

Hence, it is immediate to conclude that, for productive cities, $N_\ell > N_\ell^* \iff \mathbb{E}[\Theta(S^y)] > 0$ (and the converse holds for unproductive cities). But, we also know from Proposition 2 that $s_p \rightarrow \gamma(s, s_p)$ increasing implies $\Theta(s) > 0$. Hence, if $s_p \rightarrow \gamma(s, s_p)$, there is too much agglomeration in productive cities. Conversely, if $s_p \rightarrow \gamma(s, s_p)$ is decreasing, there is too little agglomeration in productive cities.

Proposition 5.2 The optimal skill density is

$$\pi_\ell^{y*}(s) \approx n^y(s) + \vartheta n^y(s) \mathcal{T}_\ell (\eta^*(s) - \mathbb{E}[S^y]).$$

In particular, the new average skill in city ℓ reads

$$\mathbb{E}_\ell[S^{y*}] \approx \mathbb{E}[S^y] + \vartheta \mathcal{T}_\ell \text{Cov}[\eta^*(S^y), S^y]$$

In the decentralized equilibrium, we had

$$\mathbb{E}_\ell[S^y] \approx \mathbb{E}[S^y] + \vartheta \mathcal{T}_\ell \text{Cov}[\eta(S^y), S^y].$$

Hence, for productive cities, $\mathbb{E}_\ell[S^y] > \mathbb{E}_\ell[S^{y*}] \iff \text{Cov}[\eta(S^y), S^y] > \text{Cov}[\eta^*(S^y), S^y]$. A sufficient condition for $\text{Cov}[\eta(S^y), S^y] > \text{Cov}[\eta^*(S^y), S^y]$ is $\eta' > \eta'^*$ a.e.¹⁰² I now show that γ supermodular (submodular) implies $\eta'^* > \eta'$ ($\eta'^* < \eta'$).

Differentiate the expression for η^* w.r.t. x and use covariances to simplify the integrals,

$$\eta'^*(x) = 1 + \vartheta \beta \text{Cov}[\gamma_1(x, S^y), \eta^*(S^y)] + \vartheta \beta \text{Cov}[\gamma_2(S^y, x), \eta^*(S^y)].$$

Taking a similar derivative in the decentralized equilibrium returns

$$\eta'(x) = 1 + \vartheta \beta \text{Cov}[\gamma_1(x, S^y), \eta(S^y)].$$

The two functions η and η^* are the solution to integrals equations. To prove the propositions, I therefore guess and verify the statement. First, suppose that γ is supermodular, and guess that $\eta'^* > \eta'$ a.e. Since γ is supermodular, $s \rightarrow \gamma_2(s, x)$ is an increasing function, and $\text{Cov}[\gamma_2(S^y, x), \eta^*(S^y)] > 0$ from Lemma B.1. Hence,

$$\eta'^*(x) > 1 + \vartheta \beta \text{Cov}[\gamma_1(x, S^y), \eta^*(S^y)] > 1 + \vartheta \beta \text{Cov}[\gamma_1(x, S^y), \eta(S^y)] = \eta'(x),$$

where the second inequality follows from the guess that $\eta'^*(x) > \eta'(x)$. Therefore, $\eta'^*(x) > \eta'(x)$ for all x , which verifies the guess. Suppose now that γ is submodular and guess that $\eta'^*(x) < \eta'(x)$. Then, by a similar argument, $\text{Cov}[\gamma_2(S^y, x), \eta^*(S^y)] < 0$, and

$$\eta'^*(x) < 1 + \vartheta \beta \text{Cov}[\gamma_1(x, S^y), \eta^*(S^y)] < 1 + \vartheta \beta \text{Cov}[\gamma_1(x, S^y), \eta(S^y)] = \eta'(x),$$

where $\text{Cov}[\gamma_1(x, S^y), \eta^*(S^y)] < \text{Cov}[\gamma_1(x, S^y), \eta(S^y)]$ follows from the guess. This verifies the guess, and proves Proposition 5.2.

¹⁰²Take three increasing function, f , g and h . Suppose that $g' > h'$. We want to show that $\text{Cov}[f(S), g(S)] > \text{Cov}[f(S), h(S)]$. Since the covariance is a linear operator, we have $\text{Cov}[f(S), g(S)] - \text{Cov}[f(S), h(S)] = \text{Cov}[f(S), g(S) - h(S)] > 0$, which follows from the covariance of two increasing functions being positive and $g - h$ increasing from $g' > h'$.

C Quantitative Model

C.1 Workers' problem

Consumption Young and old workers solve a standard consumption choice problem that maximize their static utility. A worker with income y thus consumes

$$c_\ell(y) = \alpha y \quad ; \quad h_\ell(y) = \left(\frac{1-\alpha}{p_\ell} \right) y$$

on the numeraire and the housing good respectively. Accordingly, the local price index is $P_\ell = p_\ell^{1-\alpha}$ and indirect utility in city ℓ for a worker with income y is y/P_ℓ .

Old workers Worker' income are made of three sources: their wage, the subsidy they might receive, and the flat tax. Hence, the income of an old worker with skill s living in city l when young and choosing to live in city ℓ when old is $y_{l\ell}^o(s) = w_\ell(s) + \tau_{l\ell}^o(s) - t$. Given this income, old workers solve a static location choice problem,

$$V_l^o(s, \boldsymbol{\varepsilon}) = \max_\ell \frac{y_{l\ell}(s)}{P_\ell} + \varepsilon_\ell - \kappa_{l\ell}^o.$$

Letting $m_l^o(s)$ denote the spatial distribution of old workers before their new location choice, the spatial allocation of workers is given by

$$n_{l\ell}^o(s) = m_l^o(s) \left(\frac{e^{\vartheta(y_{l\ell}^o(s)/P_\ell + B_\ell^o - \kappa_{l\ell}^o)}}{\sum_{\ell'} e^{\vartheta(y_{l\ell'}^o(s)/P_{\ell'} + B_{\ell'}^o - \kappa_{l\ell'}^o)}} \right), \quad (43)$$

where $n_{l\ell}^o(s)$ is the measure of workers moving from l to ℓ with skill s when old. Consistently, the (unconditional) measure of old workers in city ℓ is

$$n_\ell^o(s) = \sum_l n_{l\ell}^o(s),$$

and the mass of old workers in ℓ is $N_\ell^o = \int n_\ell^o(s) ds$. Finally, let $\mathcal{V}_l^o(s) \equiv \mathbb{E}[V_l^o(s, \boldsymbol{\varepsilon}) | s, l]$ be the expected utility before the realization of the idiosyncratic preferences $\boldsymbol{\varepsilon}$, given by

$$\mathcal{V}_l^o(s) = \frac{1}{\vartheta} \log \left(\sum_\ell e^{\vartheta(y_{l\ell}^o(s)/P_\ell + B_\ell^o - \kappa_{l\ell}^o)} \right).$$

Young workers Young workers solve a dynamic location choice problem which reads

$$V_l^y(s, \boldsymbol{\varepsilon}) = \max_\ell \frac{y_{l\ell}^y(s)}{P_\ell} + \varepsilon_\ell - \kappa_{l\ell}^y + \beta \int \int \mathcal{V}_\ell^o [e\gamma(s, s_p)] dF(e) \pi_\ell(s_p) ds_p,$$

where $y_{l\ell}^y(s) = w_\ell(s) + \tau_{l\ell}^y(s) - t$. In a similar fashion as for the old workers, the spatial allocation of young workers is given by

$$n_{l\ell}^y(s) = m_l^y(s) \left(\frac{e^{\vartheta(y_{l\ell}^y(s)/P_\ell + B_\ell^y - \kappa_{l\ell}^y + \beta O_\ell(s))}}{\sum_{\ell'} e^{\vartheta(y_{l\ell'}^y(s)/P_{\ell'} + B_{\ell'}^y - \kappa_{l\ell'}^y + \beta O_{\ell'}(s))}} \right). \quad (44)$$

I define $n_\ell^y(s)$ and N_ℓ^y in the same manner as $n_\ell^o(s)$ and N_ℓ^o .

C.2 General equilibrium

In equilibrium, the markets must clear, the expected spatial distribution of workers has to be consistent with workers' location choices, and the aggregate skill distribution must be consistent with workers' learning.

Housing prices Housing prices must clear the housing market in each location, and therefore they must satisfy¹⁰³

$$p_\ell = \left(\frac{(1-\alpha) Y_\ell}{\mathcal{H}} \right)^{\frac{1}{1+\delta}}, \quad (45)$$

where $Y_\ell = T_\ell \int s \sum_a n_\ell^a(s) ds = \mathbb{E}_\ell[W] N_\ell$ is the output produced in city ℓ . Taking logs give (20).

Skill density The within-city skill density of location ℓ must be consistent with workers' location choices, given by

$$\pi_\ell(s) = \frac{\sum_a n_\ell^a(s)}{\sum_a N_\ell^a}. \quad (46)$$

Skill distributions There are two distributions to be solved for. First, the location-specific distribution of old workers. Define $M_\ell^o(s)$ as the mass of old workers that lived in city ℓ when young and that obtained a skill less than s . Given the learning process, this is given by

$$M_\ell^o(s) = \int \int n_\ell^y(x) \pi_\ell(y) F\left(\frac{s}{\gamma(x, y)}\right) dy dx. \quad (47)$$

From here, one can define the location-specific measure as $m_\ell^o(s) = \partial M_\ell^o(s) / \partial s$ and the aggregate old skill density as $n^o(s) = \sum_\ell m_\ell^o(s)$. Finally, given the birth process, the location-specific distribution of young workers is $m_\ell^y(s) = N_\ell^y n^y(s)$.

Definition C.1 (Steady state equilibrium).

A steady state equilibrium is a collection of young and old spatial allocation, $s \rightarrow n_{i\ell}^y(s)$ and $s \rightarrow n_{i\ell}^o(s)$ for each $i, \ell \in \{1, 2, \dots, L\}$, city-specific skill distribution, $s \rightarrow m_\ell^y(s)$ and $s \rightarrow m_\ell^o(s)$ for each $\ell \in \{1, 2, \dots, L\}$, and housing prices $\{p_\ell\}_{\ell=1}^L$, such that

1. Taking as given the location decisions of other workers and housing prices, the young and old allocation satisfy (44) and (43) respectively;
2. The local skill densities are consistent with workers' location decisions, given by (46);
3. Given young workers' location decisions, the city-specific young and old skill distribution are given by $m_\ell^y(s) = N_\ell^y n^y(s)$ and (47) respectively;
4. Given workers' location decisions, housing prices solve (45).

C.3 Algorithm

I use two different algorithms to solve for the steady state equilibrium depending on whether I am estimating the model or computing counterfactuals. Both algorithms are constituted of an inner loop and an outer loop. The inner loops are identical. Given city fundamentals, \mathbf{T} and \mathbf{B} , housing prices \mathbf{p} , and skill distributions \mathbf{m}^y and \mathbf{m}^o , they iterate on (44) and (43) to solve for the local skill densities, $\boldsymbol{\pi}$.

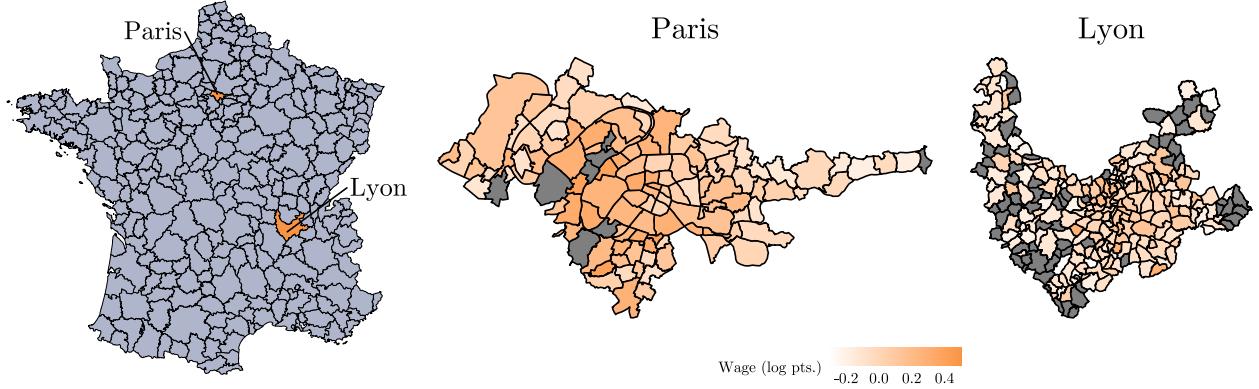
Estimation To estimate the model, I need to solve for the steady state equilibrium and recover the city characteristics, \mathbf{T} and \mathbf{B} . The targeted moments for \mathbf{T} and \mathbf{B} imply that, when TFP and amenities are estimated, I match the city average wage and city size, and therefore cities' output, $\mathbb{E}_\ell[W] N_\ell$. Given estimates for $(\alpha, \delta, \mathcal{H})$, I can therefore read off (45) the housing prices that must hold in the baseline steady state equilibrium. To solve for the baseline steady state equilibrium, the outer loop therefore takes \mathbf{p} as given and iterate on the skill distributions, \mathbf{m}^y and \mathbf{m}^o , as well as on the city TFP and amenities through (22) and (49).

Counterfactual In the counterfactuals, city TFP and amenities are taken as given. The outer loop therefore iterates on (45) to solve for the housing prices, as well as on $m_\ell^y(s) = N_\ell^y n^y(s)$ and (46) to solve for \mathbf{m}^y and \mathbf{m}^o .

Simulation I use the model to simulate a two-period panel datasets with 1,000,000 workers. The simulation follows the structure of the model. All the variables, including the local skill densities, are consistent with the model's general equilibrium. As in the data, I truncate the wage distribution at the 5% and 99.9% percentile.

¹⁰³Note that this implies $\Pi_\ell = p_\ell^{1+\delta} = (1-\alpha)Y_\ell$, where Π_ℓ are the revenues earned by the representative land owner.

Figure D.1: The geography of commuting zones and municipalities



D Descriptive Evidence

D.1 Data description

As described in the main text, the French matched employer-employee dataset comes in two formats. The first format is a long-panel that tracks the entire labor market history of 4% of the French workforce. The second format is a repeated short-panel (two years) that provides information on the job providing the main source of labor income within each year for the universe of the French workforce.¹⁰⁴ I apply a first set of similar restrictions on both datasets:

- Exclude workers younger than 25 and older than 55 years old;
- Exclude workers employed in the private sector;
- Exclude the agriculture, education and health industries;
- Keep only workers employed full-time;¹⁰⁵
- Truncate the yearly wage distribution at the 5% and 99.9%.

The long-panel comes at the job-spell level, where a job-spell is defined as a year-establishment-occupation. Workers are observed multiple times within the same year if they switch jobs. Since the focus of this paper is on middle- and long-term wage growth, I aggregate the long-panel at the yearly level. To do so, I keep for each worker the job that provides the highest earnings within the year. I exclude from the sample jobs that last less than 30 days, and I also exclude workers that have been unemployed for more than three consecutive years.

D.2 Neighborhood

As explained in Section 3.1, I define a neighborhood as a municipality, or commune in French. Commune are the most granular administrative division in France. They are also the most granular geographic unit I observe in the French matched employer-employee dataset.

Commune were introduced with the French revolution in 1789 to unify parishes (the houses and land around a church) and chartered cities (collection of parishes) under a common legal definition. By the end of the 18th century, 40,200 municipalities were created. Two reforms at the beginning of the 19th century (1831 and 1837) increased their administrative powers. Since then, both the geographic and administrative boundaries of municipalities have been stable over time. For instance, around 90% of communes have similar geographic boundaries as when they were created during the French revolution.

In 2009, France had 36 783 communes. Their legislative power are analogous to civil townships and incorporated municipalities in the United States. In terms of geography, they are closer to ZIP codes. The three largest French communes, Paris, Lyon and Marseille, are themselves sub-divided into 20, 9, and 16 arrondissements. I observe those in the French matched employer-employee dataset, and therefore refer to these arrondissements also as neighborhoods.

¹⁰⁴In the short-panel, the worker ID are shuffled every year so that it is not possible to link workers for more than two periods.

¹⁰⁵Full-time jobs are identified first by their contracts, and second by the fact that the individuals work at the job more than three hours per worked day.

Figure D.1 helps visualize the granularity of communes. The left map is a map of the French commuting zones, where I have highlighted in orange the two largest French cities, Paris and Lyon. The two maps on the right are the commune included in the Paris (112 communes) and Lyon (191 communes) commuting zones. The orange shade represents the average wage of the neighborhood relative to the French average. Grey communes are communes excluded from the sample due to their small sample sizes. In total, 112 and 191 communes are kept in the sample in Paris and Lyon respectively. Throughout France, the average number of commune by commuting zones is 40. The city with the smallest number of commune is Chatillon (0.02% of the French workforce) with 4 communes. The city with the largest number of commune is Roissy (2.7% of the French workforce) with 212 communes.

D.3 Identification

In this section, I lay down how (18) identifies the learning technology. First, write wages as $\log w_{it} = \log T + \mathcal{T}_{\ell_{it}} + \log s_{it}$, where I have decomposed the city TFP into an aggregate component T and a city-specific productivity \mathcal{T}_ℓ , $\log T_\ell = \log T + \mathcal{T}_\ell$. Alternatively, I could have decomposed $\log s_{it}$ into an aggregate component and a worker-level productivity. That is, the levels of T_ℓ and s are not separately identified. Let $\omega_{it} \equiv \log w_{it} - \log T$.¹⁰⁶ Then, ω_{it} , $\mathcal{T}_{\ell_{it}}$ and $\log s_{it}$ are all mean zero.

From here, substitute $\log s_{it} = \omega_{it} - \mathcal{T}_{\ell_{it}}$ and $s_{p_{it}} = s_{p_{it}} + \mathbb{E}_{\ell_{it}}[\log w_{it}] - \mathbb{E}_{\ell_{it}}[\log w_{it}]$ into (15) to obtain

$$\omega_{it+1} = g_0 + g_1 \omega_{it} + g_2 \mathbb{E}_{\ell_{it}}[\omega_{it}] + g_{12} \omega_{it} \mathbb{E}_{\ell_{it}}[\omega_{it}] + \log e_{it+1} + \nu_{it} + \zeta_{it}, \quad (48)$$

where

$$\nu_{it} \equiv (g_2 + g_{12} \log s_{it}) (\omega_{p_{it}} - \mathbb{E}_{\ell_{it}}[\omega_{it}]),$$

and

$$\zeta_{it} \equiv \mathcal{T}_{\ell_{it+1}} - (g_1 + g_2 + g_{12} \omega_{it} + g_{12} \mathbb{E}_{\ell_{it}}[\omega_{it}] - g_{12} \mathcal{T}_{\ell_{it}}) \mathcal{T}_{\ell_{it}}.$$

Specification (48) has three error terms. First, $\log e_{it+1}$ which captures learning sources other than interactions. Second, ν_{it} , which measures the difference between the particular interaction experienced by i and the average interaction in city ℓ_{it} . And third, ζ_{it} , which reflects the gap between worker-level productivity and wages. If the three error terms are uncorrelated with ω_{it} and $\mathbb{E}_{\ell_{it}}[\omega_{it}]$, then the local projection (18) yields unbiased estimates of the learning technology: $\hat{\beta} = g_1$, $\hat{\gamma} = g_2$ and $\hat{\delta} = g_{12}$.

Assumption 6 guarantees that the first two error terms are orthogonal to the regressors. First, Assumption 6.2 implies that $\mathbb{E}[\omega_{it} \log e_{it+1}] = \mathbb{E}[\mathbb{E}_{\ell_{it}}[\omega_{it}] \log e_{it+1}] = 0$. Second, Assumption 6.1 implies that ν_{it} is uncorrelated with the regressors. To see why, note that

$$\mathbb{E}[\nu_{it}] = \mathbb{E}[\mathbb{E}[\nu_{it} | s_{it}, \ell_{it}]] = \mathbb{E}[(g_2 + g_{12} \log s_{it}) \mathbb{E}[\omega_{p_{it}} - \mathbb{E}_{\ell_{it}}[\omega_{it}] | s_{it}, \ell_{it}]] = 0,$$

where the first equality follows from the L.I.E., the second from the definition of ν_{it} , and the third from $\mathbb{E}[\omega_{p_{it}} | s_{it}, \ell_{it}] = \mathbb{E}_{\ell_{it}}[\omega_{it}]$ when interactions are random within cities. A similar argument implies $\mathbb{E}[\nu_{it} \omega_{it}] = \mathbb{E}[\nu_{it} \mathbb{E}_{\ell_{it}}[\omega_{it}]] = \mathbb{E}[\nu_{it} \omega_{it} \mathbb{E}_{\ell_{it}}[\omega_{it}]] = 0$.

In addition, when $\{\mathcal{T}_\ell\}_\ell$ is observed, it is possible to control for the terms in ζ_{it} . In this case, ζ_{it} no longer constitutes a residual. In practice, $\{\mathcal{T}_\ell\}_\ell$ is not observed. Instead, I build a two-step estimator of the learning technology. First, suppose that $\mathcal{T}_\ell \approx 0$, and estimate $(\hat{\beta}^0, \hat{\gamma}^0, \hat{\delta}^0)$ from (18). Given those estimates, recover the vector of city TFP through (22), $\hat{\mathbf{T}}^0$. Given $\hat{\mathbf{T}}^0$, construct $\hat{\zeta}_{it}^1$, and obtain a new set of parameters $(\hat{\beta}^1, \hat{\gamma}^1, \hat{\delta}^1)$ from estimating (18) while controlling for $\hat{\zeta}_{it}^1$.

The fixed point defined by this iteration relies implicitly on the sorting of workers, and thus on the entire general equilibrium. I therefore cannot show that this iterative algorithm yields unbiased estimates of the learning technology for any (g_1, g_2, g_{12}) and \mathbf{T} . However, when the spatial TFP gaps are small, $\mathcal{T}_\ell \approx 0$ for all ℓ , and therefore $\zeta_{it} \approx 0$. In such a case, (18) yields unbiased estimates of the learning technology and the iterative algorithm converges to the true (g_1, g_2, g_{12}) .

In practice, I estimate that the dispersion in city TFP, $\text{Var}[\mathcal{T}_\ell]$, explains 2% of the aggregate wage variance. I take this as suggestive evidence that $\zeta_{it} \approx 0$. Accordingly, when controlling for ζ_{it} , I cannot statically differentiate the new sets of estimates from the baseline estimates at the 5%.

Finally, is (48) subject to the reflection problem of Manski (1993)? Manski (1993) shows that, when both “peer effects” (the composition of the group affects one’s outcome) and “correlated effects” (all members of the group behave in similar ways or experience the same treatment independently of the group’s composition) are active, specification of the form of (48) cannot separately identify peer effects from correlated effects. This identification concern is not

¹⁰⁶In the data, $\log T$ is computed as the nationwide average wage.

Table D.1: Estimated learning technology (observed vs. unobserved interactions)

	Parameter	OLS: skill observed	OLS: skill unobserved
g_0	0.170	0.170 [0.170, 0.171]	0.166 [0.166, 0.167]
g_1	0.057	0.057 [0.055, 0.059]	0.053 [0.052, 0.055]
g_2	0.327	0.327 [0.326, 0.329]	0.324 [0.318, 0.329]
g_{12}	0.393	0.390 [0.386, 0.394]	0.397 [0.389, 0.406]
R^2		0.225	0.017
Obs.		955655	955655

First column reports the learning technology parameters estimated from the data and used in the model's calibration. The second and third column estimates the learning technology from simulated data. The simulation method is presented in Section C.3. The second column estimates $\log s_{it+1} = \alpha + \beta \log s_{it} + \gamma \log s_{pit} + \delta \log s_{it} \log s_{pit} + u_{it}$. The third column estimates $\log s_{it+1} = \alpha' + \beta' \log s_{it} + \gamma' \mathbb{E}[\log s_{pit} | \ell] + \delta' \log s_{it} \mathbb{E}[\log s_{pit} | \ell] + u_{it}$.

present in (48) because Assumption 6.2 rules out the presence of correlated effects. Hence, (48) is able to recover the learning technology. As a proof of concept, Table D.1

D.4 Instrument variable

In Section 3.3, I argue that I can isolate spatial variation in skill density across neighborhoods within cities that are orthogonal to neighborhood-level wage shocks. To do so, I instrument the contemporaneous neighborhood average wage by the change in the white-collar employment share between 1993 and 2000. I define white-collar workers through their occupations. I define a white-collar occupation as the occupations with one-digit occupation code 3 in the French classification. This includes licensed professional (e.g. lawyers and doctors), professors and scientists, managers and engineers. The instrument is relevant if past changes in the white-collar employment share correlate with the current local supply of skill. It satisfies the exclusion restriction if these past changes are not correlated with contemporary neighborhood-level wage shocks.

I provide first suggestive evidence that the instrument is relevant. First, white-collar workers are relatively more skilled than the average worker along several margins. They earn higher wages (38€ per hour compared to 22€ for the average worker), they are on average more educated (XXX% of white-collar workers went to college compared to XXX% on average), and they implement tasks that are less routine and manual and more creative. Hence, the white-collar employment-share in a neighborhood is informative about the local supply of skill. Furthermore, past changes in the white-collar employment-share have long-lasting consequences on the occupational composition of neighborhoods. In Table D.2, I project the white-collar employment share in 2010 onto the change in the white-collar employment share between 1993 and 2000. Column 1 is in the cross-section and column 2 is within-city. In both cases, neighborhoods who experienced increase in their white-collar employment share in the 1990s have a higher share of white-collar today on average.

Meanwhile, the changes in the white-collar employment share between 1993 and 2000 are not correlated with the changes between 2010 and 2019 (Column 4 of Table D.2). Hence, the shocks that triggered the increase in the employment share of white collars in the 1990s have either diffused across space or faded away. Either way, I take this has suggestive evidence that the exclusion restriction is satisfied by the instrument.

D.5 Robustness

[To-do: describe the robustness exercises.]

Aggregate growth 1. Plot of stability 2. Plot of real wages 3. All the robustness we are going to include.

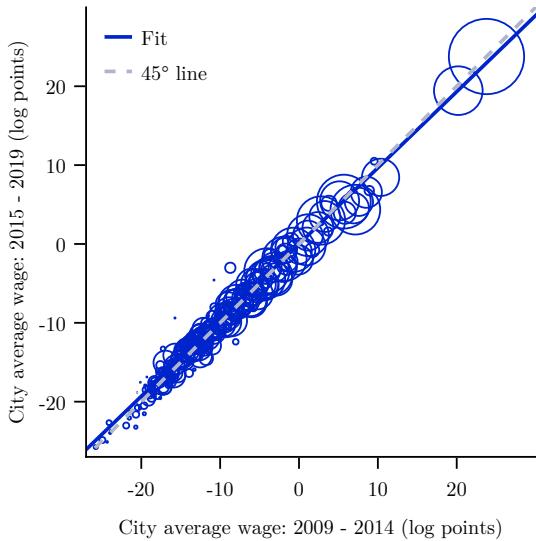
Table D.2: White-collar employment share across time

	(1) Emp. share 2010	(2) Emp. share 2010	(3) Δ Emp. share 2010-2019	(4) Δ Emp. share 2010-2019
Δ Emp. share 1993-2000	0.330*** (0.032)	0.285*** (0.029)	0.043* (0.020)	0.027 (0.020)
Standardized	0.155	0.134	0.027	0.017
City F.E.		✓		✓
Obs.	8,520	8,520	8,520	8,520

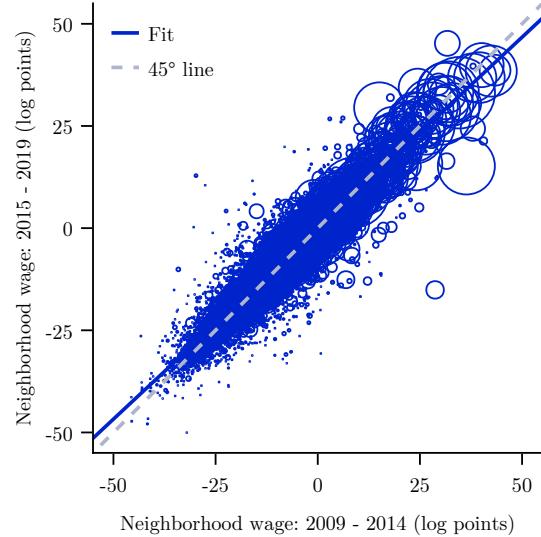
Standard errors clustered at the city level. P-value: *** $< .001$, ** $< .01$, * $< .05$ and + $< .1$. Unit of observation is the neighborhood. Left-hand side variable is the white-collar employment share in 2010 for columns 1 and 2, and the change in the white-collar employment share between 2010 and 2019 for column 3 and 4. The right-hand side variable is the change in the white-collar employment share between 1993 and 2000. All variables truncated at the 1%.

Figure D.2: Average wage at the beginning and the end of the 2010s

(a) By commuting zones

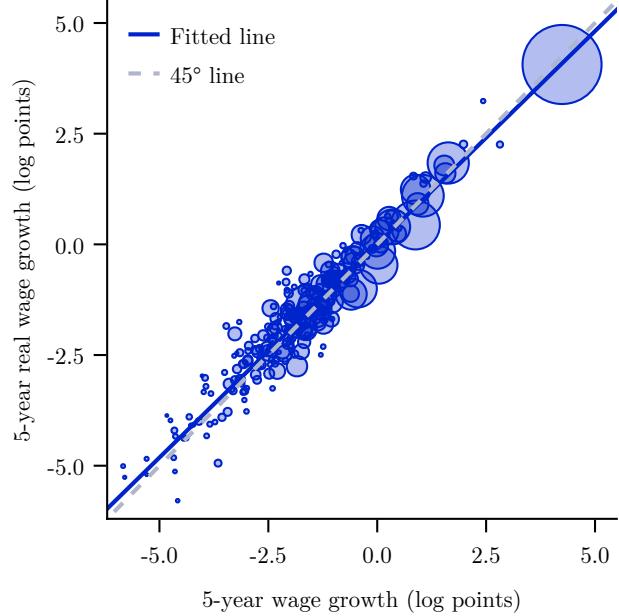


(b) By municipalities



Note: left panel shows the average wage by commuting zone between 2009-2014 on the x-axis against the average wage in the same commuting zone between 2015-2019 on the y-axis. The marker size is proportional to the size of the commuting zone. The right-panel shows the same relationship but at the municipality level. The marker size is proportional to the size of the municipality. The aggregate average wage is normalized to zero in both periods for both panels. The blue solid line is the (unweighted) best fitted line between the 2009-2014 and 2015-2019 average wages. The grey dotted line is the 45 degree line.

Figure D.3: Nominal and real wage growth



Note: figure shows the relationship between real wage growth and nominal wage growth by commuting zones. Real wage growth are computed as $\mathbb{E}_\ell[\log w_{it+1}/w_{it}] - \alpha \log(p_{t+1\ell}/p_{t\ell})$, where the second term is the growth in rental prices. The housing expenditure share is set to 0.2 (see Table E.2). The marker size is proportional to the size of the commuting zone.

Figure D.4: The returns to local interactions by time horizon

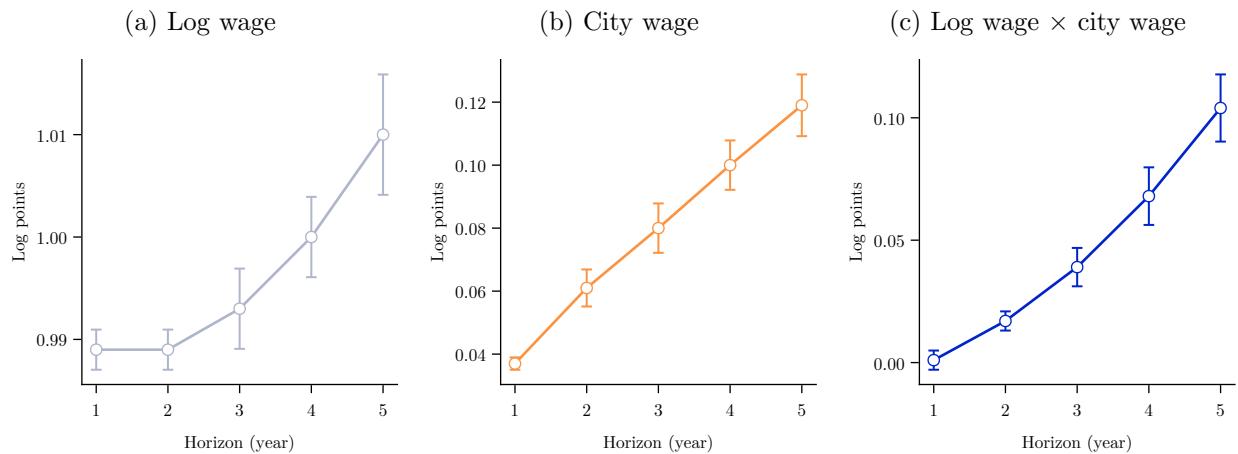


Figure D.5: The returns to local interactions by age

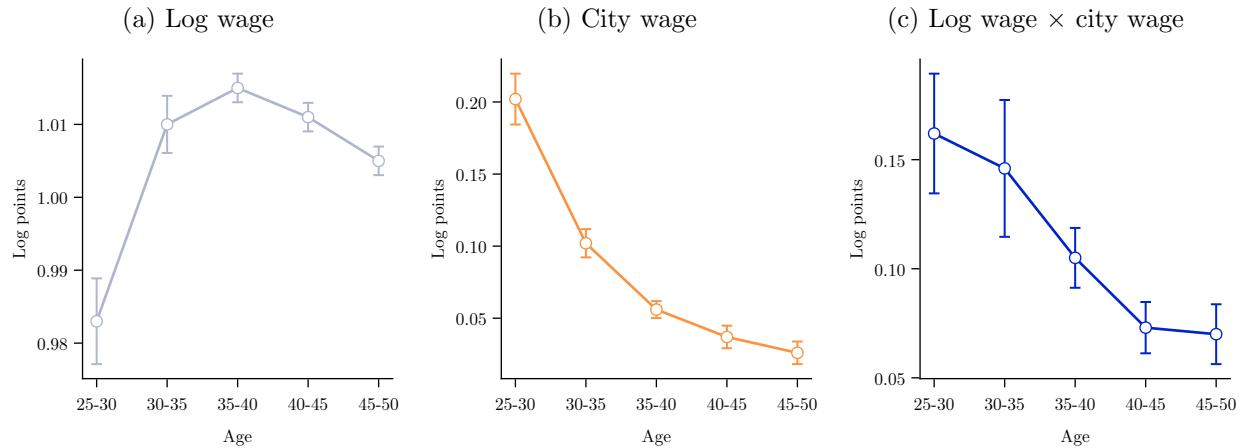


Figure D.6: The returns to local interactions by city size

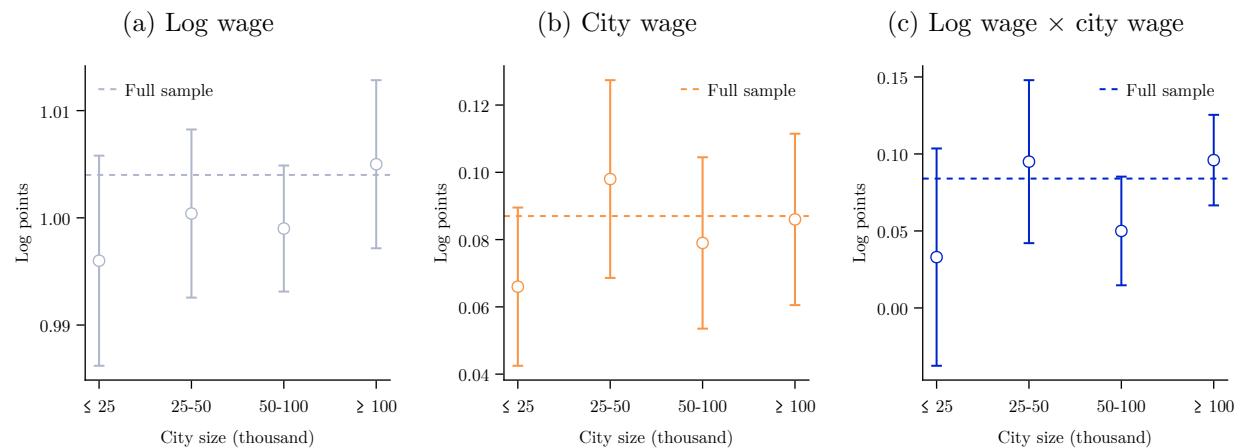


Figure D.7: The returns to local interactions by city inequality

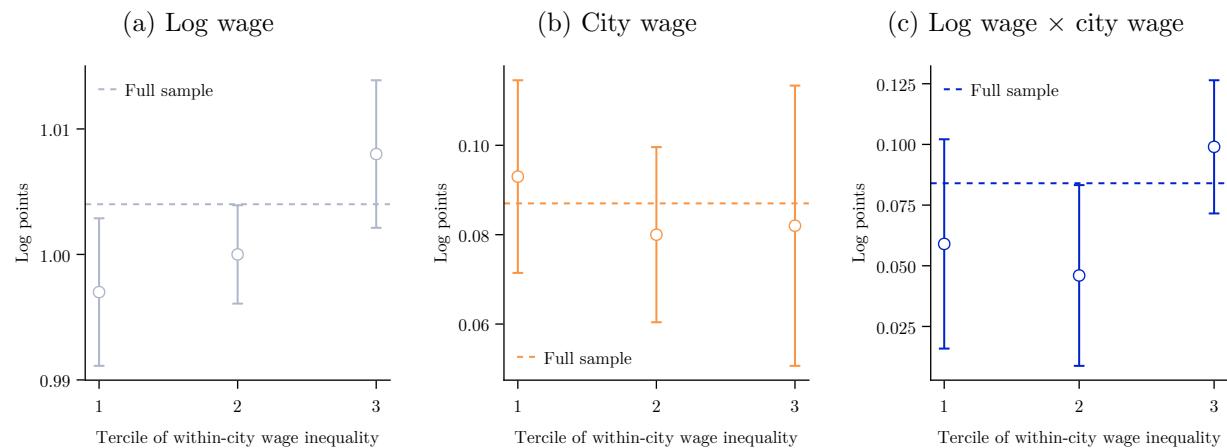
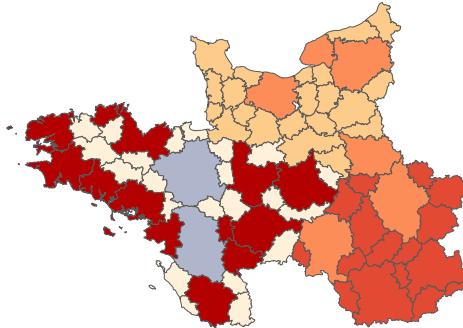


Table D.3: The returns to local interactions (robustness)

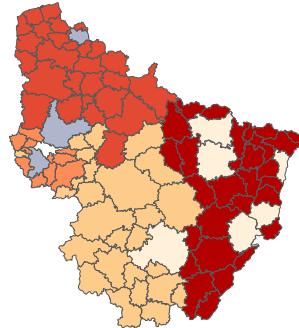
Standard errors clustered at the city level for column 1 and at the neighborhood of work for the remaining columns. All regressions include age, job tenure, occupation tenure, and industry tenure fixed effects, as well as a dummy if the worker changed employer between the five years. Column 5 and 6 instruments for the neighborhood wage by the change in the white-collar employment share between 1993 and 2000. Sample includes all workers between 25 and 40 year old. Wage growth distribution truncated at the 5% within cities. Industry and occupation in column 3 defined at the one-digit level. Each fixed effect is interacted with year fixed effects.

Figure E.1: City clustering

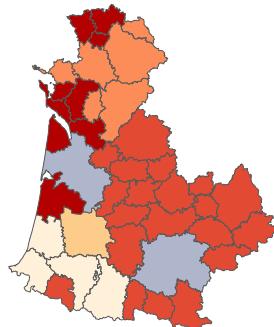
(a) North West



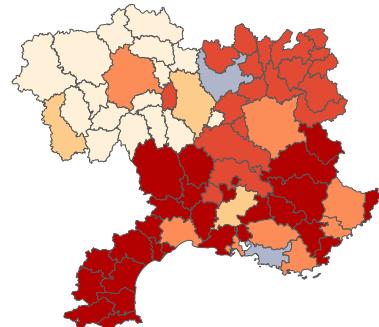
(b) North East



(c) South West



(d) South East



Note: each subplot is a French district. The grey areas are the ten largest French cities. The remaining commuting zones are subdivided into five groups within each district. Each city cluster is represented by a different color on the map. See Table E.1 for a list of the clusters.

E Model Estimation

E.1 Clustering

Cities are clustered into 30 city types. The ten first types are the ten largest French cities. The twenty remaining types are constructed by a k-mean algorithm so that there are five types within each French district (North-West, North-East, South-West, and South-East). I include in the clustering algorithm variables that proxy for the geographic primitives of the model: the coordinates of the city center to account for the migration costs, its average wage to account for city's TFP, and its population to account for its amenity.

Figure E.1 shows the mapping between cities to city types within each district. The grey areas are the ten largest French cities. Each other color represents a city type within the district. While k-mean is not a spatial clustering algorithm, including the latitude and longitude of the cities in the clustering variables is sufficient to generate city types that are spatially contiguous. Table E.1 lists the number of cities by city type, the largest city in each type, the average size, as well as the average wage.

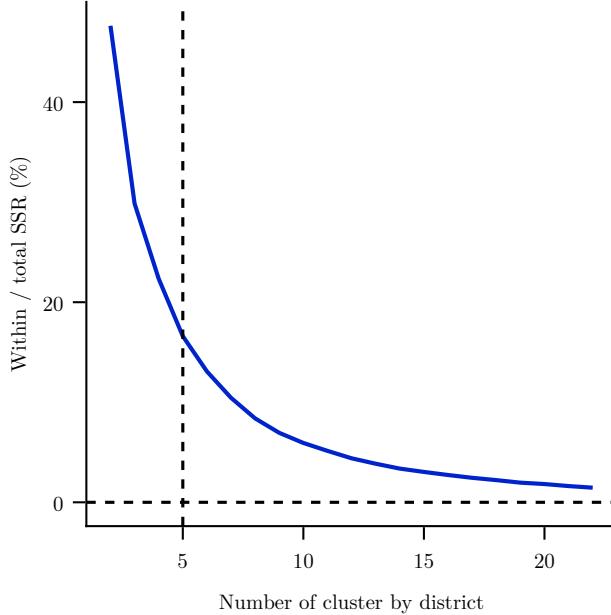
How good is the spatial approximation generate by the k-mean algorithm? Figure E.2 plots the within city-type sum of square residuals (SSR) as a fraction of the total SSR. With only 5 city types, the within city type is less than a fifth of the total SSR. A parsimonious geographic representation of France is therefore able to capture most of the variation of interest for the model.

Table E.1: City types characteristics

Cluster	District	# cities	Largest city	Average size (thousands)	Average wage
1	Paris	1	Paris	2800.6	30.03
2	SE	1	Lyon	609.8	23.38
3	NE	1	Roissy	443.0	22.50
4	NE	1	Saclay	414.1	27.32
5	SW	1	Toulouse	403.8	22.42
6	SW	1	Bordeaux	332.6	21.07
7	SE	1	Marseille	316.8	22.14
8	NW	1	Nantes	305.8	20.94
9	NE	1	Lille	258.4	22.06
10	NW	1	Rennes	218.4	20.54
11	NE	6	Strasbourg	131.9	20.67
12	NE	26	Troyes	32.64	18.61
13	NE	11	Orly	109.7	22.88
14	NE	27	Roubaix	58.53	19.46
15	NE	28	Besançon	32.47	19.57
16	NW	22	Challans	16.70	17.65
17	NW	21	Évreux	26.13	18.80
18	NW	6	Rouen	141.9	20.33
19	NW	15	Blois	28.05	18.86
20	NW	13	Angers	74.63	18.94
21	SW	4	Pau	65.64	19.31
22	SW	1	Mont-de-Marsan	29.40	17.29
23	SW	6	Poitiers	54.48	19.42
24	SW	20	Périgueux	25.87	18.22
25	SW	9	La Teste-de-Buch	17.74	17.26
26	SE	16	Limoges	34.67	18.08
27	SE	3	Saint-Étienne	127.5	19.56
28	SE	8	Grenoble	146.2	21.67
29	SE	19	Valence	52.71	20.31
30	SE	26	Nîmes	34.06	18.29

The tables report statistics on the city types used for the estimation of the quantitative model. The second column is the district in which the city type belongs (see Figure E.1). The third column is the number of cities included in the city type. For the first ten types, there is a single city by definition. For the twenty remaining types, the number of cities per city type is determined by the k-mean algorithm. The fourth column reports the largest city in the city type, the fifth column the average number of employed workers (in thousands), and the sixth column the average wage.

Figure E.2: Residual of city clustering



Note: average within cluster sum of square residuals (SSR) relative to the total SSR against the number of cluster (per district) used in the k-mean algorithm. The quantitative model features five city-types per district, as represented by the vertical dashed black line.

E.2 Estimating equations

1. housing supply
2. migration costs
3. city chars
4. amenities

$$N_\ell^a = \underbrace{e^{\vartheta(B_\ell^a - B_{\bar{\ell}}^a)}}_{\text{Emp. share}} \underbrace{\int e^{\vartheta\left(\frac{w_\ell(s)}{P_\ell} - \frac{w_{\bar{\ell}}(s)}{P_{\bar{\ell}}} + \beta [O_\ell^a(s) - O_{\bar{\ell}}^a(s)]\right)} \sum_l e^{-\vartheta(\kappa_{l\ell}^a - \kappa_{l\bar{\ell}}^a)} n_{l\bar{\ell}}^a(s) ds}_{\text{Relative attractiveness of } \ell \text{ net of amenity differentials}}, \quad (49)$$

E.3 Parameters

This section presents the parameters used in the quantitative model. Table E.2 presents the city-independent estimated parameters. Figure E.3 displays the estimated migration costs by age and city of origin as a function of the distance between the two cities. Figure E.4 plots the estimated city TFP and age-specific amenities. Figure E.5c shows the fit of the model across space by comparing the city average wage (panel a), the city employment share (panel b), and city average rents (panel c) in the data and the model.

Include discussion about migration costs and migration probabilities.

E.4 Sensitivity

[Re-read since change between city wage growth to local inequality.]

Figure E.8 and E.9 reports information to help assess the sources of identification in the indirect inference procedure. Specifically, Figure E.8 plots the value of the targeted moments in the indirect inference procedure as a function of the parameters. Each subplot is a given moment. Each line represents a particular parameter. The blue lines highlight the parameters that are meant to be identified by the moment.

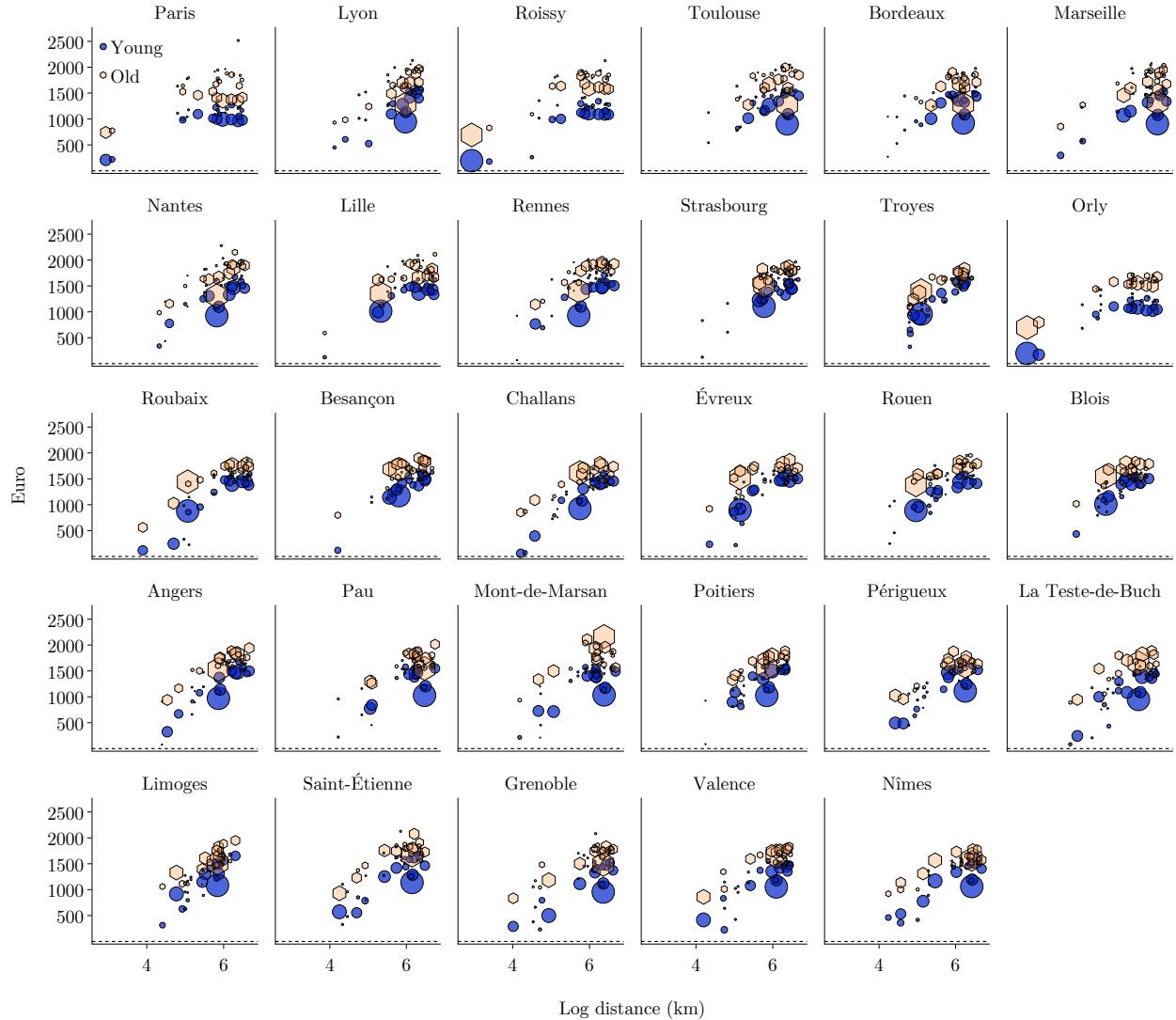
Figure E.8 confirms that all parameters are well identified locally. Each targeted moment is indeed a steep function of the parameter they are meant to identify. For instance, the flattest relationship is between the wage variance for old workers and the learning shocks dispersion. Even then, a 1% increase in σ_v leads to a 0.7% increase in the targeted moment. Figure E.8 also shows that some parameters affect mainly one moment whereas others drive several moments. For instance, the dispersion in idiosyncratic location preferences only affect the between-city share of the wage growth

Table E.2: Estimated parameters

Parameter		Value	Moment	Data	Model
A. Externally calibrated					
β	15-year discount factor	0.684		.	.
B. Model inversion					
$1 - \alpha$	Housing exp. share	0.200	Housing exp. share	0.200	0.200
$\{\kappa_{\ell\ell'}^a\}_{\ell,\ell'}$	Migration cost	.	Migration flows (21)	.	.
δ	Housing price elasticity	7.473	Housing price \sim exp.: constant (20)	.	.
\mathcal{H}	Supply stock	7.2×10^{-9}	Housing price \sim exp.: slope (20)	.	.
g_1	Learning technology	1.057	Wage growth \sim wage (18)	.	.
g_2	Learning technology	0.327	Wage growth \sim city wage (18)	.	.
g_{12}	Learning technology	0.393	Wage growth \sim wage \times city wage (18)	.	.
C. Indirect inference					
$\{T_\ell\}_\ell$	City TFP	.	Average wage	.	.
$\{B_{a\ell}\}_{a,\ell}$	City amenity	.	City size	.	.
g_0	Learning technology	0.400	Old / young wage	1.250	1.248
ϑ	Taste shock dispersion	0.009	Local inequality \sim local wage	0.29	0.28
μ_1^s	Mean young skill	-0.200	Average skill	0.000	0.003
σ_1^s	Variance young skill	0.309	Variance young wage	0.139	0.141
σ_ν	Var. learning shock	0.310	Variance old wage	0.234	0.240

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 moment used to estimate or calibrate the parameter. The fifth and sixth columns show the value of that moment in the data and in the model. The migration costs are plotted in Figure E.3, the city TFP in Figure E.4a, and city amenities in Figure E.4b.

Figure E.3: Estimated age-specific migration costs by city of origin



Note: estimated age-specific migration costs by city of origin as a function of the distance between the city of origin and the destination. Each subplot corresponds to a city of origin. The migration costs are estimated according to (21). The estimated costs are in utils, and they are reported here in euros through $\kappa_{le}^a P_e$. The blue circles and orange hexagons are the migration costs for young and old workers. Distance between two cities computed as the Haversine distance. For city types that comprise more than one city, I define the coordinates of the city type as the coordinates of the most populous city in that cluster. For reference, the average wage in the economy is 3,278€. The size of the circles is proportional to the size of the city of destination.

Figure E.4: Estimated city characteristics

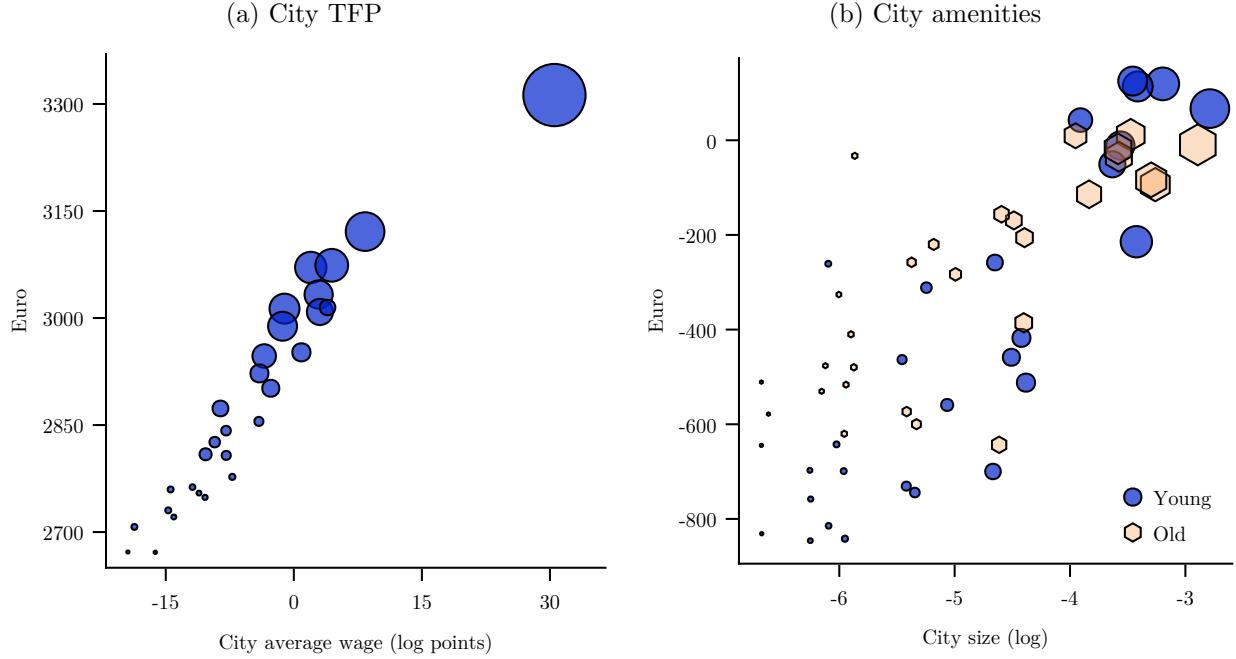


Figure E.5: Model fit

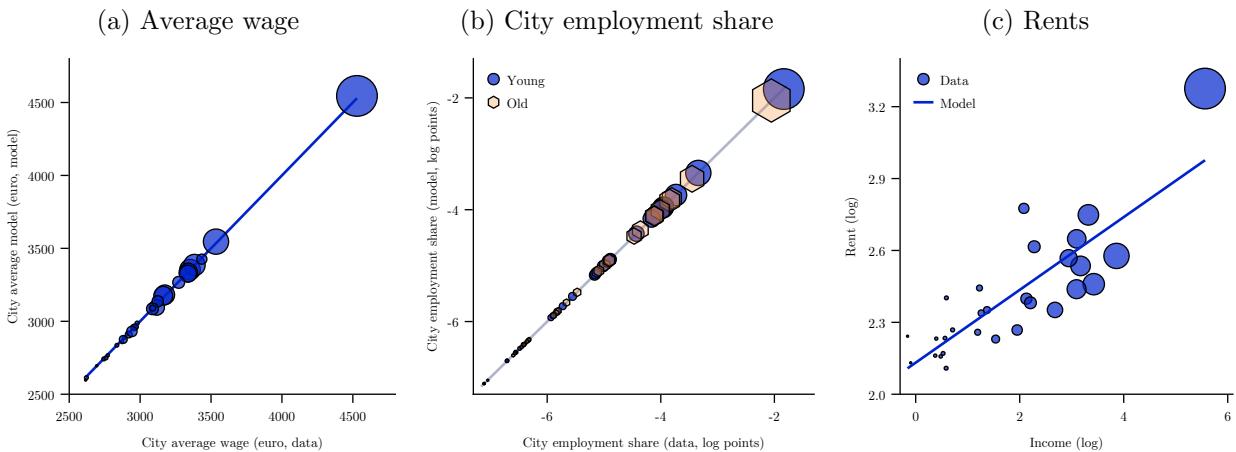


Figure E.6: Spatial allocation of workers across the skill distribution

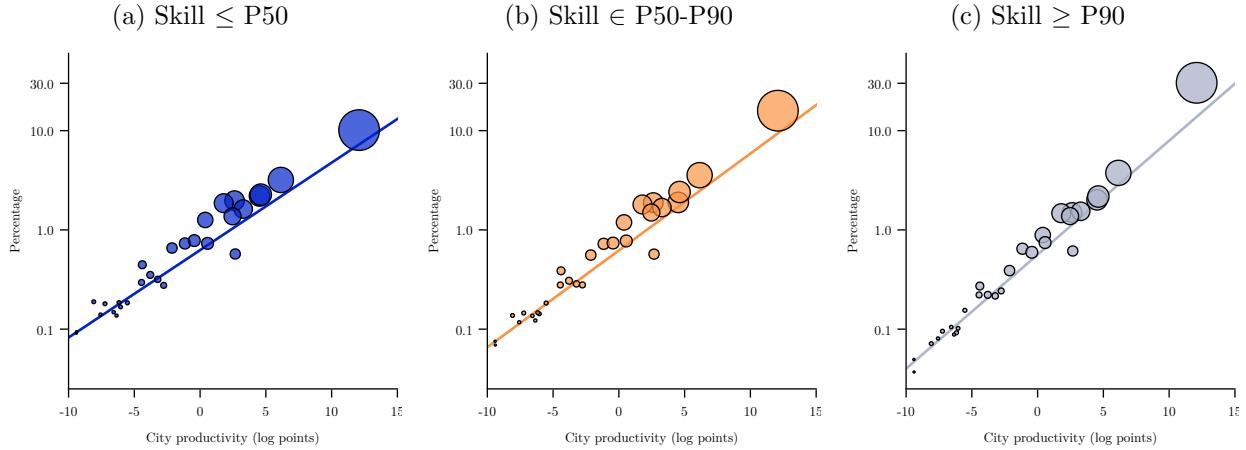


Figure E.7: Migration elasticities across space

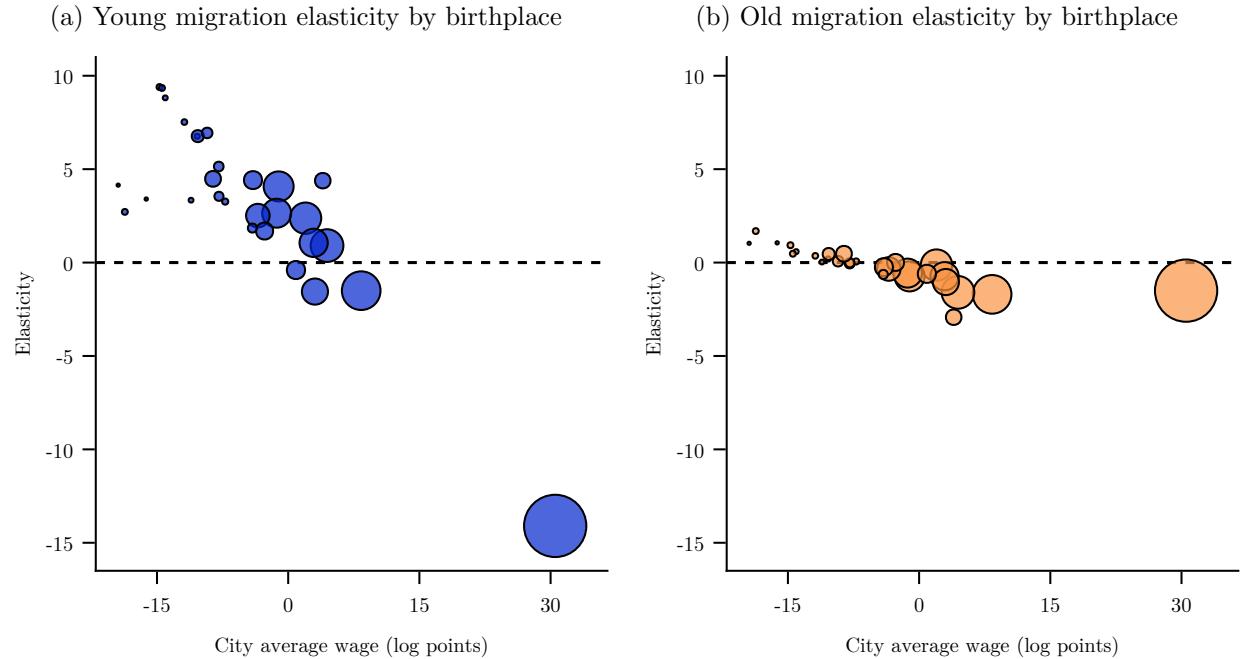
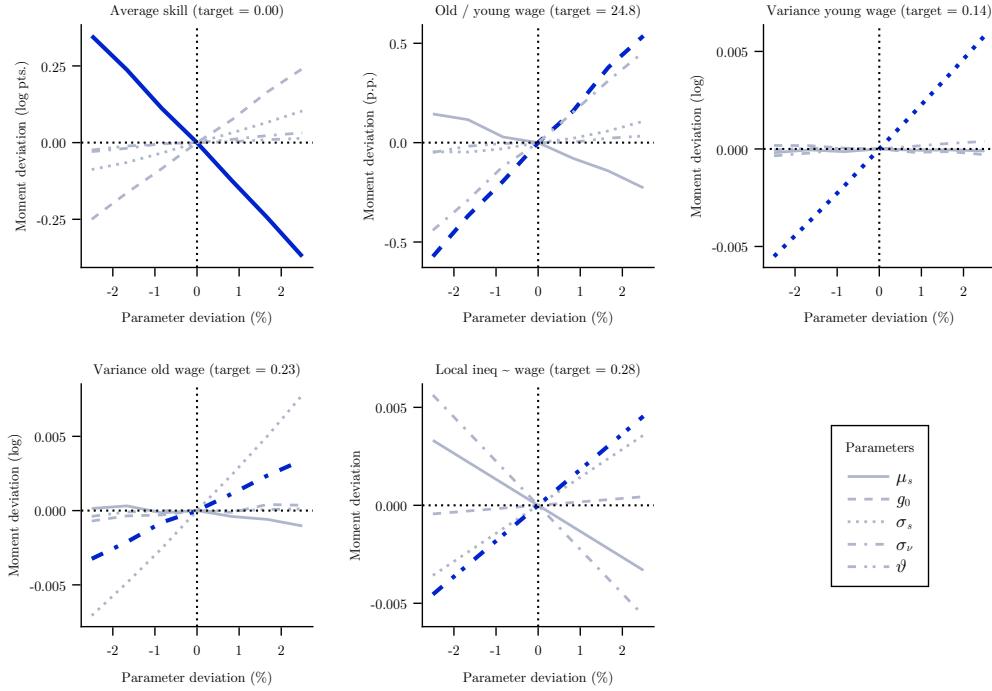


Figure E.8: Sensitivity of targeted moments to parameters



Note: each panel is a targeted moment in the indirect inference procedure. The value of the targeted moment is reported in parenthesis. The scale of the y-axis corresponds to the scale of the targeted moment. Each line is a parameter calibrated by the indirect inference procedure. The blue lines highlight the parameter that are heuristically identified by the particular moment of interest. I consider local deviations around the estimated parameters of 2.5% in each direction. The deviations are represented in percentages on the x-axis.

variance. On the contrary, the learning shocks dispersion affects both the wage variance for old workers and the old to young wage ratio.

Figure E.9 complements the analysis of Figure E.8 by reporting the sensitivity measure of Andrews et al. (2017). Intuitively, this metric is the inverse of the moment elasticities reported in Figure E.8. It quantifies how variation in targeted moments would influence estimated parameter values. Theoretically, let $\mathbf{h}(\boldsymbol{\theta})$ denote the correspondence that maps the vector of parameters $\boldsymbol{\theta}$ into the vector of targeted moments. Let \mathbf{J}_h denote the Jacobian matrix of this function evaluated at the estimated parameters. Then, the sensitivity matrix is computed as $\Lambda = (\mathbf{J}_h' \mathbf{J}_h)^{-1} \mathbf{J}_h'$. Figure E.9 displays the absolute value of Λ , and the sign of Λ is reported in parenthesis. As in Figure E.8, the blue bar highlights which moment is supposed to identify the specific parameter.

I draw two takeaways from Figure E.9. First, each moment is very informative for the parameters they are meant to identify. Second, some moments are informative for several parameters. For instance, the wage variance of old workers matters for the calibration of σ_s , σ_v and ϑ . While this sensitivity measure sheds further light on the importance of the targeted moments for the calibration of the model, the magnitude of the sensitivity cannot however be interpreted.]

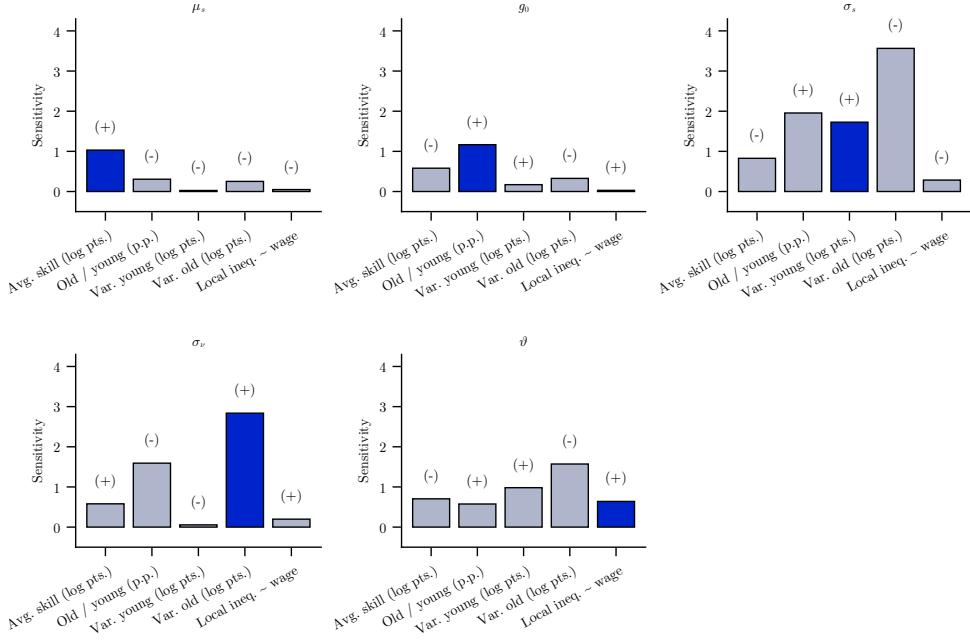
E.5 Over-identification exercises: sorting in the data and in the model

[To read / complete and merge with following paragraphs.]

Two key sets of parameters govern the impact of local interactions on human capital accumulation and agglomeration. The first set of parameters relate to the learning technology. Section 3.5 provided several robustness exercises on the estimation of g_1 , g_2 and g_{12} . The second key parameter is the dispersion in the idiosyncratic preference shocks. In addition to governing the extent to which interactions are spatially differentiated, this parameter is crucial in determining how workers respond to spatial policies. I now provide two over identification exercises that validate the calibration of ϑ .

Between-city wage gaps In the theory, the average wage of city ℓ may be high because the city is relatively productive, or because the workers living there are particularly skilled. Specifically, the between-city wage gaps can be

Figure E.9: Sensitivity of parameters to targeted moments



Note: figure reports the sensitivity measure of Andrews et al. (2017) in absolute value. The sign of the sensitivity is reported in parenthesis. Each panel is a parameter calibrated in the indirect inference procedure. Each column is a targeted moment. The blue bar highlights which moment is supposed to identify the parameter of interest.

decomposed into a TFP gap and a skill gap,

$$\underbrace{\mathbb{E}[\log W_\ell] - \mathbb{E}[\log W]}_{\text{Between-city wage gap}} = \underbrace{\log T_\ell - \mathbb{E}[\log T]}_{\text{TFP gap}} + \underbrace{\mathbb{E}[\log S_\ell]}_{\text{Skill gap}}, \quad (50)$$

where $\mathbb{E}[\log S] = 0$ by normalization. Local TFPs are calibrated to match the local average wages. However, neither the TFP gaps nor the skill gaps are targeted in the estimation. In particular, for a given spatial distribution of average wages, greater sorting implies smaller TFP gaps. Comparing the spatial TFP and skill gaps in the data and in the model thus allows to quantify the extent to which the model captures sorting correctly, and with it, whether ϑ is correctly calibrated.

Computing the wage decomposition (50) empirically requires to directly estimate local TFPs. Through the lens of the model, the wage of worker i when employed in city ℓ_{it} is $\log w_{it} = \log T_{\ell_{it}} + \log s_{it} + u_{it}$, for u_{it} some measurement error. Hence, city TFP can be estimated as a city fixed effect upon observing workers' skill s_{it} .

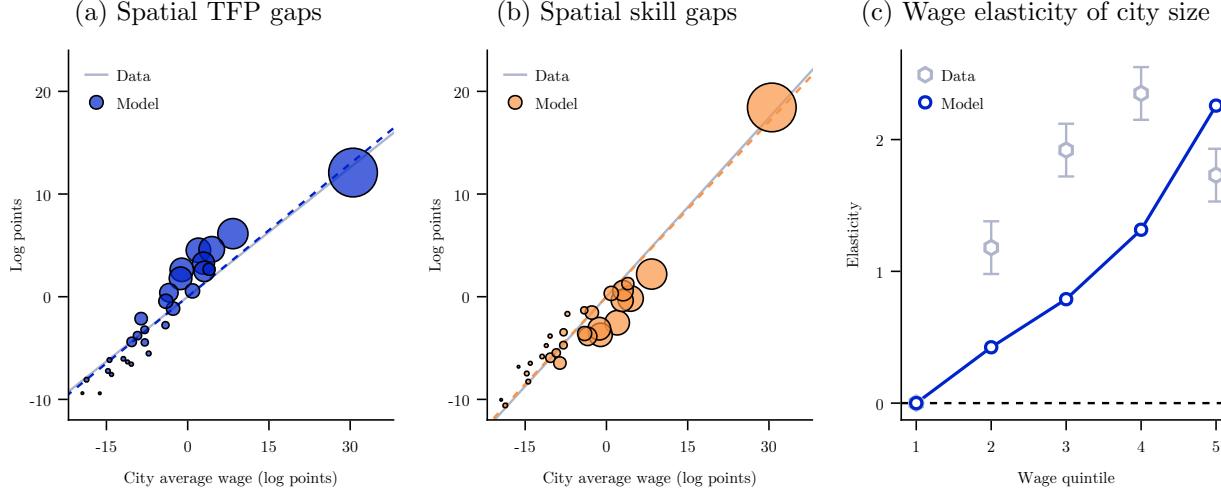
I use workers' occupation at the four-digit level, interacted with their tenure at the occupation, to proxy for their skill. Proxying skills with occupations has the advantage that skills can evolve over time, much like in my model. In particular, worker fixed effects, as in Card et al. (2023), cannot be used to estimate the productivity of a location in the presence of spatial heterogeneity in learning. Measuring skill through worker fixed effect would indeed confound the TFP estimates with the local learning opportunities since those fixed effects are constant over time (see Appendix E.6).¹⁰⁷ The occupation-based skill definition is only used in this over-identification exercise.

Figure E.10a and E.10b plots the TFP and skill gaps in the model against the between-city wage gaps. Cities with a relatively high wage are more productive and attract a higher density of skilled workers. Combined, these two panels show that skilled workers locate disproportionately in productive cities. Quantitatively, the spatial TFP differentials explain 43% of the spatial wage gaps in the model (blue dotted line in Figure E.10a), while the between-city skill gaps explain the remaining 57% of the variation (orange dotted line in Figure E.10b).¹⁰⁸ In the data, I find that the TFP

¹⁰⁷Appendix E.6 provides two robustness exercises. First, I estimate the two-way fixed effect model on young workers only to minimize the amount of learning that takes place in cities. Second, I define a skill as a four-digit occupation interacted with the wage quintile in that occupation.

¹⁰⁸Table E.3 in Appendix E.6 provides the variance decomposition of between-city wage inequality.

Figure E.10: Worker sorting in the model and in the data.



Note: panel (a) displays the estimated city TFP against the city average wage. The blue dashed line is computed as $\log T_\ell = \alpha + \beta \log w_\ell$. The grey solid line is computed as $\log \hat{T}_\ell = \alpha + \beta \log w_\ell$, where $\log \hat{T}_\ell$ are the location fixed effects estimated from a two-way fixed effect regression of log wages on a city and a skill fixed effect. Panel (b) displays the average skill in city ℓ , $\mathbb{E}[\log S_\ell]$, against the city average wage. The orange dashed line is computed as $\mathbb{E}[\log S_\ell] = \alpha + \beta \log w_\ell$. The grey solid line is computed as $\mathbb{E}[\hat{\beta}_s | \ell] = \alpha + \beta \log w_\ell$, where $\hat{\beta}_s$ are the skill fixed effects from the TWFE regression. The size of the markers in panels (a) and (b) is proportional to city size. Panel (c) plots the point estimates of $\{\gamma_q\}$ in (52) obtained from the model (blue circles) and from the data (grey hexagons).

and skill gaps explain respectively 42% and 58% of the spatial wage variation (grey lines in both panels). In addition to spatial differences in average wage, worker sorting also generates greater within-city wage inequality in larger, more productive places (Figure ??), aligned with the findings of literature.¹⁰⁹

Sorting by age In the model, workers' willingness to sort varies by skill and by age: young workers consider both the learning potential of cities and the local wage, whereas old workers only sort according to the earnings differential. When migration costs are small, the model predicts that the between-age difference in the number of workers in city ℓ with skill s is

$$\log \left(\frac{n_\ell^y(s)}{n_\ell^o(s)} \right) = \vartheta (B_\ell^y - B_\ell^o) - \log \left(\frac{\mathcal{N}^y(s)}{\mathcal{N}^o(s)} \right) + \vartheta \beta O_\ell(s), \quad (51)$$

where $\mathcal{N}^a(s) \equiv \sum_\ell e^{\vartheta [w_\ell(s) + B_\ell^a + \beta O_\ell^a(s)]}$ is independent from ℓ . The last term captures the learning motive that is present only for young workers. The shape of the learning technology affects whether young skilled workers place a relatively higher learning value on productive cities than low skill workers. The dispersion in idiosyncratic preferences modulates the between-age difference in willingness to sort. The spatial variations in young to old ratio can therefore be used to validate jointly the estimation of the learning technology and the dispersion in idiosyncratic preferences.

Motivated by (51), I measure in the data the between-age difference in willingness to sort through the reduced-form specification

$$\log \left(\frac{N_{\ell q}^y}{N_{\ell q}^o} \right) = \alpha_\ell + \beta_q + \gamma_q \mathbb{E}[\log W_\ell] + e_{\ell q}, \quad (52)$$

where $N_{\ell q}^a$ is the number of workers living in city ℓ with age a in wage quintile q , and $e_{\ell q}$ is some residual. The parameters α_ℓ and β_q are a city and wage quintile fixed effects respectively. I proxy the quality of interactions in city ℓ by the city log wage, and let workers in different wage quintile value those interactions differently, as captured by γ_q . If $\gamma_q > 0$, young workers in quintile q are more sensitive to spatial variations in wages than old workers in the same quintile. If $\gamma_{q'} > \gamma_q$, this between-age difference in willingness to sort is greater for workers in quintile q' than q . The parameters $\{\gamma_q\}$ are identified up to a constant, and I normalize $\gamma_1 = 0$ to focus on the difference in between-age willingness to sort across skills. I estimate (52) in the data and in the model by OLS.

Figure E.10c presents the point estimates. In the data, the extra incentives of young workers to sort to high-wage places is greater for skilled workers. The same pattern old in the model. Figure E.11 plots the model-implied spatial

¹⁰⁹See for instance Baum-Snow and Pavan (2013), Eeckhout et al. (2014), Papageorgiou (2022) and Lhuillier (2022).

differences in option values for low, middle and high-skill. The future opportunities offered by productive cities are more attractive to skilled workers, which generates further sorting from them.¹¹⁰

E.6 Over-Identification Exercises

The between-city wage gaps can be decomposed into a TFP gap and a skill gap,

$$\mathbb{E}_\ell[\log W] - \mathbb{E}[\log W] = \log T_\ell - \mathbb{E}[\log T] + \mathbb{E}_\ell[\log S]. \quad (53)$$

The TFP and skill gaps are plotted in Figure E.10a and E.10b respectively. The blue and orange dashed lines correspond to the (employment-weighted) fitted lines of the TFP gaps on wage gaps skill gaps on wage gaps respectively. These fitted lines have a theoretical interpretation. From (53), the variance of spatial wage gaps can be broken down into three terms

$$\text{Var}(\mathbb{E}_\ell[\log W] - \mathbb{E}[\log W]) = \text{Var}(\log T_\ell - \mathbb{E}[\log T]) + \text{Var}(\mathbb{E}_\ell[\log S]) + 2\text{Cov}(\log T_\ell - \mathbb{E}[\log T], \mathbb{E}_\ell[\log S]).$$

The first term is the employment-weighted dispersion in TFP. The second term captures the extent to which skills are segmented over space. Finally, the third term represents the extent to which the spatial skill segmentation is correlated with city TFPs. The first two columns of Table E.3 displays the variance decomposition in the model, for all workers and young workers only respectively. The slopes of the blue and orange dotted lines Figure E.10a and E.10b correspond to

$$\frac{\text{Var}(\log T_\ell - \mathbb{E}[\log T]) + \text{Cov}(\log T_\ell - \mathbb{E}[\log T], \mathbb{E}_\ell[\log S])}{\text{Var}(\mathbb{E}_\ell[\log W] - \mathbb{E}[\log W])}$$

and

$$\frac{\text{Var}(\log S) + \text{Cov}(\log T_\ell - \mathbb{E}[\log T], \mathbb{E}_\ell[\log S])}{\text{Var}(\mathbb{E}_\ell[\log W] - \mathbb{E}[\log W])}$$

respectively.

To estimate the TFP and skill gaps in the data, I run

$$\log w_{it} = \alpha_t + \beta_{\ell_{it}} + \gamma_{s_{it}} + u_{it}, \quad (54)$$

and define $\log T_\ell = \hat{\beta}_\ell$ and $\mathbb{E}_\ell[\log S] = \mathbb{E}_\ell[\hat{\gamma}_{s_{it}}]$. I use two skill definitions. First, I set s_{it} as a four-digit occupation fixed effect interacted with three-year bins of occupation tenures. I estimate (54) on the full sample of workers as well as on young workers only to minimize the amount of learning that took place within cities. Second, I set s_{it} as a four-digit occupation fixed effect interacted with the wage quintile within that occupation.

When cities differ in their learning opportunities, worker fixed effects cannot be used to estimate the productivity of a location. Indeed, when $s_{it} = i$ in (54), the city F.E. are estimated off within-worker time variation in wages for workers who switch location,

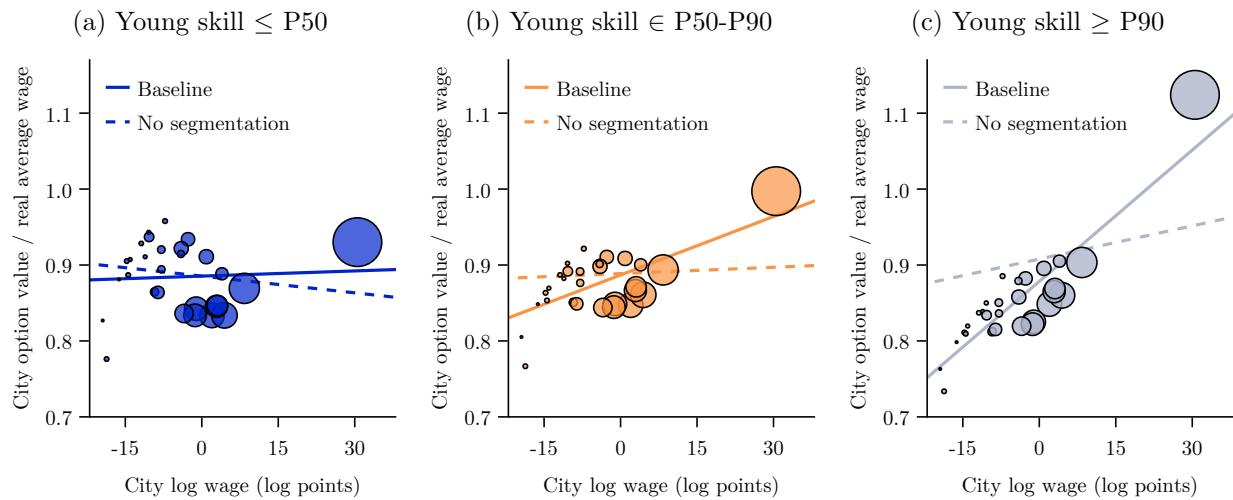
$$\log w_{it+h} - \log w_{it} = \alpha_{t+h} - \alpha_t + \beta_{\ell_{it+h}} - \beta_{\ell_{it}} + u_{it+h} - u_{it}.$$

That is, the city F.E. are estimated off wage growth variation for movers. Hence, the city F.E. conflates TFP estimates with estimates of the learning technology.

Table E.3: Between-city variance decomposition in the model and in the data

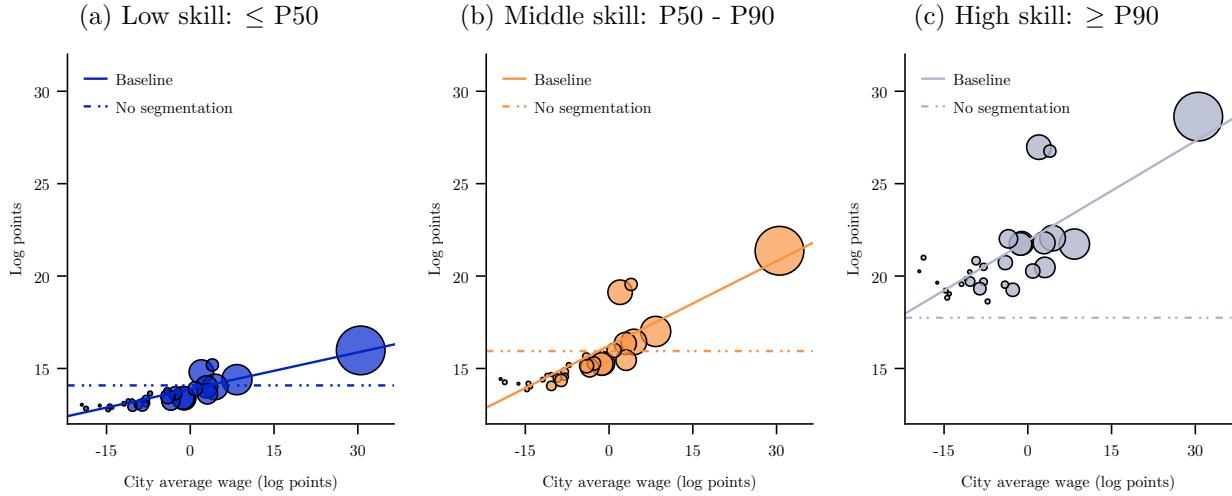
	Model		Data		
	(1)	(2)	(3)	(4)	(5)
Var[log w]	0.020	0.019	0.020	0.019	0.020
Var[log T] (%)	19.66	19.66	19.80	19.60	16.80
Var[log S] (%)	33.54	33.54	35.20	36.30	41.00
Cov[log T , log S] (%)	46.79	46.79	45.20	44.00	42.20
R ²	1.00	1.00	0.640	0.600	0.930
Skill def.	.	.	Occ. × tenure	Occ. × tenure	Occ. × quintile
Sample	All	Young	All	Young	All

Figure E.11: The option value of cities across the skill distribution



Note: discounted option value of cities over real average wage.

Figure F.1: Skill growth by birthplace and initial skill



F The Tradeoff Between Human Capital and Inequality

Figure F.2: Skill growth by birthplace

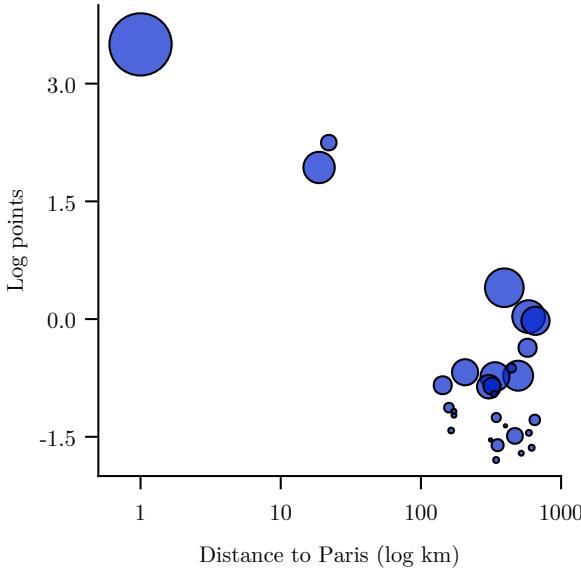
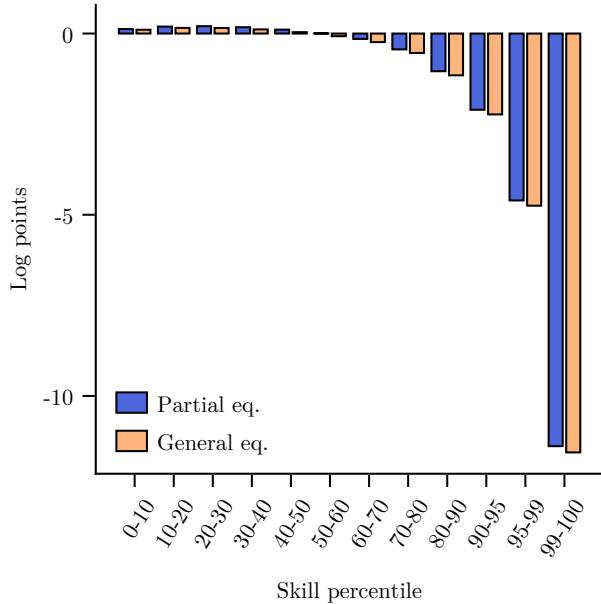


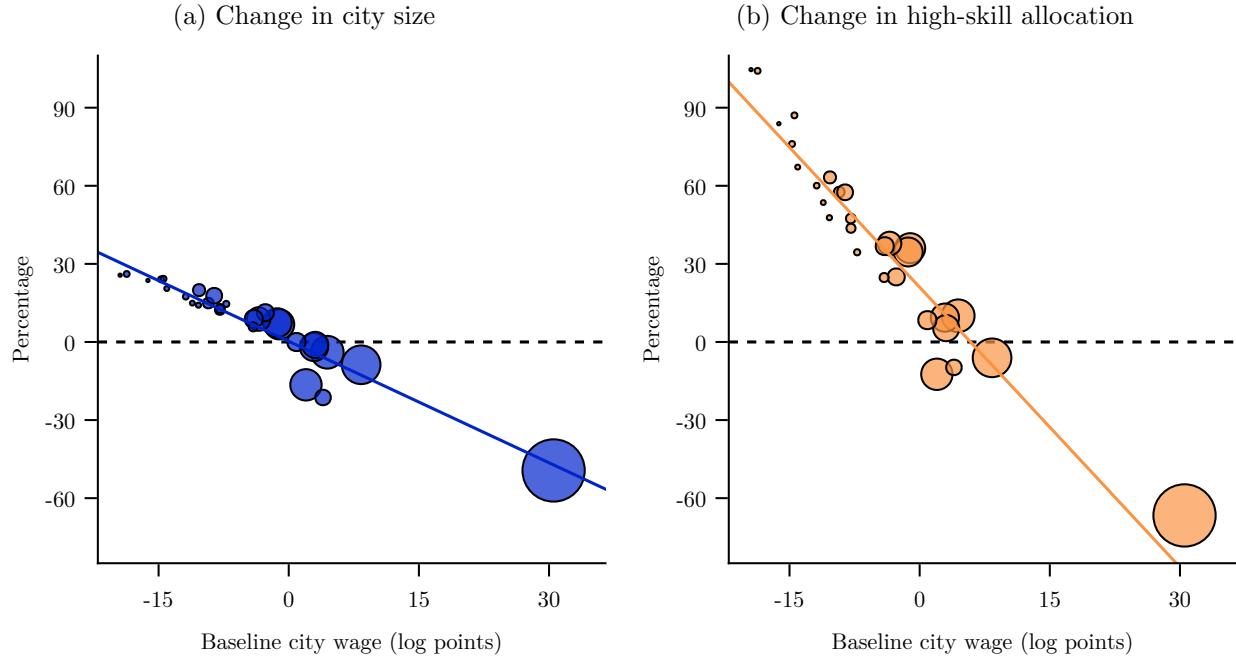
Figure F.3: The partial and general equilibrium effect of local interactions on skill growth



Note: panel (a) displays the average skill growth by birthplace against the distance from that birthplace to Paris. The size of the markers is proportional to city size. Panel (b) plots the change in average skill growth between the baseline equilibrium and the no segmentation equilibrium across the skill distribution of young workers. The blue bars are the change in skill growth when interactions are no longer spatially segmented but the aggregate skill distribution is held constant (partial equilibrium). The orange bars are in general equilibrium letting the aggregate skill distribution adjusts.

¹¹⁰When migration costs are positive, the option value of productive cities reflect both the learning opportunities and the future migration costs. Figure E.11 plots the spatial differences in option values when interactions are not segmented by cities (Section 5). In this case, skilled workers continue to place a higher option value on productive cities to front-load the future migration costs, but the between-city differences are four times smaller.

Figure F.4: Local interactions as a source of agglomeration



Note: panel (a) displays the percentage change in city size between the baseline equilibrium and the equilibrium without segmented interaction against the baseline city average wage. The blue line is the fitted line. Panel (b) plots the percentage change in the propensity of high-skill workers (top 10% of the skill distribution) to work in a particular city. The orange line is the fitted line. The size of the markers is proportional to the baseline city size in both panels.

G The Consequences of Spatial Policies

Figure G.1: Average take-up rate of moving vouchers by birthplace

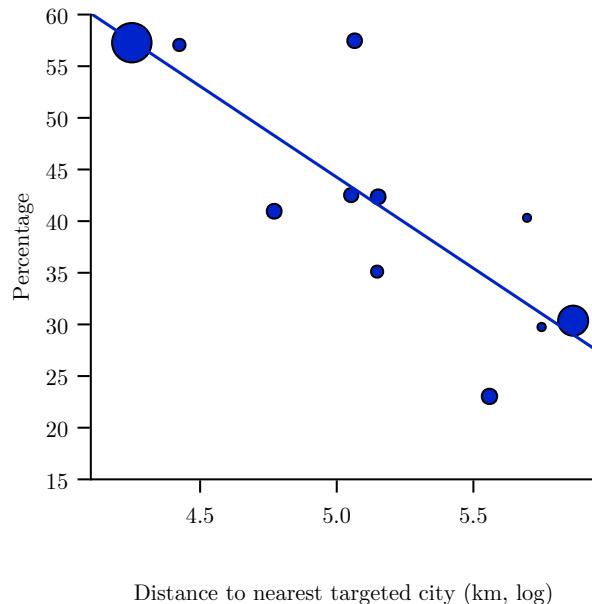
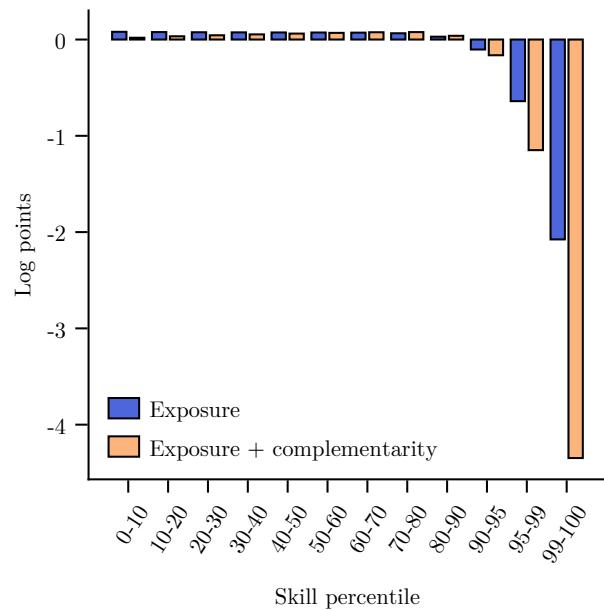


Figure G.2: The role of complementarities in shaping the learning costs of the voucher policy



Note:

Figure F.5: The agglomeration effect of local interactions by age

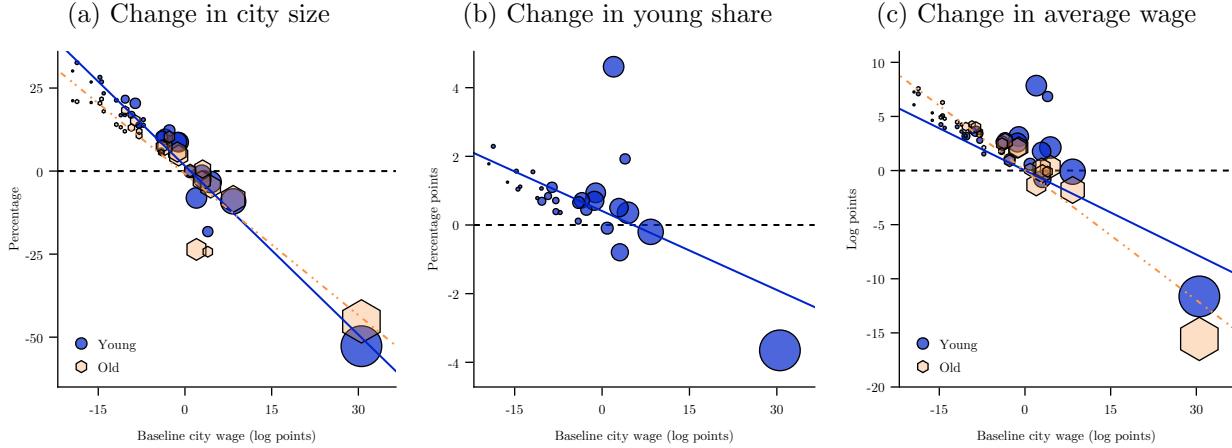
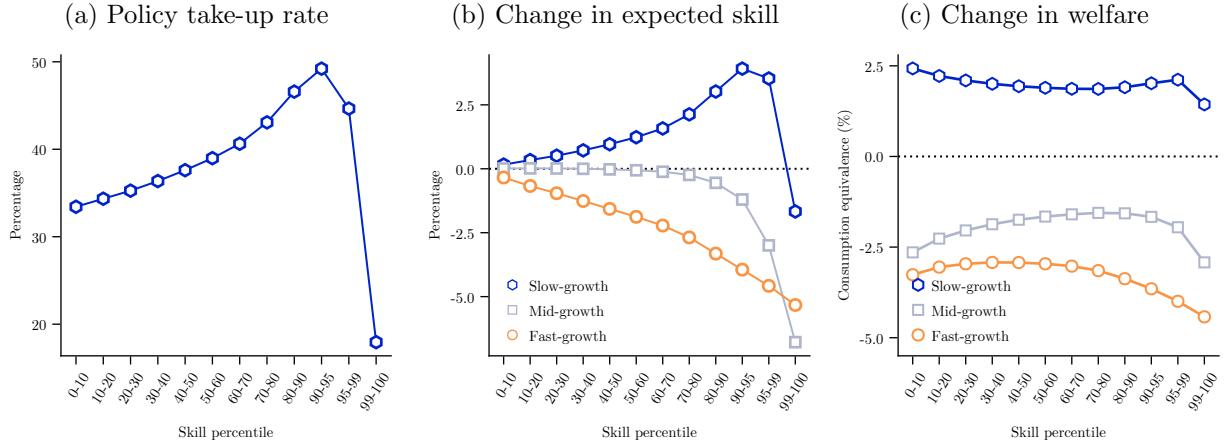


Figure G.3: The consequences of moving vouchers by skill and birthplace



G.1 Welfare analysis

Consumption equivalence I first present how I derive the consumption-equivalent welfare metric of Section 6.3. Let $\mathcal{V}_l^y(s, \zeta, \tau)$ denote the lifetime utility of a young worker born in l with skill s when their lifetime consumption is multiplied by ζ and they face a transfer function τ ,

$$\mathcal{V}_l^y(s, \zeta, \tau) = \frac{1}{\vartheta} \log \left(\sum_{\ell} e^{\vartheta \left(\frac{[s T_{\ell} + \tau_{\ell}^y(s)] \zeta}{P_{\ell}} + B_{\ell}^y - \kappa_{\ell}^y + \beta O_{\ell}(s, \zeta, \tau) \right)} \right),$$

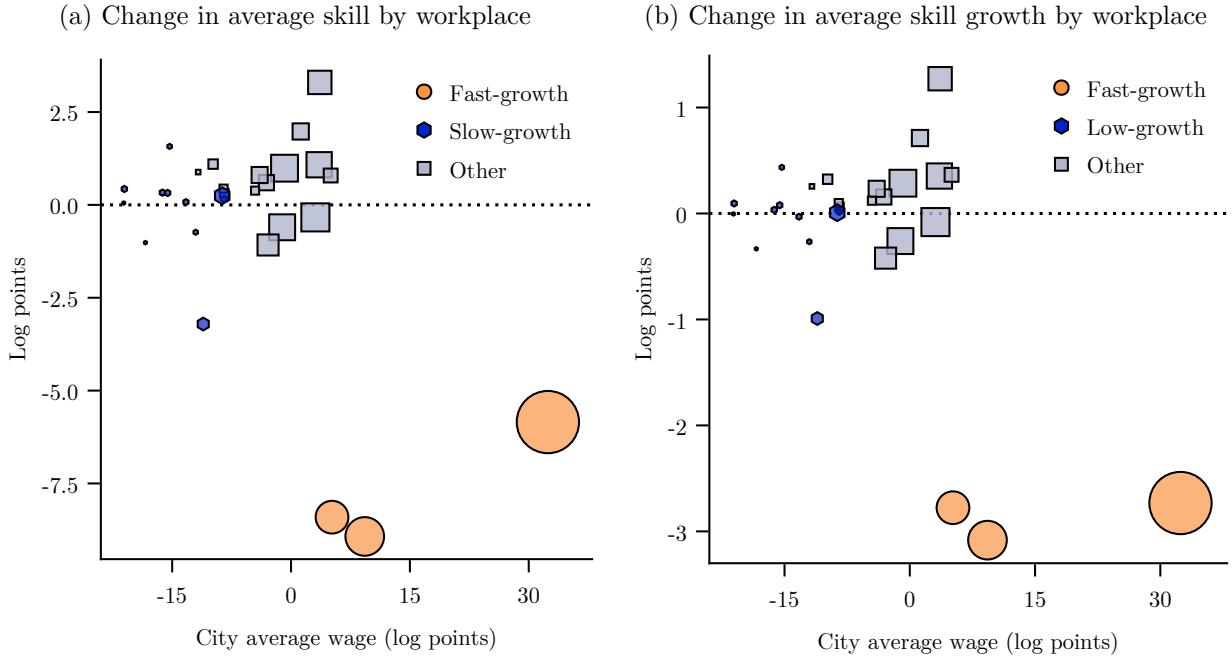
where¹¹¹

$$O_{\ell}(s, \zeta, \tau) = \frac{1}{\vartheta} \int \int \log \left(\sum_{\ell'} e^{\vartheta \left(\frac{[s^o T_{\ell'} + \tau_{\ell'}^o(s^o)] \zeta}{P_{\ell'}} + B_{\ell'}^o - \kappa_{\ell'}^o \right)} \right) dF \left(\frac{s^o}{\gamma(s, s_p)} \right) \pi_{\ell}(s_p).$$

Let $\zeta_l(s)$ denote the consumption-equivalent change in welfare induced by the policy τ for workers born in l with skill ℓ . This consumption-equivalent measure is defined implicitly by $\mathcal{V}_l^y[s, \zeta_l(s), 0] = \mathcal{V}_l^y(s, 0, \tau)$. Intuitively, $\zeta_l(s)$ measure by how much does the lifetime consumption of workers born in l with skill s needs to be multiplied in the baseline equilibrium to make these workers indifferent between the policy τ and the baseline economy.

¹¹¹I use the change of variable $e\gamma(s, s_p) \rightarrow s^o$ to derive the option value of city ℓ .

Figure G.4: The consequences of the voucher policy on local interactions



This metric can only be used to quantify the welfare impact of the policy for workers with identical skill born in the same location. In particular, it cannot be aggregated across skills or places. I therefore complement the worker-level metric with a welfare measure for “representative” workers. Specifically, I measure the welfare impact of the policy on group g as the change in lifetime consumption required to make the average worker in that group indifferent between the two equilibria,

$$\int \mathcal{V}_{\ell_i}^y(s_i, \zeta_g, 0) dF_i^g = \int \mathcal{V}_{\ell_i}^y(s_i, 0, \tau) d\tilde{F}_i^g,$$

where ζ_g is the welfare measure, and dF_i^g denote the distribution of workers in group g for simplicity.¹¹² This second welfare metric is consistent with a utilitarian social welfare function that places equal weights on workers within group g .¹¹³

Welfare decomposition The total welfare impact of the policy can be decomposed into several margins. To see this, note that the expected lifetime utility of a young worker be written as

$$\mathcal{V}_i^y(s) = \mathbb{E} \left[\max_{\ell} \left\{ \frac{sT_{\ell} + \tau_{\ell}}{P_{\ell}} - \kappa_{i\ell}^y + \beta O_{\ell}(s) + \varepsilon_{\ell} \right\} \right] = \sum_{\ell} \left(\frac{sT_{\ell} + \tau_{\ell}}{P_{\ell}} - \kappa_{i\ell}^y + \beta O_{\ell}(s) \right) \frac{n_{i\ell}^y(s)}{m_{\ell}^y(s)} + \chi_i^y(s).$$

where $\chi_i^y(s) \equiv \mathbb{E} [\varepsilon_{\ell}^y \mid \ell > \ell' \forall \ell' \neq \ell]$ and I have subsumed the amenity value of cities into $\chi_i^y(s)$.¹¹⁴ The first equality follows from the definition of lifetime utility, and the second line from $n_{i\ell}^y(s)/m_{\ell}^y(s) = \Pr[\varepsilon_{\ell} \geq \max_{\ell' \neq \ell} \varepsilon_{\ell'} + U_{i\ell'}(s) - U_{i\ell}(s)]$. Similarly, the expected option value of city ℓ can be rewritten

$$\begin{aligned} O_{\ell}(s) &= \int \int \mathbb{E} \left[\max_{\ell'} \left\{ \frac{e\gamma(s, s_p)T_{\ell'}}{P_{\ell'}} - \kappa_{\ell\ell'}^o + \varepsilon_{\ell'} \right\} \right] \pi_{\ell}(s_p) dF(e) ds_p \\ &= \int \left(\sum_{\ell'} \frac{n_{\ell\ell'}^o(s^o)}{m_{\ell}^o(s^o)} \left(\frac{s^o T_{\ell'}}{P_{\ell'}} - \kappa_{\ell\ell'}^o \right) + \chi_{\ell}^o(s^o) \right) \omega_{\ell}(s^o, s) ds^o. \end{aligned}$$

¹¹²Note that dF_i^g and $d\tilde{F}_i^g$ need not be the same as the policy is reallocating workers across space.

¹¹³Importantly however, no restrictions are placed on the social welfare function across groups. By making the groups more granular, one therefore recovers the worker-level welfare metric.

¹¹⁴No closed-form solution exists for $\chi_i^y(s)$ but it can be obtained as utility residual.

Figure G.5: The consequences of the moving voucher policy across skills and birthplaces

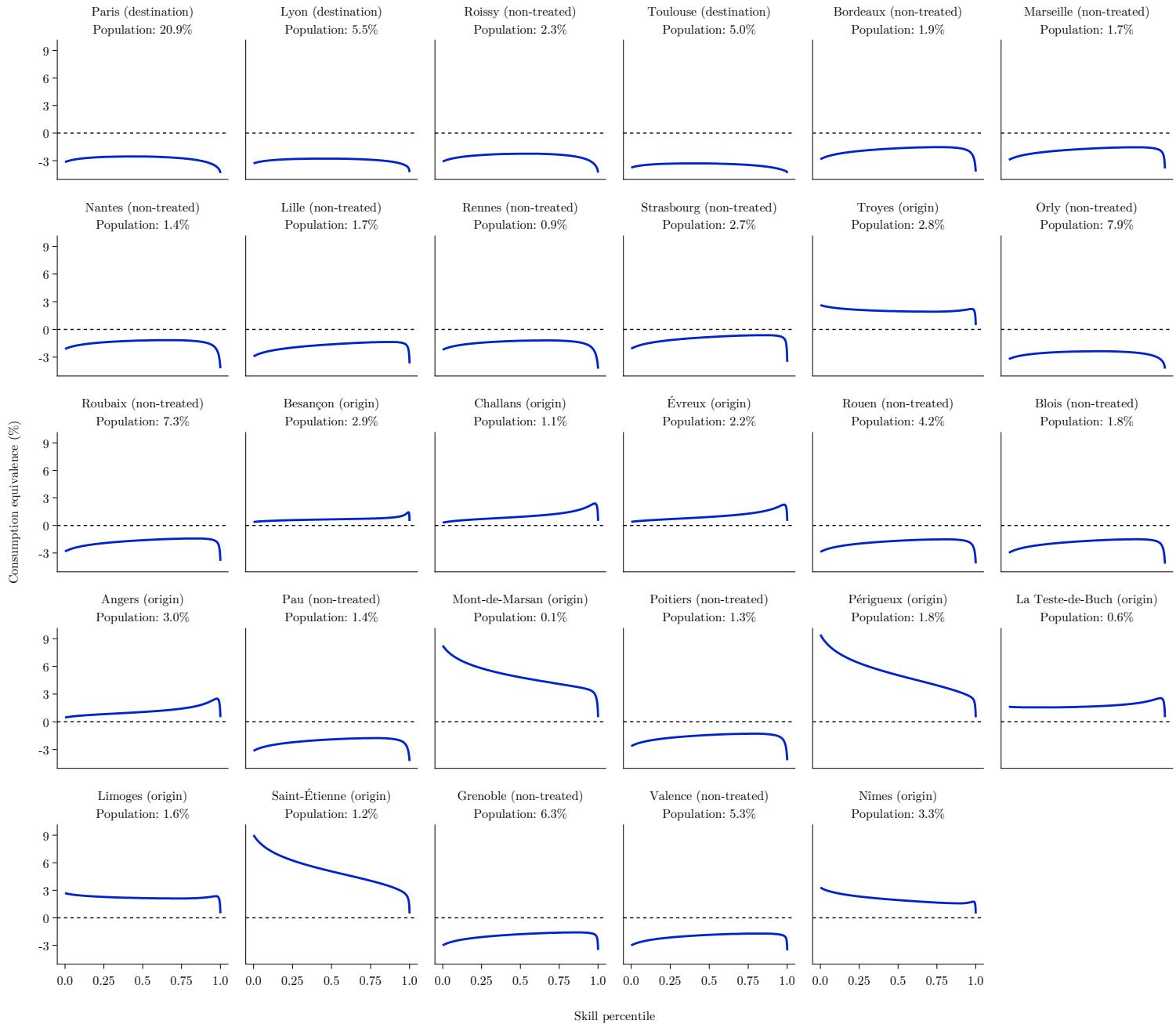
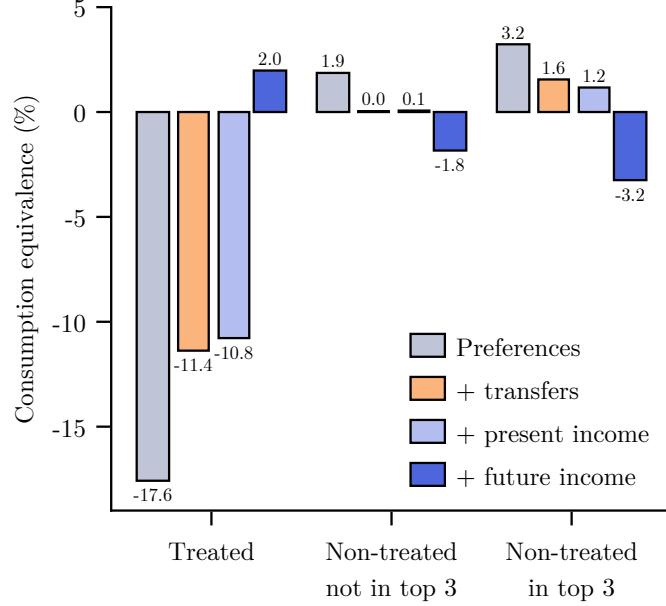


Figure G.6: Welfare decomposition of the moving voucher policy by birthplaces



where the second line follows from the change of variable $e\gamma(s, s_p) \rightarrow s^o$ and the definition

$$\omega_\ell(s^o, s) \equiv \int \frac{\pi_\ell(s_p)}{\gamma(s, s_p)} f\left(\frac{s^o}{\gamma(s, s_p)}\right) ds_p.$$

Combined with the expression for young workers, we can therefore write lifetime utility as

$$\begin{aligned} V_l^y(s) &= \underbrace{\sum_\ell \left(\frac{\tau_{l\ell} - \kappa_{l\ell}^y P_\ell}{P_\ell} \right) \frac{n_{l\ell}^y(s)}{m_\ell^y(s)} - \beta \sum_\ell \frac{n_{l\ell}^y(s)}{m_\ell^y(s)} \int \omega_\ell(s^o, s) \left(\sum_{\ell'} \frac{n_{\ell\ell'}^o(s^o)}{m_\ell^o(s^o)} \kappa_{\ell\ell'}^o \right) ds^o}_{\text{Transfers net of lifetime migration costs } \equiv V_l^T(s)} \\ &\quad \underbrace{\sum_\ell \left(\frac{sT_\ell}{P_\ell} \right) \frac{n_{l\ell}^y(s)}{m_\ell^y(s)} + \beta \sum_\ell \frac{n_{l\ell}^y(s)}{m_\ell^y(s)} \int \omega_\ell(s^o, s) \left(\sum_{\ell'} \frac{n_{\ell\ell'}^o(s^o)}{m_\ell^o(s^o)} \frac{s^o T_{\ell'}}{P_{\ell'}} \right) ds^o}_{\text{Present real income } \equiv V_l^I(s)} + \\ &\quad \underbrace{\chi_l(s) + \beta \sum_\ell \frac{n_{l\ell}^y(s)}{m_\ell^y(s)} \int \chi_\ell(s^o) \omega_\ell(s^o, s) ds^o}_{\text{Preferences } \equiv V_l^A(s)}, \end{aligned}$$

Lifetime utility can therefore be decomposed into four terms. First, the value of the transfers net of the lifetime migration costs. Second, the present real income these workers have access to. Third, their expected future real income. And third, their preferences for the location they live in. Hence, $V_l^y(s) = V_l^A(s) + V_l^T(s) + V_l^I(s) + V_l^{EI}(s)$.

This utility decomposition can be used to decompose the welfare impact of the policy. The consumption-equivalent welfare change can indeed be rewritten

$$\begin{aligned} 0 &= V_l^y[s, \zeta_l(s)] - V_l^{y*}(s) = V_l^y[s, \zeta_l(s)] - V_l^y(s) + V_l^y(s) - V_l^{y*}(s) \\ &= V_l^y[s, \zeta_l(s)] - V_l^y(s) + (V_l^A(s) - V_l^{A*}(s)) + (V_l^T(s) - V_l^{T*}(s)) + \\ &\quad (V_l^I(s) - V_l^{I*}(s)) + (V_l^{EI}(s) - V_l^{EI*}(s)), \end{aligned}$$

where the first equality is the definition of $\zeta_l(s)$, the second is an identity, and the third follows from the decomposition

I just derived. From there, we can define the four consumption-equivalent welfare metric:

$$\begin{aligned}\mathcal{V}_l^y[s, \zeta_l^A(s)] &= \left(V_l^{A\star}(s) - V_l^A(s) \right) + \mathcal{V}_\ell^y(s), \\ \mathcal{V}_l^y[s, \zeta_l^{A+T}(s)] &= \left(V_l^{A\star}(s) - V_l^A(s) \right) + \left(V_l^{T\star}(s) - V_l^T(s) \right) + \mathcal{V}_\ell^y(s), \\ \mathcal{V}_l^y[s, \zeta_l^{A+T+I}(s)] &= \left(V_l^{A\star}(s) - V_l^A(s) \right) + \left(V_l^{T\star}(s) - V_l^T(s) \right) + \left(V_l^{I\star}(s) - V_l^I(s) \right) + \mathcal{V}_\ell^y(s), \\ \mathcal{V}_l^y[s, \zeta_l(s)] &= \mathcal{V}_l^{y\star}(s).\end{aligned}$$

The term $\zeta_l^A(s)$ measure the (consumption-equivalent) change in welfare coming solely from the idiosyncratic preferences for the locations. The second term $\zeta_l^{A+T}(s)$ adds to the first term the net value of the transfer. The third term $\zeta_l^{A+T+I}(s)$ brings in the value of the present real income opportunities. Finally, $\zeta_l(s)$ adds the expected future lifetime opportunities and corresponds to the total change in welfare. These four metrics are *not* additive but allow to measure the relative importance of each term.

Figure G.6 presents this welfare decomposition separately for treated workers, non-treated workers born outside of Paris, Lyon and Toulouse, and non-treated workers born in those three cities. The welfare impact of the policy on the treated is mainly explained by two offsetting forces. On the one hand, workers born in the treated locations that were choosing to stay there in the baseline equilibrium had on average strong preferences for these cities. On average, the policy is therefore reallocating treated workers to cities they dislike, which reduces their lifetime utility. On the other hand, the policy improves their future real income opportunities by increasing their lifetime human capital. In net, the human capital channel dominates.¹¹⁵

To understand the welfare impact of the policy on the non-treated, recall from Proposition 5 that local interactions engender two externalities. First, a pulling externality: the concentration of skilled workers in a few cities requires many workers to forego their idiosyncratic spatial preferences. Second, a teaching externality: in the presence of strong within-skill complementarities, the economy features too few interactions between skilled workers. The voucher policy decreases the density of skilled workers in productive cities, and in doing so, mitigates the pulling externality while amplifying the teaching externality. Holding constant the human capital of non-treated workers, these workers would therefore also gain from the policy. However, in general equilibrium, the policy depresses their future income, which, together with the tax they have to pay to finance the policy, triggers welfare losses.

¹¹⁵Treated workers also experience welfare gains from the direct income effect of the subsidy.