THE GEOGRAPHY OF UNEMPLOYMENT*

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Unemployment rates differ widely across local labor markets. I offer new empirical evidence that high local unemployment emerges because of elevated local job-losing rates. Local employers, rather than local workers or location-specific factors, account for most of the spatial gaps in job stability. I propose a theory in which spatial differences in job loss emerge in equilibrium because of systematic differences between employers across local labor markets. The spatial sorting decisions of employers in turn shape heterogeneity across locations. Labor market frictions induce productive employers to overvalue locating close to each other. The optimal policy incentivizes them to relocate toward areas with high job-losing rates, providing a rationale for commonly used place-based policies. I estimate the model using French administrative data. The estimated model accounts for over three-quarters of the cross-sectional dispersion in unemployment rates and for the respective contributions of job-losing and job-finding rates. Inefficient location choices by employers amplify spatial unemployment differentials fivefold. Both real-world and optimal place-based policies can yield sizable local and aggregate welfare gains. *JEL Codes:* E20, E24, E60, F16, H21, J42, J61, J63, J64, R13, R23.

I. Introduction

Unemployment rates vary enormously across local labor markets. In 2017 in Versailles, an affluent French city close to Paris,

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5% of workers were unemployed. In southern Marseille, the unemployment rate exceeded 12%. Comparable differences arise in the United States and in most other developed countries.[1] Despite their magnitude, these spatial gaps persist over decades. Although local governments devote billions of dollars every year to attract jobs, the determinants of spatial unemployment differentials remain elusive. Why is the unemployment rate persistently high in some places and low in others? What are the welfare implications of this spatial dispersion for workers? Can place-based policies improve the prospects of local residents and the aggregate economy?

This article proposes answers to these questions with four contributions. First, I offer new empirical evidence showing that spatial unemployment differentials result from spatial gaps in the rate of job loss, which are in turn shaped by local employers rather than local workers. Second, I propose a theory in which the location choice of employers together with labor market frictions leads to spatial differences in job stability. Third, I estimate the framework on French administrative data. Fourth, I quantify the local and aggregate welfare gains from place-based policies in general equilibrium.

Specifically, in the first part of the article, I examine how local labor market flows differ between locations. I assess whether differences in unemployment rates across commuting zones reflect differences between job-losing (inflow) versus job-finding (outflow) rates using French matched employer-employee data and Current Population Survey data for the United States. Differences in job-losing rates emerge as the primary source of spatial unemployment differentials, accounting for 77% of the variation in France and 73% in the United States. By contrast, job-finding rates are nearly constant across locations. Using a two-way fixed effect approach, I establish that employer-specific heterogeneity accounts for two-thirds of spatial job loss differences, while worker-specific heterogeneity accounts for only one-third. The contribution of employers is robust to controlling for location-specific factors.

The dominant role of the job-losing rate indicates that locations have high unemployment because workers repeatedly lose their job there, not because finding a job is particularly hard. This result contrasts with aggregate unemployment fluctuations, as

1. In 2017, the unemployment rate was 5% in Boston, Massachusetts. It was 13% in Flint, Michigan. See the OECD (2005) report for more countries.

well as with existing models of spatial unemployment that have focused on the job-finding rate.[2] The composition analysis reveals that spatial gaps in the rate of job loss arise because of systematic differences in job stability between employers.

In the second part of the article, I propose an analytical theory to account for spatial gaps in job-losing rates and the key role of employer heterogeneity. Workers choose freely where to live and work, and employers choose where to open jobs.[3] They meet in local labor markets subject to standard search frictions. Housing is in limited supply. Employers offer jobs that differ in initial productivity, which subsequently fluctuates due to idiosyncratic shocks. As a result, endogenous job loss arises, and initially more productive jobs are more stable. Together, these elements build on the Diamond-Mortensen-Pissarides search-and-matching framework embedded in a Rosen-Roback spatial equilibrium setting, which I enrich with two crucial features. First, bilateral decisions of workers and employers shape job loss. Second, the location choice of employers determines local productivity in equilibrium.

Local labor market flows reflect spatial differences in employer productivity, regardless of whether employer productivity is taken as given or determined in equilibrium. The job-losing rate is high where employers are unproductive and jobs have low surplus. Job-finding rates depend on two components: the meeting rate of workers and the probability that a meeting successfully results in a viable match. Whether job-losing rates vary strongly across locations while job-finding rates remain largely flat thus depends on cross-sectional patterns of employer productivity and labor market tightness.

The location decisions of employers shape spatial heterogeneity in productivity. Employers value two types of location characteristics. First, they value exogenous location fundamentals. Standard production complementarities imply that more productive employers are willing to pay more for locations that are inherently better suited for production. There, less productive employers are priced out by high wages and thus self-select into locations with poor fundamentals but low wages.

2. Changes in the job-finding rate have been found to be the dominant force in aggregate unemployment fluctuations over the business cycle. See Hall (2005), Shimer (2005), Fujita and Ramey (2009), and Krusell et al. (2017).

3. As is common in the search literature, there is no difference between employers, firms, and jobs in my framework.

Second, employers value endogenous recruiting conditions. The location choice of employers then interacts with labor market frictions to uncover labor market pooling complementarities. Productive employers make high profits. Thus, they forgo relatively more than unproductive employers while waiting for a worker: productive employers have a higher opportunity cost of time. At the margin, they are willing to pay more for slack labor markets where they recruit rapidly. By contrast, unproductive employers are priced out by high wages and self-select into low-wage areas where they fill vacancies slowly.

Sorting emerges in spatial equilibrium as a result of the differential valuation of both exogenous and endogenous local characteristics by different employers. Of course, when differences in local fundamentals are large, cross-sectional sorting patterns based on vacancy-filling rates alone hold only conditionally. Unconditional sorting patterns are more complex.

The spatial sorting of employers has strong predictions for local labor market flows. Spatial gaps in job-losing rates are large because different employers locate in different places. Job-finding rates vary less across locations because workers make offsetting decisions that stabilize the two components of job-finding rates. At the margin, productive employers are drawn toward slack labor markets. If the labor market was too slack, workers would out-migrate. In addition, higher success probabilities of meetings in locations with productive employers are partially balanced by workers being more selective there.

Reduced-form evidence using administrative establishment-level productivity and vacancy data supports these implications. Consistent with predicted sorting patterns, labor productivity correlates negatively with job-losing rates across French establishments and commuting zones. Consistent with the limited variation in local job-finding rates, labor market tightness varies little across locations. The sign of the correlation between local labor market tightness and unemployment is sensitive to measurement choices, mirroring the corresponding ambiguity of the predictions of the theory. If anything, local labor market tightness rises modestly with local unemployment.

Next, I show that the spatial equilibrium features misallocation because of a labor market pooling externality. Labor market frictions enable unproductive employers to attract more workers than would be socially optimal, should they enter a location with more productive competitors. Hence, employers privately colocate too much with more productive competitors that attract a larger pool of workers and ease recruiting.[4] A utilitarian planner thus chooses an optimal policy that incentivizes productive employers to relocate toward high job loss areas. A corporate tax credit whose generosity rises with local job-losing rates implements the optimal allocation, providing a rationale for commonly used place-based policies that subsidize employers in high-unemployment locations.

The third part of the article develops and structurally estimates a quantitative version of the framework with four main additions. First, locations also differ in residential amenities that capture nonmonetary compensating differentials, such as pleasant weather. Second, migration frictions introduce empirically plausible migration elasticities. Third, firms face convex recruiting costs that control how job creation depends on local and aggregate labor market conditions. Fourth, workers differ in human capital that depreciates while they are unemployed. In equilibrium, localized scarring effects in high-unemployment areas produce clusters of workers with low human capital. There, productive stable jobs are less likely to open, further worsening local labor market conditions and magnifying spatial disparities.

Despite its richness, the quantitative model retains the tractability of the analytical framework. As a result, it produces estimating equations that allow for transparent identification by leveraging the many dimensions of the French administrative data. A recursive scheme delivers a sequence of regression equations that identify all but 1 of the 19 parameters without requiring simulation from the model. The model can match a number of nontargeted moments such as the declining tenure profile of job loss within and across locations. The estimation directly targets neither the cross-sectional dispersion of local unemployment rates nor its breakdown into job-losing and job-finding rates.

The fourth part of the article reveals that the estimated model accounts for the primary margins of spatial unemployment differentials. It generates over 75% of the cross-sectional dispersion of local unemployment rates in the data. It also closely replicates the respective contributions of job-losing and job-finding rates: 77% stem from the job-losing rate in the data, against 73% in the model. The model matches the empirical relationship between

4. The labor market pooling externality is a consequence of the location choice of heterogeneous employers. Assuming away their location choice shuts down the externality.

local labor market flows on the one hand, and local wages, population, and labor market tightness, on the other hand. Pooling externalities are crucial for rationalizing the location choice of employers, and hence job-losing rate differences. Shutting down pooling externalities diminishes the incentives of employers to sort and strongly reduces gaps in job-losing rates. As a result, the spatial variation in unemployment rates shrinks by 82%.

Two counterfactuals then quantify the effect of place-based policies in general equilibrium. I start with the optimal policy. It takes the form of a corporate tax credit that is more generous in high-unemployment locations. The optimal policy thus offsets the labor market pooling externality, and incentivizes more productive employers to relocate toward high-unemployment locations. The optimal policy cuts the local unemployment rate by 5 to 10 percentage points and achieves 5% to 10% local welfare gains in cities such as Marseille. Long-run scarring effects of unemployment are central to these welfare gains, accounting for the vast majority of the total. Aggregate welfare gains are just over 2%. They are more modest than local gains in high-unemployment locations because they average over a sizable redistribution of resources across locations. As the most productive and stable jobs leave the lowest-unemployment locations, residents experience welfare losses there.

I contrast the optimal policy with the French Enterprise Zones (EZ) program—the Zone Franches Urbaines. The program was rolled out in 1996 and consisted of heavy subsidies for businesses opening jobs in high-unemployment areas. Qualitatively, the French EZ policy resembles the optimal policy and should deliver positive welfare gains. Quantitatively however, the program is much smaller than the optimal policy in scale and scope. I find that the French EZ program reduces unemployment in treated areas by 2 to 3 percentage points, consistent with existing difference-in-difference estimates. Local welfare gains do not exceed a few percent. In the aggregate, the EZ program raised welfare by 0.14%. Although modest, the impact of the EZ program is eight times higher per dollar taxed than the optimal policy, due to decreasing returns to redistribution. This comparison suggests that small-scale place-based policies are likely to be more efficient than large-scale ones in the presence of fiscal optimization or political-economy constraints.

This article adds to four strands of literature. First and most closely related is the body of work that examines persistent spatial unemployment differentials.[5] Kline and Moretti (2013), Şahin et al. (2014), Marinescu and Rathelot (2018), and Schmutz and Sidibé (2018) study spatial variants of the Diamond (1982), Mortensen (1982), and Pissarides (1985) model embedded in spatial equilibrium à la Rosen (1979) and Roback (1982). All of these papers focus on job-finding rates. By contrast, I stress that job-losing rates and employers are the key drivers of spatial unemployment differentials. As a result, a different theory is required. Thus, I enrich this standard Diamond-Mortensen-Pissarides-Rosen-Roback setting with two key elements. First, I introduce endogenous separations. Next, I micro-found local productivity differences through the location decision of employers. This environment brings about that subsidies to high-unemployment areas raise welfare, reconciling theory with real-world place-based policies.[6]

Second, this article adds to the literature that studies the location decisions of agents. A first subset focuses on the location decisions of workers based on income prospects (Roback 1982; Kennan and Walker 2011; Desmet and Rossi-Hansberg 2013; Bilal and Rossi-Hansberg 2021).[7] A second set of papers studies the location choices of firms (Combes et al. 2012; Gaubert 2018). Both literatures abstract from unemployment, while I show that including it leads to distinct policy implications. A final strand of literature proposes theoretical assignment models to study sorting between workers and employers (Sattinger 1993; Shimer and Smith 2000; Eeckhout and Kircher 2018; Davis and Dingel 2020), which I build on.

Third, this study adds to the body of work that studies the efficiency properties of search models (Hosios 1990; Mortensen and Pissarides 1994).[8] The labor market pooling externality is a spatial analogue of the externality in Acemoglu (2001): when

5. The seminal work of Blanchard and Katz (1992) found little evidence of state-level unemployment persistence between 1975 and 1985. Kline and Moretti (2013) and Amior and Manning (2018) show that unemployment and labor force participation differentials between U.S. commuting zones are highly persistent after 1980 but abstract from variation in job-losing rates.

6. Since this article was first circulated, Kuhn, Manovskii, and Qiu (2021) have confirmed its findings for Germany and the United Kingdom. See Section V.A for a more detailed discussion. See also Hall (1972) for a study of 12 U.S. cities and Topel (1984) for an analysis across U.S. states.

7. See also Diamond (2016), Giannone (2017), Glaeser, Kim, and Luca (2018), Couture et al. (2019), and Caliendo et al. (2021).

8. See Jarosch (2021) and Mangin and Julien (2021) for recent contributions.

heterogeneous jobs coexist, too many low-productivity jobs open because they fail to internalize that they divert workers away from productive jobs. In my model, similar forces push unproductive jobs to inefficiently locate in places that are too productive for them. In contemporaneous work, Brancaccio et al. (2020) emphasize a related mechanism in transport markets.

Finally, this article is closely tied to the large literature on agglomeration and congestion externalities. Going back to at least Marshall (1920) who coined labor market pooling as a key agglomeration force, local externalities have formed the basis for place-based policies.[9] Empirical analyses of the latter have found mixed employment effects (Glaeser and Gottlieb 2008; Hanson 2009; Busso, Gregory, and Kline 2013; Neumark and Simpson 2014; Mayer, Mayneris, and Py 2015; Slattery and Zidar 2020). Several papers propose spatial models to analyze place-based policies, but all abstract from unemployment (Ossa 2017; Fajgelbaum et al. 2018; Slattery 2019; Fajgelbaum and Gaubert 2020). Agglomeration economies often imply subsidies to high-income locations. I emphasize instead a particular mechanism whereby labor market pooling externalities favor subsidies to low-income locations, consistent with many real-world place-based policies. The idea that redistributing a given set of jobs across locations can improve aggregate outcomes goes back at least to Bartik (1991) and has been recently revived by Austin, Glaeser, and Summers (2018). This article proposes a theory of frictional local labor markets that makes this idea precise.

The remainder of the article is structured as follows. Section II presents the data and empirical analysis. Section III builds and empirically validates a simple model of spatial unemployment differentials with endogenous job loss. Section IV lays out the quantitative extensions and estimation. Section V discusses spatial unemployment gaps and policy counterfactuals. The last section concludes. An Online Appendix collects proofs and additional details.

II. Descriptive Evidence

This section first describes the data. Then I highlight that spatial unemployment gaps are large and persistent. I show that

9. See Krugman (1991) and Amiti and Pissarides (2005) for a study of labor pooling without search frictions.

spatial unemployment gaps are primarily driven by spatial differences in job-losing rates, in turn tied to employers rather than workers or location-specific factors. My main analysis focuses on France, where I can exploit the richness of administrative data, but I also confirm the main findings in the United States.

II.A. Data

Worker flows in and out of unemployment are central components of labor market studies. Aggregate time-series exercises typically break down the contribution of job-losing and job-finding rates in accounting for the unemployment rate. Although they are jointly determined equilibrium variables, separating their contributions is a useful diagnostic device that informs the underlying economic mechanisms.

Adapting this approach to a geographic setting is challenging. On the one hand, large repeated cross sections like the Census or the American Community Survey are ill-suited for measuring worker flows. On the other hand, surveys with a short panel dimension such as the Current Population Survey (CPS) typically have a much smaller cross section.[10] This limitation leads to measurement error concerns, particularly for the outflow from unemployment, and prevents any compositional split. In addition, panel surveys often stop tracking movers who change location.

To circumvent these difficulties, I turn to administrative matched employer-employee data from France. I use a combination of the DADS and of the French Labor Force Survey (LFS) between 1997 and 2007.[11] The DADS has two advantages. First, it is a representative data set containing almost 1 million individuals in any cross section. Second, the DADS is a panel covering the entire work history of individuals, with rich demographic, geographic, and firm-level information. The sample size lets me break down the analysis by city and finely disaggregated employer and worker groups to control for composition.

The DADS is well-suited to study individual-level employment and nonemployment across space.[12] To further separate

10. The CPS has about five unemployed people per metropolitan area on average in any cross section.

11. DADS: Déclarations Annuelles de Données Sociales. The LFS is the Enquête Emploi.

12. Consistent with the definition of the International Labour Organization, I define an employed individual as one who has a job. A nonemployed person is

nonemployment into unemployment and nonparticipation, I restrict my sample to men between 30 and 52 years old. This group has a high and stable labor force participation rate, thereby limiting concerns related to life cycle changes therein. Second, I complement the DADS with the LFS. I compute conditional transition probabilities between employment, unemployment, and nonparticipation in the LFS by broad city and worker group. I use those conditional transition probabilities from the LFS to probabilistically discriminate between nonparticipation and unemployment in the DADS.[13] In practice, this imputation has a limited effect on the results. I aggregate the resulting sample at the quarterly frequency. Online Appendix Table A1 compares aggregate statistics in this sample and in the LFS.

I complement these data sets with several other data sources. I compute city-level and establishment-level variables with a repeated cross-section version of the DADS that covers the universe of French workers. For overidentifying exercises in Section III.F, I use firm-level balance sheet data covering the near universe of French businesses for the same period, as well as establishment-level vacancy data from a large-scale survey. I use a single cross section of housing prices from the French notaries.

I define a location as a commuting zone as defined by the French statistical institute INSEE.[14] A commuting zone is an area where most of the residents work at jobs in that same area. There are 328 commuting zones that partition the French territory. This definition is most natural as a spatial notion of a local labor market. In what follows, location, commuting zone, and city are used interchangeably. I construct a measure of skill from occupation and age data because the main DADS panel data set does not have education data. Skill is defined as the average age and occupation wage premium for a worker, derived from a Mincer regression. Online Appendix I.A provides more details.

one who is not working for a wage. An unemployed individual is one who is not working but is actively looking for a job and available to start work within two weeks.

13. This imputation exercise resembles Blundell, Pistaferri, and Preston (2008) who use the Panel Study of Income Dynamics to complement consumption categories in the Consumption Expenditure Survey. For instance, if a person goes through an employment to nonemployment transition in the DADS, I define her employment status after the transition (unemployment or nonemployment) based on the LFS transition probabilities.

14. INSEE: Institut National de la Statistique et des Études Économiques.

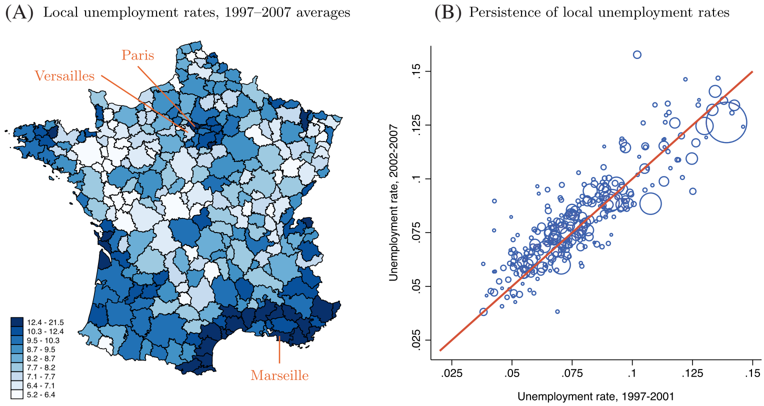

FIGURE I

Unemployment Rates in France, by Commuting Zone and over Time

Panel A maps commuting-zone unemployment rates from the DADS panel. Corsica and overseas territories are omitted for exposition. Panel B plots commuting-zone unemployment in two subperiods of the sample. Blue circles represent a commuting zone. Size is proportional to population.

For the United States, I use the CPS. I define a location as a metropolitan statistical area, and use a skill definition similar to France.[15] I focus on white men between 30 and 52 years old that are household heads, and I use the definition of unemployment of the CPS.

II.B. Dispersion and Persistence of Spatial Unemployment Differentials

I start by showing that local unemployment rates are widely dispersed and highly persistent across locations in France. Figure I, Panel A maps commuting zone-level unemployment rates in mainland France. Darker shades of blue (color version available online) encode higher unemployment rates. Figure I, Panel A highlights that commuting zones with unemployment rates above 12% or below 6% can be found throughout the country. The cross-sectional standard deviation is 2.5 percentage points, twice as much as the time-series standard deviation of the aggregate unemployment rate, 1.3 percentage points.

15. I also check that using education to define skill in the CPS leaves the results unchanged.

To assess the persistence of spatial unemployment differentials, I split the sample into two subperiods, 1997–2001 and 2002–2007. Figure I, Panel B plots the local unemployment rate in the second subperiod against the unemployment rate in the first subperiod for every city. Local unemployment rates are highly persistent, as they line up closely around the orange 45-degree line. The five-year autocorrelation is 0.91.[16]

Figure I confirms earlier findings from Kline and Moretti (2013) and Amior and Manning (2018) for the United States. I turn to the main empirical contribution of this article: unpacking how worker flows into and out of unemployment differ between commuting zones.

II.C. Worker Flows into and out of Unemployment

Inflows from local employment, from nonparticipation and in-migration from other locations all contribute to local unemployment. Similarly, outflows into local employment, into nonparticipation, and out-migration reduce the number of unemployed workers. In what follows, I use standard terminology from the literature and call the rate at which employed workers flow into unemployment the job-losing rate. Similarly, I call the rate at which unemployed workers flow into employment the job-finding rate.

To guide the analysis, I start with a simple two-state accounting model. Suppose that employed workers in city c face a constant job-losing rate s_c per unit of time (separation rate to unemployment), and that unemployed workers face a constant job-finding rate f_c per unit of time. Abstract from movements into and out of the labor force and migration. In steady state, the local unemployment rate u_c satisfies

$$\log \frac{u_c}{1-u_c} = \log s_c - \log f_c. \tag{1}$$

Both s_c and f_c map to transition probabilities between employment and unemployment in the data.

I depict the contribution of job-losing and job-finding rates to local unemployment using equation (1). Figure II plots the log of job-losing rates s_c and minus the log of job-finding rates f_c against

16. In Online Appendix I.B, I show that controlling for economy-wide industry business cycles increases local persistence, with a conditional autocorrelation of 1.05.

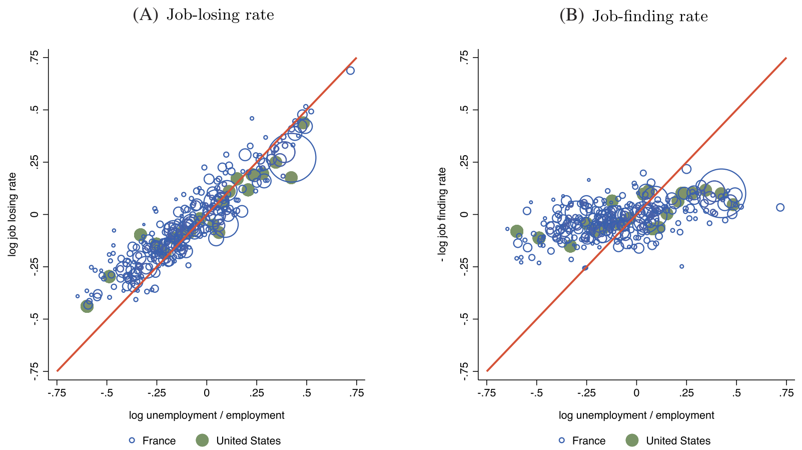

FIGURE II

Local Labor Market Flows and Unemployment in France and in the United States

Panel A scatterplots the log of the job-losing rate against the log of the unemployment-employment ratio, across commuting zones in France (DADS panel) and in the United States (CPS). Open blue circles represent commuting zones in France, with size proportional to population. Solid green dots represent metro area groups in the United States. U.S. metro areas are grouped into 20 equally populated bins to reduce measurement error due to the smaller cross-sectional size of the CPS. The 45-degree line is in orange. Panel B scatterplots minus the log of the job-finding rate against the log of the unemployment-employment ratio, across commuting zones in France and in the United States.

the log of the unemployment-employment ratio $\frac{u_c}{1-u_c}$ across commuting zones, for France and the United States.

Job-losing rates emerge graphically as the main driver of spatial unemployment differentials. The data align closely with the 45-degree line in orange for both countries in Figure II, Panel A. In contrast to job-losing rates, job-finding rates appear nearly flat across locations in Figure II, Panel B.[17]

I confirm quantitatively the key role of job-losing rates. I use equation (1) for an exact variance decomposition by constructing a predicted unemployment rate from job-losing and job-finding rates. I find that the job-losing rate accounts for 77% of the cross-sectional variation of the spatial unemployment rate in France. The job-finding rate accounts for the remaining 23%. In the United

17. Similarly, job-to-job mobility covaries little with local unemployment in Online Appendix Figure A1(b).

States, the job-losing rate accounts for 73% of the cross-sectional variation in spatial unemployment rates.[18]

I establish the robustness of these results with several additional exercises. First, the central role of job loss is robust to deviations from the exact variance decomposition. Online Appendix Table A2 shows that neither movements into and out of the labor force, migration, local transitional dynamics, time aggregation of quarterly probabilities into instantaneous rates, using the LFS only, nor other residual mechanisms introduce a significant wedge between the left and right sides of equation (1).

Second, I verify that mechanical correlates of job loss such as temporary contracts, seasonality, firm exit, or job reallocation cannot provide a systematic explanation for spatial differences in job-losing rates. Online Appendix I.D establishes that these phenomena account for at most 8% to 23% of spatial gaps in job loss. By contrast, Table II in Section V.A shows that job-losing rates are strongly negatively associated with local wages, but only weakly with local population. Job-finding rates do not correlate strongly with either variable.

Third, I relate long-run differences across locations to changes over time. I split the sample into two subperiods and use equation (1) in changes over time. Consistent with the business cycle literature, Online Appendix Figure A2 finds that job-finding rates play a larger role for spatial unemployment differentials at shorter frequencies. Thus, variation in job-losing rates is key in the long run rather than in the short run even at the city level.[19]

II.D. Employer and Worker Composition

Three main reasons may lead to spatial differences in job-losing rates. First, workers who live in some locations may separate into unemployment more frequently. Second, employers in these same locations may offer jobs that are particularly unstable. Third, city-specific factors may affect local job stability.

18. This variance decomposition across locations resembles the analysis in Elsby, Michaels, and Solon (2009) for the aggregate unemployment rate over the business cycle. By contrast, I find that the job-losing rate plays a much larger role across locations than over the business cycle.

19. Elsby, Hobijn, and Şahin (2013) document that the role of the job-finding rate for aggregate business cycles is strongest in Anglo-Saxon economies. Albeit somewhat less pronounced, the job-finding rate remains dominant in other OECD economies. Figure II indicates that the job-losing rate is equally important for spatial differences in both the United States and France.

To disentangle these explanations, I estimate a fixed effect model in the spirit of Abowd, Kramarz, and Margolis (1999):

$$\mathrm{EU}_{i,t} = \alpha_i + \beta_{J(i,t)} + \gamma_{C(i,t)} + \varepsilon_{i,t}, \tag{2}$$

where i indexes workers and α_i denotes a worker fixed effect. $J(i, t)$ denotes the employer of worker i in quarter t, and $\beta_{J(i,t)}$ denotes an employer fixed effect. $C(i, t)$ denotes the city of worker i in quarter t, and $\gamma_{C(i,t)}$ denotes a city fixed effect. $\mathrm{EU}_{i,t}$ is an indicator variable taking the value one if worker i separates into unemployment in quarter t, and zero otherwise.

I use two main specifications. First, I define an employer as a firm-by-four-digit-occupation. This definition captures spatial heterogeneity in the type of jobs to the extent that different firms operate in different locations. This definition also captures heterogeneity in the type of jobs across occupations in the same firms. Identification follows from the well-known conditional random mobility assumption (Card, Heining, and Kline 2013). Worker mobility across firm-occupations identifies employer effects separately from worker effects. Worker mobility across locations separates city effects from worker effects. In this spatial context, I exploit multi-establishment firms to separately identify firm-occupation effects from city effects. To alleviate concerns associated with limited mobility bias, I follow Bonhomme, Lamadon, and Manresa (2019) and cluster worker, employers, and commuting zones into groups before estimating equation (2). I provide more details in Online Appendix I.E.

In the second main specification, I define an employer as an establishment-by-four-digit-occupation. This definition captures both spatial heterogeneity in the type of jobs across establishments in the same firm, as well as heterogeneity in the type of jobs across occupations in the same establishment. Because establishments do not move by definition, I do not include a city fixed effect in this specification.

After estimating equation (2), I retrieve the estimated fixed effects, and average them within every commuting zone group c to obtain a sample analogue of

$$\mathrm{EU}_c = \mathbb{E}_c[\alpha_i] + \mathbb{E}_c[\beta_{J(i,t)}] + \gamma_c. \tag{3}$$

Equation (3) breaks down the commuting-zone quarterly job-losing rate EU_c into an average worker component $\mathbb{E}_c[\alpha_i]$, an

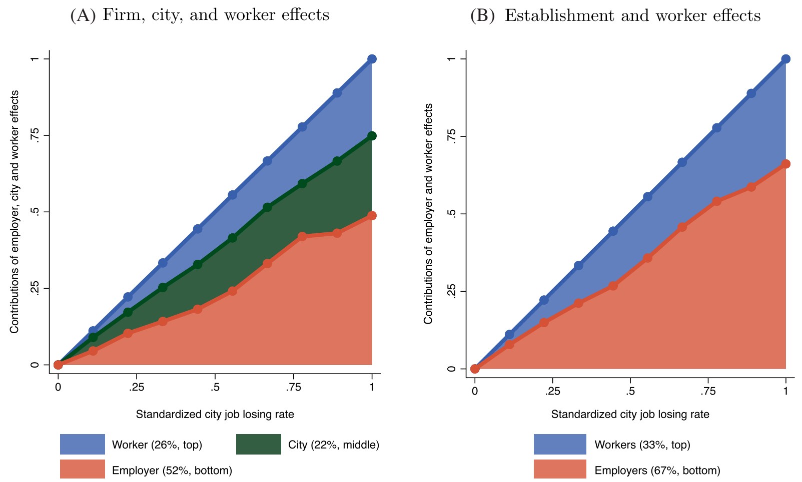

FIGURE III

Contribution of Employer, City, and Worker Effects to Local Job-Losing Rates in France

Panel A: firm-by-four-digit-occupation, city, and worker fixed effects. Panel B: establishment-by-four-digit-occupation and worker fixed effects. Orange (bottom): average employer effect. Green (middle): average city effect. Blue (top): average worker effect. DADS panel, France. Workers, employers, and commuting zones are clustered into 10 population-weighted groups based on their unconditional job-losing probability. The x-axis represents the sum of employer, city, and worker effects, standardized between zero and one.

average employer component $\mathbb{E}_c[\beta_{J(i,t)}]$, and, in the first specification, a city component γ_c. I use this decomposition to assess whether worker composition, employer composition, or city-specific factors contribute most to spatial job loss differentials.

I find that systematic differences in the type of employers operating across cities are the primary reason why job-losing rates differ across space. To reach this conclusion, Figure III, Panel A plots the contributions of the average employer (firm-by-occupation), worker, and city components to the unconditional local job-losing rate. Employer effects account for 52% of the cross-sectional variation in job-losing rates, whereas city effects account only for 22% and worker effects account for 28%.

Of course, different establishments are likely to offer jobs with different attributes, even within the same firm. Figure III, Panel B plots the same decomposition as in Panel A when employers are defined as an establishment-by-occupation rather than a firm-by-occupation. In this case, employer effects account for 67% of the cross-sectional variation in job-losing rates, while worker effects account for only 33%.

Comparing both specifications confirms that employer heterogeneity is the dominant source of variation in local job-losing rates. Its contribution lies between 52% and 67%. The exact proportion depends on how much within-firm cross-establishment variation stems from within-firm sorting of establishments as opposed to truly location-specific factors. Yet location-specific factors can account for no more than 22% of the overall variation, and worker composition accounts for no more than 33%.

What are the characteristics of employers with high job-losing rates? I correlate employer fixed effects with a number of firm-level observables in Online Appendix Figure A5. Firms with unstable jobs sell less than but employ a comparable workforce to firms with stable jobs. Firms with unstable jobs have low labor productivity, are less capital intensive, and less profitable. They pay low wages, but their labor share is high. They are largely present in both tradable and nontradable industries. Together, these observations indicate that employers with unstable jobs have high labor costs relative to revenues and are found throughout the economy.

A number of additional exercises confirm the dominant role of employer composition. First, I demonstrate that industry heterogeneity plays only a limited role. Online Appendix Figure A6 shows that the comovement between unemployment, job-losing, and job-finding rates holds for tradable and nontradable industries. I residualize local job-losing rates from industry and observable skill heterogeneity similarly to the specification in equation (2), and plot the estimated city fixed effects in Online Appendix Figure A7. While there is heterogeneity in job-losing rates across industries, the mix of industries in cities does not covary enough with industry-specific job-losing rates to account for a sizable share of spatial variation in job-losing rates. Instead, the key heterogeneity driving job loss differentials arises within three-digit industries rather than between industries, as well as within observable worker skills.

Second, I verify that my findings are robust to alternative econometric specifications. Online Appendix Table A3 shows that results remain similar when using alternative definitions of employers, such as establishments or firms without interacting with occupation, or when varying the number of clusters.

Third, I assess whether the conditional random mobility assumption that underpins identification in equation (2) is likely to hold. I correlate changes in individual-level job-losing rates with changes in city-level and firm-level job-losing rates for movers, and split the results for movers toward cities or firms with systematically higher or lower job-losing rates. Violations of the conditional random mobility assumption should manifest as larger coefficients on city and firm-level job-losing rates after splitting the sample. Online Appendix Table A4 finds no evidence against the conditional random mobility assumption.

Overall, the results in this section indicate that spatial differences in job-losing rates are by far the largest contributor to spatial unemployment rate differentials in France and the United States. These spatial differences are not explained by the local industry mix or the composition of the workforce. Instead, spatial gaps in job loss primarily reflect systematic differences in the type of jobs offered by employers. These findings are, to the best of my knowledge, new to the literature. They elude existing models of local unemployment that focus on job-finding rates and abstract from the role of employers. By contrast, job-losing rates and employer heterogeneity lie at the heart of the theory I propose below.

III. A Model of Spatial Unemployment Differentials

This section develops a theory of spatial unemployment differentials. I build on the spatial equilibrium model of frictional unemployment in Kline and Moretti (2013). I add two key ingredients. First, job loss is endogenous and tied to employers. Second, heterogeneous employers decide where to locate.

III.A. Setup

Time is continuous. There is a single final good used as the numeraire and freely traded across locations.

1. *Geography.* There is a continuum of ex ante heterogeneous locations endowed with one unit of housing. Locations differ in productivity ℓ with cumulative distribution function F_ℓ on a connected support $[\underline{\ell}, \overline{\ell}]$, with continuous density F'_ℓ. Thus, a location is characterized by its productivity ℓ rather than its particular name.[20]

20. Revenue productivity ℓ captures factors that determine whether a location is well suited for production. For instance, a location with high-quality

2. *Workers.* There is a unit measure of infinitely lived, homogeneous workers. Their preferences over streams of consumption of the final good c_t and housing services h_t are

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

with $\omega \in (0, 1)$. Workers consume their income each period. They only search when unemployed. Workers are freely mobile across locations.[21]

3. *Employers and Jobs.* As is common in the search literature, the productive unit is an employer-worker match. Thus, the notions of employers, firms, establishments, and jobs are interchangeable in the model.[22] An employer pays a fixed cost c_e to open a new job. After paying c_e, the employer draws a job quality—or expected productivity—z that informs their initial productivity draw. The population distribution of quality z is F_z, with connected support $[\underline{z}, \overline{z}]$ and density F_z'.[23] After observing job quality z, employers choose a location ℓ to open their job and search for workers by posting a single vacancy in the local labor market. After they match with a worker, they draw their initial, idiosyncratic match productivity y_0 from a conditional distribution $G_0(y_0|z)$ that depends on employer quality z. Drawing a higher

transportation infrastructure has high ℓ. Productivity can also encode that local demand for nontradables may be particularly high or that local workers may be particularly skilled. In the quantitative model of Section IV, I micro-found local productivity with the human capital of local residents.

21. Ruling out borrowing and saving is immaterial given risk neutrality. See Bilal and Rossi-Hansberg (2021) for a location choice model with risk-averse workers who borrow and save. I do not incorporate job-to-job mobility, for three reasons. First, job-to-job moves do not directly affect the unemployment rate: they relocate workers from one job to another. Second, I show in Online Appendix Figure A1(b) that just like the job-finding rate, the job-to-job mobility rate is only weakly correlated with the unemployment rate. Finally, adding job-to-job mobility would break the tractability of the model and make estimation and identification much more challenging.

22. The model can also be seen as one in which there are large, constant-returns-to-scale firms that open many jobs at cost c_e per job. For models with a well-defined notion of firm size through decreasing returns to scale and search frictions, see Elsby and Michaels (2013), Schaal (2017), Bilal and Lhuillier (2021) and Bilal et al. (2022).

23. I also require that $0 < \underline{z} < \overline{z} < 1$ and that F_z' is continuous and bounded away from zero.

z implies that the job is more productive on average, in a sense made precise in Assumption 1. After observing this initial draw, the matched pair decides to start producing together or not. If not, the worker returns to unemployment, and the job disappears.

An active job with productivity y_t in a location ℓ produces $y_t\ell$: local productivity ℓ and job productivity y_t are technological complements. Over time, the productivity of every job evolves independently according to a geometric Brownian motion

$$d\log y_t = -\delta dt + \sigma dW_t, \tag{4}$$

where $\delta > 0$ implies that productivity depreciates on average. This assumption implies that all jobs eventually separate and is required to obtain a well-defined steady-state distribution.[24] σ is the volatility of shocks. A geometric Brownian motion is the continuous-time analogue of a random walk with drift. Importantly, the productivity process is identical in all locations, so that any spatial differences in job loss must originate from differences between employers. For values to remain finite, I impose that $\rho + \delta > \frac{\sigma^2}{2}$. If the match breaks up, the job disappears.

4. *Local Labor Markets.* Unemployed workers search for jobs only in the location where they live, and employers search for workers only in the location where their job is open. Workers randomly meet vacancies in a single labor market in each location according to a Cobb-Douglas matching function $\mathcal{M}(\mathcal{U}(\ell), \mathcal{V}(\ell)) = m\mathcal{U}(\ell)^{\alpha}\mathcal{V}(\ell)^{1-\alpha}$. $\mathcal{U}(\ell)$ denotes the local number of unemployed workers, and $\mathcal{V}(\ell)$ denotes the local number of vacancies in that market.

Local labor market tightness is $\theta(\ell) = \frac{\mathcal{V}(\ell)}{\mathcal{U}(\ell)}$. The local meeting rate for workers is then $f(\theta(\ell)) = m\theta(\ell)^{1-\alpha}$ and the vacancy meeting rate for employers is $q(\theta(\ell)) = m\theta(\ell)^{-\alpha}$. Meeting rates differ from realized rates when some meetings do not result in viable jobs. Denote realized rates by $f_R(\ell)$ and $q_R(\ell)$.

5. *Flow Value of Unemployment.* Unemployed workers in location ℓ consume $b\ell$. This specification captures the idea that unemployment benefits are a constant replacement rate of past

24. $\delta > 0$ reflects the difference between parameters governing productivity growth at new jobs relative to incumbent jobs in endogenous growth models such as Engbom (2018).

wages, because wages will scale with local productivity ℓ. It also helps with analytical tractability.[25]

6. *Wage Determination.* Workers and employers set wages according to generalized Nash bargaining, with worker bargaining power β. For simplicity, I assume that renegotiation occurs each instant.

7. *Ownership.* A representative mutual fund owns housing and claims to the profits of employers. The mutual fund rents land to workers at equilibrium rents $r(\ell)$ and collects profits from employers. For simplicity, I assume in this section that risk-neutral absentee owners receive the profits from housing rents and firms.[26]

III.B. Value Functions

In what follows, the economy is in steady state.

1. *Unemployment and Employment.* Let U be the value of unemployment. Because unemployed workers are freely mobile, their value is equalized across all locations that they populate. The Inada property of the matching function ensures that any populated location must have some unemployed workers.[27]

To keep the exposition simple in the main text, I consider wage functions $w^*(y, \ell)$ that only depend on productivity y and the location ℓ. As shown in Online Appendix II.A, this restriction is without loss of generality. Let $V(y, \ell)$ be the value of employment

25. The specification can also be seen as home production or self-employment with the same production function as firms, but with an efficiency b. Because the model features aggregate constant returns to scale in production, defining unemployment benefits to be directly a constant replacement rate of past wages leads to multiplicity.

26. Alternatively, the proceeds from land rents and profits can be rebated to workers as a flat income subsidy. Given risk neutrality, shares of the mutual fund could also be traded. In these cases the cross-sectional implications are unchanged. To keep the focus on the efficiency properties of the location choice of employers and abstract from distributional considerations between owners and workers, I use the flat income subsidy rebate in the quantitative exercises.

27. This argument is valid under a trembling-hand equilibrium refinement in which workers and firms make small mistakes around their preferred location choices. The two-sided location choice of workers and employers can otherwise result in coordinating on empty locations. I impose this trembling-hand refinement in the rest of this article.

at wage $w^*(y, \ell)$ in location ℓ. U and V satisfy the recursions

$$\rho U = b\ell r(\ell)^{-\omega} + f(\ell)\mathbb{E}_\ell\big[\max\{V(y_0, \ell) - U, 0\}\big] \tag{5}$$

$$\rho V(y, \ell) = w^*(y, \ell) r(\ell)^{-\omega} + (L_y V)(y, \ell), \tag{6}$$

where the recursion for V holds as long as the worker finds it optimal to remain in the match.

The first term on the right-hand side of equations (5) and (6) reflects indirect utility when unemployed or employed. Workers spend a constant share ω of their income on housing due to Cobb-Douglas preferences, and local housing prices $r(\ell)$ enter indirect utility. The second term on the right-hand side of equation (5) reflects future expected employment opportunities of unemployed workers. At rate $f(\ell)$, they meet potential employers. The latter then draw initial productivity y_0, with a distribution that may depend on location ℓ because employers may differ across locations. Provided initial productivity y_0 is high enough, the worker is hired and the matched pair starts producing together. The second term on the right-hand side of equation (6) reflects the expected continuation value of employment due to productivity shocks. Given the geometric Brownian motion assumption in equation (4), the functional operator L_y is defined by

$$L_y V = \left(\frac{\sigma^2}{2} - \delta\right) y \frac{\partial V}{\partial y} + \frac{\sigma^2}{2} y^2 \frac{\partial^2 V}{\partial y^2}.$$

2. *Employers.* The value of a matched employer with productivity y in location ℓ solves

$$\rho J(y, \ell) = y\ell - w^*(y, \ell) + (L_y J)(y, \ell)$$

as long as the employer finds it optimal to keep the worker. Employers value flow profits $y\ell - w^*(y, \ell)$ as well as future productivity changes.

3. *Joint Surplus and Wage Determination.* Generalized Nash bargaining implies that worker-employer pairs set wages by maximizing the Nash product. Even though the marginal utility of a dollar differs between workers and employers due to housing consumption, Lemma 4 in Online Appendix II.B shows that the traditional micro-foundation of generalized Nash

bargaining with an alternative-offers game à la Rubinstein (1982) continues to hold in my environment.

Lemma 4 lets me restrict attention to a single object that I call the adjusted surplus, defined as

$$S(y,\ell) = J(y,\ell) + r(\ell)^{\omega}(V(y,\ell) - U). \tag{7}$$

The adjusted surplus is independent from wages because it puts the value of each side on a common numeraire scale. Online Appendix II.A shows that it follows a recursion similar to that of employers. Lemma 4 then states that wages split the adjusted surplus into constant shares:

$$r(\ell)^{\omega}(V(y,\ell) - U) = \beta S(y,\ell), \qquad J(y,\ell) = (1-\beta)S(y,\ell). \tag{8}$$

In particular, both sides agree to break up the match when the adjusted surplus drops to zero. In that case, a separation occurs. Existing matches therefore solve a forward-looking optimal-stopping problem, which is detailed in Online Appendix II.B. I characterize its solution in the following Lemma.

LEMMA 1. (Adjusted surplus) There exists a unique adjusted surplus, given by

$$S(y,\ell) = \frac{\ell \underline{y}(\ell)}{\underline{y}_0} \mathcal{S}\left(\frac{y}{\underline{y}(\ell)}\right), \quad \forall y \geqslant \underline{y}(\ell),$$

and $S(y,\ell) = 0$ for $y \leqslant \underline{y}(\ell)$, where

$$\rho \frac{\underline{y}(\ell)}{\underline{y}_0} = b + v(\ell), \quad v(\ell) = \frac{f(\ell) r(\ell)^{\omega} \mathbb{E}_{\ell}[\max\{V(y_0,\ell) - U, 0\}]}{\ell},$$

$$\mathcal{S}(Y) = \frac{\tau Y + Y^{-\tau}}{1+\tau} - 1,$$

and $\tau > 0$, $\underline{y}_0 > 0$ are transformations of ρ, δ, σ given in Online Appendix II.B.

Proof. See Online Appendix II.B.

The local equilibrium separation threshold $\underline{y}(\ell)$ increases as the value of unemployment relative to housing prices, $b + v(\ell)$, rises. $v(\ell)$ is the productivity-adjusted value of future employment opportunities to a worker. The value of future employment opportunities $v(\ell)$ depends on the meeting rate $f(\ell)$ and the local mix of employers. The adjusted surplus S is an increasing function of current productivity y relative to the local endogenous threshold $\underline{y}(\ell)$. The nonlinearity in the function $\mathcal{S}$ arises because of the option value of separation, which rises as productivity y approaches the threshold $\underline{y}(\ell)$. Hence, the adjusted surplus S satisfies both the value-matching and smooth-pasting conditions at the threshold: $S(\underline{y}(\ell), \ell) = \frac{\partial S}{\partial y}(\underline{y}(\ell), \ell) = 0$.

Local reservation wages $\underline{w}(\ell)$ in efficiency units of local productivity ℓ satisfy

$$\underline{w}(\ell) = \underline{w}_0 \underline{y}(\ell), \tag{9}$$

where $\underline{w}_0 = (1-\beta)\frac{\rho}{\underline{y}_0} + \beta$ follows from the wage equation (30) in Online Appendix II.B. When the local separation threshold is higher, matches break up at higher productivity levels because workers value more the option to search for a different job in the same local labor market relative to local housing prices. Thus, the local reservation wage is higher.

The free-mobility condition takes a simple form given reservation wages $\underline{w}(\ell)$:

$$U = \frac{\ell \underline{w}(\ell)}{\underline{w}_0 \underline{y}_0 r(\ell)^{\omega}}. \tag{10}$$

Across locations, higher housing prices compensate for either higher productivity or higher reservation wages. Employed workers do not move because their value exceeds the common value of unemployment.

With those results at hand, I describe in Section III.C how spatial job loss and unemployment differentials emerge, taking as given the spatial distribution of employer quality $z(\ell)$. Section III.D discusses how the location decision of employers shapes the spatial distribution of employer quality $z(\ell)$ in equilibrium.

III.C. Equilibrium Job Loss and Unemployment

Suppose for now that the spatial distribution of employer quality is given by some function $z(\ell)$. At this stage it can be exogenous or determined in equilibrium. In every location, the job-losing rate depends on three forces: the average starting productivity at new jobs, the productivity separation threshold, and how fast productivity depreciates from the starting productivity down to the threshold. The productivity depreciation rate is governed by the productivity process in equation (4) and is constant across locations by assumption. Therefore, any differences in local job-losing rates must arise because of differences between the average starting productivity and the separation threshold. Both are related to local quality $z(\ell)$ and the reservation threshold $\underline{y}(\ell)$.

To determine exactly how many workers lose their job per unit of time, it is necessary to solve for the invariant distribution of employment across productivities in each location ℓ. Denote its density function as $g(y, \ell)$. In steady state, $g(y, \ell)$ solves the Kolmogorov Forward (KF) equation,

$$0 = (L_y^* g)(y, \ell) + n(\ell) g_0(y, \ell), \qquad y > \underline{y}(\ell), \tag{11}$$

where $g_0(\cdot, \ell)$ is the density associated with the entry distribution $G_0(y_0|z(\ell))$, which in turn depends on the quality of jobs $z(\ell)$ that open in location ℓ. $n(\ell)$ is the equilibrium inflow of unemployed workers into employment. The operator L_y^* encodes how productivity shocks shape the distribution, and is given by

$$(L_y^* g)(y) = -\left(\frac{\sigma^2}{2} - \delta\right) \frac{\partial}{\partial y}(y g(y, \ell)) + \frac{\sigma^2}{2} \frac{\partial^2}{\partial y^2}(y^2 g(y, \ell)).$$

By construction, the density g integrates to unity in each location: $1 = \int_{\underline{y}(\ell)}^{\infty} g(y, \ell) dy$. Brownian shocks imply that the distribution satisfies the boundary condition $g(\underline{y}(\ell), \ell) = 0$.[28]

To facilitate exposition, I assume that the starting distribution G_0 is Pareto in the main text. I require that the lower bound of its support is low enough that $\underline{y}(\ell) \geqslant Y$ in all locations. I show that the Pareto assumption is empirically plausible in Section III.F. Nonetheless, I provide more general distributional conditions under which my results hold in Online Appendix VI.E.

28. In a small time period, the Brownian motion shocks dominate the negative drift. Because these shocks are symmetric, half of the workers close to the threshold are pushed into unemployment in any small time period. Compounded over a nonzero time interval, this process leaves no workers at the threshold. Although it is a standard mathematical result, a formal proof is provided for completeness in Online Appendix VI.C.

ASSUMPTION 1. (Initial productivity distribution) The conditional starting distribution is Pareto with support $[Y, +\infty)$, with $Y \leqslant \frac{b\underline{y}_0}{\rho}$:

$$G_0(y_0|z) = 1 - \left(\frac{Y}{y_0}\right)^{\frac{1}{z}}, \qquad z \in (0, 1).$$

Lemma 2 solves the KF equation (11) under Assumption 1. Online Appendix VI.D reports its general solution.

LEMMA 2. (Employment distribution) Let $\kappa = \frac{2\delta}{\sigma^2}$. Under Assumption 1, the solution to the KF equation (11) with $g(\underline{y}(\ell), \ell) = 0$ satisfies

$$g(y, \ell) = \frac{\kappa}{\kappa z(\ell) - 1} \frac{1}{y} \left[\left(\frac{y}{\underline{y}(\ell)}\right)^{-\frac{1}{z(\ell)}} - \left(\frac{y}{\underline{y}(\ell)}\right)^{-\kappa} \right], \qquad \forall y \geqslant \underline{y}(\ell).$$

Proof. See Online Appendix II.C.

The invariant distribution has two components. The first component reflects the productivity distribution of new jobs. The invariant distribution inherits the right tail from the starting distribution $\frac{1}{z(\ell)}$. The right tail is thicker in locations with high quality $z(\ell)$. The second component reflects the productivity process. When the negative drift δ is higher, κ is higher, implying that the distribution is more left skewed as productivity depreciates faster. When volatility σ is higher, κ is lower and the distribution is more right skewed: more jobs receive large positive shocks, while large negative shocks are truncated due to endogenous job loss. Finally, the entry rate n does not appear because it simply scales the overall measure of employed workers, as in Hopenhayn and Rogerson (1993).

The equilibrium local job-losing rate $s(\ell)$ (or separation rate into unemployment) follows from the invariant distribution in location ℓ. The job-losing rate depends on how many workers are close to the threshold in every location and the volatility of shocks:

$$s(\ell) = \frac{\sigma^2 \underline{y}(\ell)^2}{2} \frac{\partial g}{\partial y}(\underline{y}(\ell), \ell). \tag{12}$$

Online Appendix II.D proves this standard accounting result for completeness. Close to the threshold, only workers who receive a negative shock become unemployed. The second-order contribution of the measure of workers close to the threshold $\frac{\partial g}{\partial y}(\underline{y}(\ell), \ell)$ then shapes the number of job losers, because $g(\underline{y}(\ell), \ell) = 0$.

Combining expression (12) for the local job-losing rate with the solution to the distribution in Lemma 2 produces a simple solution for local labor market flows. The main text reports the expression under Assumption 1. Proposition 8 in Online Appendix VI.D describes the general solution.

PROPOSITION 1. (Spatial unemployment differentials) Under Assumption 1, the local job-losing, job-finding, and unemployment rates in location ℓ are

$$s(\ell) = \frac{\delta}{z(\ell)}, \qquad f_R(\ell) = f(\theta(\ell)) \times \left(\frac{Y}{\underline{y}(\ell)}\right)^{\frac{1}{z(\ell)}},$$

$$u(\ell) = \frac{s(\ell)}{s(\ell) + f_R(\ell)}.$$

Proof. See Online Appendix II.E.

When the negative drift δ is higher, productivity depreciates faster everywhere and job-losing rates rise uniformly. In locations with low quality $z(\ell)$, new jobs draw from a left-skewed productivity distribution and enter close to the equilibrium threshold $\underline{y}(\ell)$. They fall below the threshold early on and the local job-losing rate is high. Where quality $z(\ell)$ is high, jobs start far from the threshold $\underline{y}(\ell)$. There, it takes more time for productivity to depreciate and the job-losing rate is low.[29]

Of course, the reservation threshold $\underline{y}(\ell)$ depends on quality $z(\ell)$ in equilibrium. But the threshold rises less than one for one with quality because of discounting. Unemployed workers must search for some time before finding a job and earning wages comparable to those of employed workers. The strength of this discounting effect thus increases with the discount rate ρ and

29. The volatility σ does not affect the job-losing rate. When volatility rises, matches receive larger negative shocks, pushing them to break up more frequently. But matches also receive larger positive shocks, raising the option value of producing and lowering the threshold. With a Pareto entry distribution, both channels exactly offset each other.

decreases with the equilibrium job-finding rate $f_R(\ell)$ as shown in Online Appendix II.H.

Two forces in turn shape the job-finding rate $f_R(\ell)$: the worker meeting rate $f(\theta(\ell))$ and the probability that a given meeting results in a job, the success probability of a meeting $(\frac{Y}{\underline{y}(\ell)})^{\frac{1}{z(\ell)}}$. Whether these forces closely balance depends on the cross-sectional patterns of labor market tightness $\theta(\ell)$ and employer quality $z(\ell)$. In equilibrium, they are determined by the location choice of employers.

III.D. The Location Choice of Employers

An employer with quality z contemplates the expected value from entering in each location, and chooses the location that delivers the highest payoff. After matching at rate $q(\ell)$, the employer receives a share $1-\beta$ of the adjusted surplus. The expected payoff of employer z in location ℓ, $\bar{J}(z,\ell)$, then follows from integrating over the initial productivity distribution $G_0(y_0|z)$:

$$\rho\bar{J}(z,\ell) = q(\ell)(1-\beta)\int S(y_0,\ell)G_0(dy_0|z). \tag{13}$$

Under Assumption 1, I show in Online Appendix II.F that the expected payoff of employer z in location ℓ satisfies

$$\log\left(\left(\bar{\rho}\bar{J}(z,\ell)\right)^{\frac{z}{1-z}}\right) = \underbrace{\frac{z}{1-z}\log\bar{S}(z)}_{\substack{\text{Absolute}\\ \text{advantage}}} + \underbrace{\frac{z}{1-z}\log\ell}_{\substack{\text{Production}\\ \text{complementarities}}} + \underbrace{\frac{z}{1-z}\log q(\ell)}_{\substack{\text{Pooling}\\ \text{complementarities}}} - \underbrace{\log\underline{w}(\ell)}_{\substack{\text{Cost of}\\ \text{labor}}}, \tag{14}$$

where $\bar{\rho} = \rho + \frac{\beta}{1-\beta}\underline{y}_0$ and $\bar{S}(z) = (\frac{Y}{\underline{w}_0})^{\frac{1}{z}}\frac{z}{1-z}\frac{\tau z}{\tau z+1}$.

Four forces shape how employers value different locations. The first term on the right-hand side of equation (14) encodes the absolute advantage of employers according to their job quality z. High-quality jobs draw from a better starting distribution, have higher productivity on average, and earn higher profits everywhere. This term does not affect the location choice of employers.

The second term reflects standard technological complementarities in production. Some locations may be particularly well suited for production for reasons unrelated to labor market frictions. The production function implies that more productive employers benefit relatively more from high local productivity ℓ. As a result, they value locating in highly productive locations more than unproductive employers.

The third term in equation (14) lies at the core of the mechanism this article uncovers. It reveals that more productive employers value relatively more locations where recruiting is easy—where the vacancy meeting rate $q(\ell)$ is high. Because more productive employers generate higher profits, waiting longer until they meet a worker and start producing is relatively more costly for them. Higher forgone profits thus translate into a higher opportunity cost of time for more productive employers.[30]

The vacancy meeting rate $q(\ell) = m\theta(\ell)^{-\alpha}$ depends on local labor market tightness $\theta(\ell)$ in equilibrium. Ultimately, it depends on the pool of employers and workers who choose to locate in ℓ. Therefore, I follow the terminology in Marshall (1920) and call the complementarity between employer quality z and local recruiting conditions $q(\ell)$ a labor market pooling complementarity. In contrast to technological complementarities in the assignment literature without frictions, the pooling complementarity emerges because the location choice of heterogeneous employers interacts with local labor market frictions.

The fourth term in equation (14) simply reflects the expected cost of labor in a particular location ℓ, which can be summarized by the reservation wage $\underline{w}(\ell)$. All employers prefer locations with low labor costs where the reservation wage is low.

An employer with quality z thus solves

$$(15)\quad \ell^*(z) = \underset{\ell}{\operatorname{argmax}} \; \frac{z}{1-z}\log \ell + \frac{z}{1-z}\log q(\ell) - \log \underline{w}(\ell).$$

Employers face a trade-off between local productivity, recruiting conditions, and wages. The technological complementarity implies that more productive employers are willing to pay more to locate in places with high productivity. There, unproductive

30. Some meetings do not result in a viable match, so that the vacancy-filling rate and the vacancy meeting rate differ. The probability that a meeting results in a match, $(\frac{Y}{\underline{y}(\ell)})^{\frac{1}{z}}$, depends on both the employer type z (first term in equation (14)) and on local reservation wages $\underline{w}(\ell)$ through the separation threshold $\underline{y}(\ell)$ (last term in equation (14)).

employers are priced out by high wages and locate instead in low-productivity places.

The pooling complementarity implies that more productive employers are willing to pay more to locate in places with favorable recruiting conditions. There, unproductive employers are priced out by high wages. At the margin, they self-select into low-wage areas with low vacancy meeting rates. Importantly, the pooling complementarity determines employer sorting conditional on local productivity ℓ. Unconditionally, both local productivity and recruiting conditions drive location decisions, and sorting patterns are more complex.

The differential valuation of locations by different employers plays the role of a single-crossing condition. Although employers face a dynamic optimal stopping problem in each location, Lemma 1 simplifies location decisions to equation (15), which resembles standard static assignment problems. Apart from the underlying dynamic production decision, another distinction with static assignment problems arises. Traditional assignment problems resolve the sorting between two-sided markets with exogenous payoffs. By contrast, in the present model, local labor markets clear through the adjustment of labor market tightness $\theta(\ell)$. The latter in turn feeds back into recruiting conditions, adding an additional layer of general-equilibrium effects to the payoffs that determine the assignment. This feedback acts as an agglomeration force, with two implications. First, cities with different ex post characteristics emerge in equilibrium even in the absence of ex ante heterogeneity. Second, well-known multiplicity issues may arise.[31]

I define an assignment pair as a pair of functions $\ell \mapsto (z(\ell), \underline{w}(\ell))$, where $z(\ell)$ is the assignment function of employers to locations. It is the inverse of $\ell^*(z)$. In this article, I call $z(\ell)$ the assignment function, and $\mathcal{M}$ is the matching function that determines meetings in the labor market. $\underline{w}(\ell)$ is the equilibrium reservation wage that supports this location choice. Proposition 2 characterizes the assignment.

31. See Sattinger (1993), Topkis (1998), Villani (2003), Galichon (2016), and Davis and Dingel (2020) for standard assignment models. Gaubert (2018) generates differences across cities when employer technology depends directly on population. See Grossman and Rossi-Hansberg (2012) for multiple equilibria in a spatial context with agglomeration economies. See Chade and Eeckhout (2019) for multiplicity in a search and matching context.

PROPOSITION 2. (Sorting) Impose Assumption 1. Fix the equilibrium value of unemployment U and the measure of new jobs M_e. There exists a unique solution $\ell \mapsto (z(\ell), \underline{w}(\ell))$ to equation (15) among all possible assignments with increasing z. There exists a threshold $\underline{\alpha} > 0$ such that for all $\alpha \in [0, \underline{\alpha}]$, this solution is unique among all possible assignments. z and $\underline{w}$ are strictly increasing. In addition, the job-losing rate $s(\ell)$ is decreasing in ℓ.

Proof. See Online Appendix II.I.

Proposition 2 establishes existence of the assignment with positive assortative matching between local productivity ℓ and employer quality z: more-productive employers locate in more-productive locations. Restricting attention to assignments that exhibit positive assortative matching is only a mild restriction, for two reasons. First, positive assortative matching emerges as the only possibility when the matching function elasticity α is not too large. Proposition 9 in Online Appendix VI.E extends this result to more general distributional conditions for G_0. Second, any other potential steady-state assignment is dynamically unstable for any value of α, in a sense made precise in Proposition 10 in Online Appendix VI.F.

The spatial sorting of employers immediately implies that job-losing rates $s(\ell) = \frac{\delta}{z(\ell)}$ given in Proposition 1 are decreasing in local productivity ℓ. This monotonicity property equips the model to account for large dispersion in job-losing rates across local labor markets.

The equilibrium response of local reservation wages $\underline{w}(\ell)$ sustains the assignment. Reservation wages adjust up to the point where the marginal employer $z(\ell)$ is indifferent between locations ℓ and $\ell + d\ell$. Reservation wages reflect expected future wages conditional on starting work, which depend on equilibrium employer quality $z(\ell)$. Therefore, reservation wages rise with ℓ. However, recall that reservation wages rise less than one for one relative to wages of employed workers due to discounting.

Worker mobility limits the variation in both components of job-finding rates $f_R(\ell) = f(\theta(\ell)) \times (\frac{Y}{\underline{y}(\ell)})^{\frac{1}{z(\ell)}}$ given in Proposition 1. Even though high-quality employers value slack labor markets at the margin, workers out-migrate from locations with excessively slack labor markets. Thus, there can be only limited spatial variation in worker meeting rates $f(\theta(\ell))$. Similarly, the success probability of meetings $(\frac{Y}{\underline{y}(\ell)})^{\frac{1}{z(\ell)}}$ reflects offsetting forces. Locations with high-quality employers $z(\ell)$ tend to have higher success probabilities of meetings because jobs start out further away from any given threshold $\underline{y}(\ell) = \frac{w(\ell)}{\underline{y}_0}$. There, however, workers are also more selective and have high reservation thresholds $\underline{y}(\ell)$. These forces need not offset each other exactly, but when they nearly do, the job-finding rate is close to flat across locations.

III.E. Equilibrium and Comparative Statics

Having described how the location choice of employers shapes spatial unemployment differentials, I close the economy in the decentralized equilibrium. Local housing and labor markets clear in each location ℓ:

$$r(\ell) = \omega L(\ell)(u(\ell)b\ell + (1 - u(\ell))\overline{w}(\ell)), \quad \theta(\ell) = \frac{M_e F_z'(z(\ell))z'(\ell)}{u(\ell)L(\ell)F_\ell'(\ell)}, \tag{16}$$

where $L(\ell)$ is population in location ℓ, and $\overline{w}(\ell) = \int w^*(y, \ell)g(y, \ell)dy$ is the average wage in location ℓ.

Local housing prices reflect local expenditures on housing. Labor market clearing simply states that labor market tightness is the ratio between the number of vacancies and the number of unemployed workers in locations with productivity ℓ. The number of unemployed workers is the unemployment rate times total population across the $F_\ell'(\ell)d\ell$ locations with productivity in $[\ell, \ell + d\ell)$. The number of vacancies in a location reflects the total number of new jobs, M_e, but also the spatial sorting of employers. There are fewer employers in locations where the assignment function z is steep. In that case, a given measure of employers is stretched across a wider set of locations.

Employers enter freely each period, so that the cost of entry is equal to the expected value from entering.[32] Population in the

32. Here, the free-entry condition (17) holds at the aggregate level: local job creation is entirely determined by the sorting decisions of employers up to aggregate job creation. In Section IV.A I introduce convex recruiting costs. There, local job creation responds directly to local labor market conditions in addition to sorting decisions, and nests both aggregate and local free entry. See equation (73) in Online Appendix IV.J for more details.

economy adds up to unity:

$$(17)\qquad c_e = \int \bar{J}(z, \ell^*(z))dF_z(z), \qquad\qquad 1 = \int L(\ell)dF_\ell(\ell).$$

A decentralized equilibrium is composed of a measure of entering employers M_e, a value of unemployment U, an assignment function $z(\ell)$, a reservation wage function $\underline{w}(\ell)$, wages of employed workers $w^*(y, \ell)$, an employment distribution $g(y, \ell)$, a distribution of unemployment $u(\ell)$ and market tightness $\theta(\ell)$, housing prices $r(\ell)$, and a population distribution $L(\ell)$, such that equations (5), (6), (8), the definitions in Lemma 1, equations (9), (10), (15), (11), (12), (16), and (17) hold. Proposition 3 guarantees that there exists a unique steady-state equilibrium with positive assortative matching, when there is not too much dispersion in spatial and productivity primitives.

PROPOSITION 3. (Existence and uniqueness) Under Assumption 1, there exists a decentralized steady-state equilibrium with positive assortative matching. There exist d_z, $d_\ell > 0$ such that for $|\bar{z} - \underline{z}| < d_z$ and $|\bar{\ell} - \underline{\ell}| < d_\ell$, the equilibrium is unique.

Proof. See Online Appendix II.J.

I shed more light on how the labor market pooling complementarity shapes spatial unemployment gaps using a particular limiting equilibrium and Proposition 3. Suppose that ex ante spatial differences in ℓ become arbitrarily small. In that case, the pooling complementarity alone drives sorting and any ex post differences across locations. Corollary 1 shows that spatial gaps in job-losing and unemployment rates arise even in the absence of any ex ante heterogeneity between locations.

COROLLARY 1. (Equilibrium spatial gaps with ex ante identical locations) Suppose that the conditions in Proposition 3 hold and that the matching function elasticity α is strictly positive. Then the variance of local job-losing and unemployment rates remain strictly positive and bounded above zero as the variance in exogenous differences ℓ goes to zero.

Proof. See Online Appendix II.K.

This result highlights that the pooling complementarity suffices to sustain sorting in equilibrium, irrespective of technological complementarities.[33] When technological differences ℓ vanish, locations are ex ante identical and ex post differences emerge endogenously. In particular, job-losing and unemployment rates differ across locations. This is possible because housing prices adjust in the background to allow differences in reservation wages. By contrast, if housing played no role $\omega = 0$, all locations would become ex post identical because free mobility equation (10) would equalize reservation wages across locations.

Propositions 1, 2, 3, and Corollary 1 conclude the positive implications of the theory. Before turning to its normative implications, the next section proposes reduced-form empirical evidence supporting the key mechanisms that determine job-losing and job-finding rates in the model.

III.F. Model Validation

This section provides empirical support for two crucial mechanisms. The first is the link between labor productivity and job-losing rates. The second mechanism is the response of labor market tightness that determines job-finding rates.

1. *Labor Productivity and Job-Losing Rates.* The productivity process in equation (4) and the distribution in Lemma 2 deliver testable implications linking labor productivity to job-losing rates.

COROLLARY 2. (Labor productivity and job-losing rates)

- (i) Matches with higher labor productivity are less likely to separate into unemployment in all locations.
- (ii) Log labor productivity growth of incumbent jobs is independent from location.
- (iii) Average log labor productivity is higher in locations with lower job-losing rates.
- (iv) The labor productivity distribution first-order stochastically decreases with local job-losing rates.

33. The limit of arbitrarily small differences selects one particular equilibrium in the limit without any exogenous spatial heterogeneity. When exogenous spatial differences are exactly zero, locations can be arbitrarily reshuffled. There are two possible spatial distributions of equilibrium outcomes: the mixing distribution in which all locations are identical, and the separating distribution in which locations differ due to sorting. Taking the limit under vanishing spatial heterogeneity always selects the separating distribution. In addition, the mixing distribution is trembling-hand unstable.

(v) The labor productivity distribution has a Pareto tail with index $\frac{1}{z(\ell)}$ in each location.

(vi) The ratio of Pareto tails indices equals the ratio of job-losing rates between locations.

Proof. See Online Appendix II.L.

To test implications (i) to (vi), I compute labor productivity in single-establishment firms using the firm-level balance sheet data described in Section II.A. Figure IV, Panel A tests implication (i). It scatterplots job-losing rates for workers across labor productivity percentiles of their employer. Consistent with persistence in the productivity process in equation (4) that ties together the productivity of a match at a given point in time and the probability of job loss, matches at more productive employers are more stable. Online Appendix Table A5 correlates labor productivity growth with local job-losing rates. Consistent with a single productivity process across locations and implication (ii), there is no evidence of systematic variation of labor productivity growth.

Figure IV, Panel B tests implications (iii) and (iv). It displays the labor productivity distribution in the bottom and top quartiles of commuting zones, ranked by their job-losing rate. The vertical lines are local averages. Consistent with implication (iii), average labor productivity is higher in locations with low job-losing rates. Consistent with the more subtle implication (iv), the cumulative distribution function of labor productivity in low job-losing rate locations is always below the cumulative distribution function in high job-losing rate locations: the labor productivity distribution first-order stochastically decreases with the job-losing rate. Online Appendix Figure A9 provides empirical support for implications (v) and (vi) and therefore the Pareto assumption.

2. *Labor Market Tightness.* Proposition 1 delivers a single robust prediction for labor market tightness: spatial variation in labor market tightness must be small relative to spatial variation in job-losing rates. Otherwise, job-finding rates would vary too much relative to the data.

Should tightness correlate positively or negatively with local unemployment? The answer is ambiguous in general. Corollary 1 indicates that without any variation in local fundamentals ℓ across locations, tightness and unemployment should be

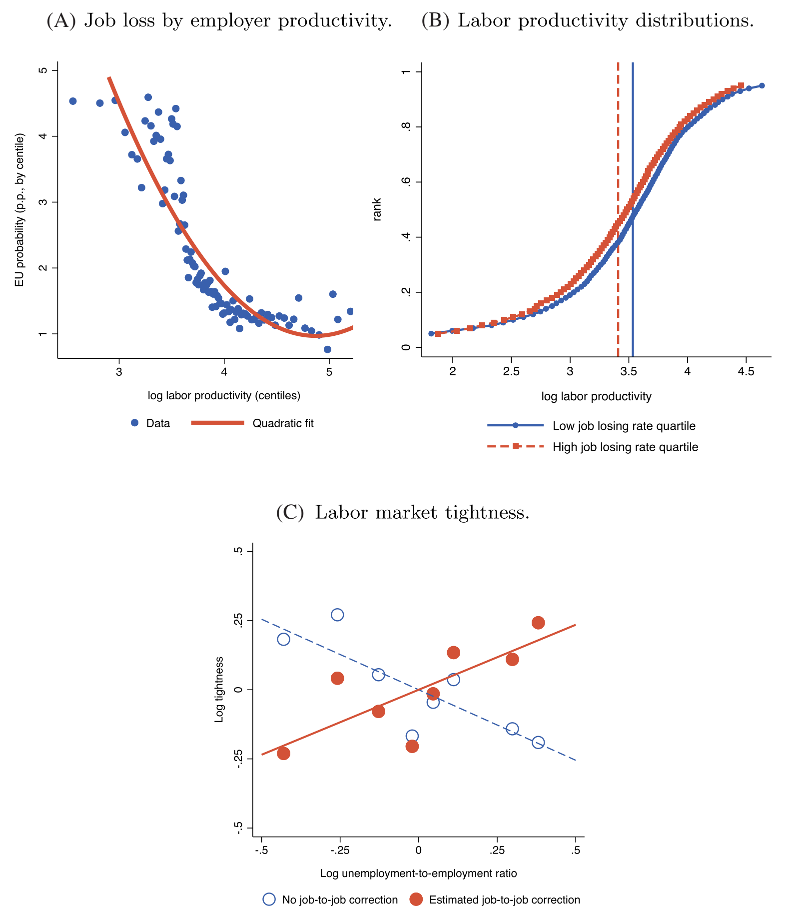

FIGURE IV

Labor Productivity, Job Loss, and Labor Market Tightness in France

Panel A scatterplots the employment-to-unemployment transition probabilities for workers, across labor productivity percentiles of their employer. Panel B plots empirical cumulative labor productivity distribution functions in the bottom and top quartiles of commuting zones, ranked by job-losing rate. Vertical lines mark within-quartile averages of labor productivity. Panel C scatterplots two measures of log labor market tightness across eight groups of French commuting zones c. Open blue circles represent the raw measure of labor market tightness without job-to-job adjustments: $\theta_c = \frac{\mathcal{V}_c}{\mathcal{U}_c}$, where $\mathcal{V}_c$ is the number of vacancies and $\mathcal{U}_c$ the number of unemployed workers. Solid orange dots represent the adjusted measure that include employed workers as effective job seekers: $\tilde{\theta}_c = \frac{\mathcal{V}_c}{\mathcal{U}_c+\xi\mathcal{E}_c}$, where $\mathcal{V}_c$ is the number of vacancies, ξ the relative search efficiency of employed workers, and $\mathcal{E}_c$ the number of employed workers.

positively correlated as the labor market pooling complementarity pulls stable jobs toward slack labor markets. Corollary 1 is an extreme case, however. When firms sort based on local fundamentals ℓ and the labor market pooling complementarity, the correlation between tightness and unemployment can take any sign. In fact, I show numerically in Section V.A that the model can generate both positive and negative correlations depending on parameter values.

I use establishment-level vacancy data from France to evaluate the cross-sectional variation in labor market tightness. I correct for job-to-job search and construct tightness using effective job seekers to be consistent with the model in which workers only search from unemployment.[34]

Figure IV, Panel C reveals that the cross-sectional dispersion in tightness is unambiguously small relative to the variation in job-losing rates in Figure II, Panel A, regardless of the job-to-job correction. The variation in tightness is similar to that in job-finding rates in Figure II, Panel B. If anything, labor market tightness after the job-to-job correction correlates positively with local unemployment rates. Without the correction, the correlation is negative. Thus, the correlation between tightness and unemployment remains largely ambiguous both theoretically and empirically.

III.G. Efficiency and Planning Allocation

Having validated the positive implications of the model, this section investigates its normative properties. A utilitarian planner maximizes a possibly weighted sum of values of all individuals in the economy, taking search frictions as given.[35] The planner decides where to send workers to search for jobs and when to break up matches. The infinite-dimensional distribution of employment across productivities and locations is a state variable because idiosyncratic productivity shocks are persistent.

34. In the data, employed workers capture a sizable fraction of vacancies, while in the model only unemployed workers apply to vacancies. Therefore, I estimate the relative search intensity of employed workers ξ in Online Appendix I.F. I then adjust the number of effective job seekers to compute labor market tightness in city c: $\tilde{\theta}_c = \frac{\mathcal{V}_c}{\mathcal{U}_c + \xi \mathcal{E}_c}$, where $\mathcal{V}_c$ is the number of vacancies, $\mathcal{U}_c$ the number of unemployed workers, and $\mathcal{E}_c$ the number of employed workers.

35. Because the planner can reallocate the final good across locations while workers can only consume their income in the decentralized equilibrium, only one set of utility weights delivers planning allocations that may coincide with the decentralized equilibrium. They are standard Negishi weights and defined in equation (49), Online Appendix III.A.

Nevertheless, I establish a well-defined planner problem building on Moll and Nuño (2018) in Online Appendix III.A. For brevity, I simply characterize its solution in the main text. Denote with *SP* superscripts variables in the planning solution, and with *DE* superscripts variables in the decentralized equilibrium.

PROPOSITION 4. (Planning solution)

(i) Local labor market flows (Proposition 1), sorting (Proposition 2), and existence and uniqueness (Proposition 3) results extend to the planning solution under the same conditions using Negishi utility weights from equation (49).

(ii) The decentralized equilibrium is inefficient for all values of α, $\beta \in (0, 1]$.

(iii) Suppose $\beta = \alpha$. Under the conditions of Proposition 3, for all ℓ:
- $z^{SP}(\ell) \geqslant z^{DE}(\ell)$ with equality if and only if $\ell \in \{\underline{\ell}, \overline{\ell}\}$.
- $\frac{\partial \log \underline{w}^{DE}}{\partial \ell}(\ell) > \frac{\partial \log \underline{w}^{SP}}{\partial \ell}(\ell)$.

(iv) The planning and decentralized equilibrium allocations coincide when search is directed.

Proof. See Online Appendix II.B.

Proposition 4 first establishes that the basic sorting, labor market flows, existence, and uniqueness properties of the decentralized equilibrium also hold in the planning solution. To interpret the normative implications of Proposition 4, recall that in a single-location search model such as Mortensen and Pissarides (1994), the only sources of inefficiency are the entry and separation margins. Both margins are efficient only when employers are compensated for opening and shutting down jobs by exactly as much as they congest the matching function. This is the case when the Hosios (1990) condition $\alpha = \beta$ holds. The same logic carries through to the multilocation model for the overall entry and separation decisions.

With geography, employers make an additional location decision. When employers enter a local labor market, the composition of local competitors affects their ability to recruit: they are pooled in the same matching function. The labor market pooling complementarity in equation (14) embeds this externality. This externality ultimately distorts the location decisions of employers regardless of whether the Hosios (1990) condition $\alpha = \beta$ holds. Thus, I call it a labor market pooling externality.

To understand the nature of the labor market pooling externality, first recall the composition externality that arises when different employers compete in the same labor market as in Acemoglu (2001). Consider two locations $\ell_1 < \ell_2$. Each location is populated with employers $z_1 = z(\ell_1) < z(\ell_2) = z_2$. Consider a marginal employer $z \in (z_1, z_2)$ contemplating entry in locations ℓ_1 or ℓ_2. If employer z enters in location ℓ_2, it is worse than the average local employer. Due to labor market frictions however, it meets as many workers as its more productive competitors. This composition externality is socially harmful, as workers are redirected toward a less productive employer, $z < z_2$. Symmetrically, entrant z meets as many workers as its less productive competitors if it enters in location ℓ_1. The composition externality is socially beneficial in this case, as workers are redirected toward a more productive employer, $z > z_1$.

The labor market pooling externality is an equilibrium outcome that materializes once heterogeneous employers choose which market to enter. It is a spatial manifestation of the composition externality in Acemoglu (2001). Although all locations have a single employer quality in equilibrium, the pooling externality affects off-equilibrium valuations and hence equilibrium location decisions. Consider the private and the planner's values of entry of job z in a particular location. Conditional on the separation threshold $\underline{y}(\ell)$, they satisfy

$$\left(\frac{\bar{J}^{DE}(z,\ell)}{\bar{J}^{SP}(z,\ell)}\right)^{\frac{1-\alpha}{\alpha}} = \frac{\overline{S}(z^{DE}(\ell))}{\overline{S}(z)} \cdot \left(\frac{Y}{\underline{y}(\ell)}\right)^{\frac{1}{z^{DE}(\ell)}-\frac{1}{z}}, \tag{18}$$

where $\overline{S}(z)$ is increasing and defined in Online Appendix II.F. The planner's valuation of opening job z in location ℓ only depends on that particular job quality z. The planner internalizes that it is suboptimal to pool different employers in the same local labor market and chooses as if all jobs of the same quality located identically. By contrast, the private value from entering in the same location ℓ for job z also depends on the quality of local competitors $z^{DE}(\ell)$. Private employers take the location decisions of their competitors as given, which determine the local vacancy meeting rate in equilibrium.

Every employer z has an incentive to free-ride on favorable recruiting conditions in better locations than the planner's choice. Indeed, the vacancy meeting rate of employer z does not reflect that employer z is worse than its competitors in locations where $z < z^{DE}(\ell)$. In equation (18), $z^{DE}(\ell)$ is increasing, leading employers to overvalue opening jobs in locations where other employers are productive. This free-riding incentive emerges off equilibrium since all locations end up with a single employer type in equilibrium. Yet, on net, employers concentrate too much in the best labor markets relative to the social optimum. The labor market pooling externality trickles down across locations and generates misallocation throughout the economy. Reservation wages rise faster in equilibrium than the planner's shadow value. For any location ℓ, local employers are not productive enough in the decentralized equilibrium, and $z^{DE}(\ell) \leqslant z^{SP}(\ell)$.

The labor market pooling externality rests on the assumption that matches are formed with some degree of randomness. In that case, wages are bargained after matches are formed. This lack of commitment prevents wages from fully pricing meeting rates. By contrast, the decentralized equilibrium is efficient when search is fully directed. In that case, the key assumptions are that employers can commit to contracts, and that workers can frictionlessly arbitrage between contracts in segmented submarkets in each location. Employers then internalize that by entering in a local labor market with higher quality than their own, they depress their meeting rate as workers direct their search away toward the more productive jobs. As a result, wage contracts exactly price congestion effects, which leads to efficiency. Whether search is directed or random is ultimately an empirical question with data requirements that go beyond the scope of this study. In principle, reality is likely to lie between the models.

Nevertheless, I propose two checks to lend credibility to the welfare implications of this article. First, I allow employers to post many vacancies in the extended model of Section IV.A. More productive employers post more vacancies than less productive ones. Thus, they meet with relatively more workers, mitigating the strength of the externality, akin to directed search. The vacancy cost elasticity then determines where the model lies between random and directed search. At the estimated elasticity, I find large welfare effects from place-based policies. Second, Table I in Section V.A shows that reestimating the model under the directed-search assumption delivers too little dispersion in local unemployment rates relative to the data and misses the variance decomposition into job-losing and job-finding rates described in Section II. The directed-search model lacks the labor market pooling externality, which increases the incentives for productive employers to colocate. Thus, spatial sorting is weaker and job-losing and unemployment rate differentials are smaller under directed search. Conditional on the rest of the model and in this spatial context, the data thus support the random-search assumption among those two extreme cases.

III.H. Optimal Policy

Given that the decentralized equilibrium does not attain the first best, a natural question is whether it can be restored using standard policy instruments. An optimal policy should achieve the following. First, it should correct the pooling externality by incentivizing employers to open jobs in low-profitability locations. Second, it should enforce the Hosios (1990) condition. I introduce place-based policies into the model in Online Appendix III.C. Proposition 5 shows that they can implement the first best.

PROPOSITION 5. (Optimal policy) Constrained efficiency is restored with a combination of place-based policies:

- (i) A labor subsidy, increasing in local productivity ℓ if and only if $\beta < \alpha$.
- (ii) A profit subsidy τ^* decreasing in local productivity ℓ. Under the conditions of Proposition 3 and when α is small enough, to first order: $\frac{\tau^*(\ell_2)}{\tau^*(\ell_1)} = (\frac{s^{DE}(\ell_2)}{s^{DE}(\ell_1)})^{\frac{r\alpha}{1-\alpha}}$, where r is a general-equilibrium constant.
- (iii) A lump-sum transfer to owners.[36]

Proof. See Online Appendix III.C.

The labor subsidy implements the Hosios (1990) condition. As in Kline and Moretti (2013), spatial variation in the value of search of workers makes that policy place-specific. Similar to their results, labor needs to be taxed more heavily in low-productivity locations on the empirically relevant side of the Hosios (1990) condition $\beta < \alpha$. Because this particular trade-off has been extensively studied, I focus primarily on the externality in the location choice of jobs.

A profit subsidy—or corporate tax credit relative to a base rate—is the simplest way to correct the spatial misallocation that

36. Alternatively, if there are no absentee owners and profits are rebated to workers with a flat income subsidy, then a flat income tax replaces the lump-sum tax on owners.

results from the labor market pooling externality. The corporate tax credit corrects the labor market pooling externality that equation (18) obviates. Subsidies rise as local productivity ℓ diminishes. Hence, subsidies are more generous in locations with high job-losing rates $s(\ell)$ as per Proposition 1. The local job-losing rate thus provides a sufficient statistic for the direction of optimal place-based policies.

Proposition 5 provides a formula for the optimal policy under additional restrictions. The optimal policy depends on few parameters and outcomes. The profit subsidy τ^* is increasing in the job-losing rate with a combined elasticity $\frac{r\alpha}{1-\alpha}$ that rises with the matching function elasticity α. When $\alpha = 0$, recruiting conditions are exogenous, there is no labor market pooling externality, and so there is no need for policy. The combined elasticity also depends on a constant r that captures the surplus and success probability elasticities consistently with equation (18). This constant r ultimately depends on parameters of the productivity process and the observed success probability, and turns out to be close to two in the estimated model of Section IV.A. Although the closed-form formula holds only under additional restrictions, it provides a tight approximation to the exact optimal policy as shown in Online Appendix Figure A12.

The optimal policy thus resembles real-world place-based policies that target areas with high job-losing and unemployment rates. For instance, the Empowerment Zone program in the United States and its French equivalent—the Zones Franches Urbaines—grant large effective corporate tax credits for firms that open jobs in distressed areas. The labor market pooling externality offers a structural justification for subsidizing these high-unemployment areas: high-productivity employers fail to internalize their positive labor market spillovers there. To the best of my knowledge, this is the first article to propose a structural justification for such policies based on frictional labor markets and two-sided mobility of workers and employers.

In practice, profit subsidies raise clear concerns of fiscal optimization and profit shifting between establishments within firms. Can the first best be attained with employment, wage, or value-added taxes or subsidies alone? I explore alternative tax schemes in Online Appendix III.C. A value-added subsidy restores the efficient location decisions provided that its distortive effects on job creation and separations are offset by wage or unemployment subsidies. Yet, value-added subsidies are subject to similar concerns to profit subsidies. Employment and wage subsidies alone cannot restore efficiency. They affect the location decision of employers through reservation wages, thereby distorting job creation and separation.

These differences between different subsidies can help rationalize why the evidence on place-based policies remains ambiguous. If the mix of actual subsidies changes from case to case, the results in Online Appendix III.C indicate that effects should be variable. I leave the design of a robust subsidy scheme to fully or at least partially correct the labor market pooling externality for future research. Instead, I focus on the optimal profit subsidies to highlight the potential gains from place-based policies.

So far the spatial and individual heterogeneity in the model has remained minimal. To quantitatively account for local labor market flows and the welfare effects of place-based policies, I enrich this baseline framework in Section IV.

IV. Extended Model and Estimation

In this section, I first describe the extensions of the model. I then establish how the results from Section III extend to the richer environment. Finally, I detail the estimation strategy, identification, and validation.

IV.A. Quantitative Setup

1. *Geography.* Locations now differ in productivity p and residential amenities a. Locations are indexed by productivity-amenity pairs $\ell = (p, a)$ with cumulative function F_ℓ on a connected support. This flexible parameterization of amenities captures unobserved physical or institutional attributes that attract workers beyond labor and housing market conditions, such as pleasant weather or high-quality schools and hospitals. Quantitatively, amenities let the model fit joint variation in population, wages, and unemployment across places.

2. *Housing Supply.* Perfectly competitive land developers now use the final good to produce housing on a unit endowment of land with an isoelastic production function. The resulting housing supply curve $H(r(\ell)) = H_0 r(\ell)^\eta$ flexibly captures local congestion from housing prices.[37]

37. The distribution of location types F_ℓ together with unit land in each location can capture long-run land use policies such as zoning restrictions in a stylized

3. *Migration Frictions.* Workers now receive the opportunity to move at Poisson rate $\mu \geqslant 0$. When hit by this moving opportunity, they draw a set of Fréchet-distributed preference shocks for locations $\{\varsigma_\ell\}_\ell$ with shape parameter $\frac{1}{\varepsilon}$, and choose where to locate. Those shocks stay constant until the next moving opportunity arrives. $\frac{1}{\varepsilon}$ then governs the migration elasticity to real income differences.[38]

4. *Preferences.* The flow utility function becomes $u(c, h, a, \overline{\varsigma}) = (\frac{c}{1-\omega})^{1-\omega}(\frac{h}{\omega})^{\omega} a\overline{\varsigma}$, where $\overline{\varsigma}$ denotes the product of all past taste shocks which the worker received for locations they chose.[39]

5. *Nonparticipation.* Workers now exit the labor force at Poisson rate $\Delta > 0$. When they do, a single new worker replaces them.

6. *Scarring Effects and Human Capital.* Workers now differ in their time-varying human capital k. When employed, human capital grows at rate $\lambda \geqslant 0$. When unemployed, human capital grows at rate $\lambda - \varphi$. The scarring rate $\varphi \geqslant 0$ encodes the relative depreciation rate of human capital during unemployment. For simplicity, the distribution of human capital of new workers k_t shifts at rate λ.[40] All workers in the same location search in the same labor market: potential employers cannot discriminate between workers with different human capital before meeting them.

way. Zoning restrictions manifest in part as a limited supply of high-productivity locations. The model captures this pattern if the distribution F_ℓ puts low mass in high-ℓ places.

38. The shifter is normalized to $\frac{1}{\Gamma(1-\varepsilon)}$, where Γ is Euler's gamma function, because it is not separately identified from amenities a. This normalization ensures that preferences shocks have mean one. Online Appendix IV.A extends standard discrete-choice results to a continuum of locations.

39. As in Desmet, Nagy, and Rossi-Hansberg (2018) and Caliendo, Dvorkin, and Parro (2019), $\overline{\varsigma}_t = \prod_{i=1}^{N_t} \varsigma_{t_i}(\ell_{t_i})$, where $(t_i)_{i=1}^{N_t}$ denote times when workers received migration opportunities between calendar times 0 and t.

40. The rescaled distribution $k_t e^{-\lambda t}$ for new workers does not depend on calendar time t and is denoted F_k. This assumption can be micro-founded if young workers learn from older workers before entering into the labor force. The economy is therefore on a balanced growth path determined by λ. In levels, the distribution of knowledge of new workers is a “traveling wave with constant shape.” I also assume that F_k has a density with full support equal to $\mathbb{R}_+$.

7. *Production.* Employers now use housing in production, to capture that local congestion due to higher population affects production costs. The production function becomes $(ypk)^{\frac{1}{1+\psi}} h^{\frac{\psi}{1+\psi}}$, where y is employer productivity, p is location productivity, k is worker human capital, and h is housing.

8. *Recruiting Intensity.* Employers can now adjust their recruiting efforts. Employers with open jobs may post many vacancies v at cost $\frac{\gamma}{1+\gamma} c_v v^{\frac{1+\gamma}{\gamma}}$. This extension has two implications. First, it potentially mitigates the strength of labor market pooling externalities. Second, it implies that local job creation responds directly to local labor market conditions in addition to sorting decisions, and nests both aggregate and local job creation.[41]

IV.B. Characterization

The extensions preserve the basic structure of the location choice of employers. Online Appendix IV shows that to a first order when migration opportunites are rare enough $\mu \ll 1$ and the depreciation rate of human capital is small enough $\varphi \ll 1$, the location choice of employer z in equation (15) becomes

$$\text{(19)} \quad \underset{(p,a)=\ell}{\operatorname{argmax}} \ \frac{z}{1-z}\Bigg\{ \underbrace{\log(p^{\mathcal{Q}} a^{-\psi\mathcal{P}})}_{\substack{\text{Exogenous}\\ \text{production \& housing}\\ \text{complementarities}}} + \underbrace{\log(C(\underline{w}(\ell), z(\ell))^{\psi\mathcal{P}})}_{\substack{\text{Endogenous}\\ \text{housing}\\ \text{complementarity}}} + \underbrace{\log(\bar{k}(u(\ell))^{\mathcal{Q}})}_{\substack{\text{Endogenous}\\ \text{human capital}\\ \text{complementarity}}} + \underbrace{\log q(\ell)}_{\substack{\text{Endogenous}\\ \text{pooling}\\ \text{complementarity}}} \Bigg\} - \underbrace{\log \underline{w}(\ell)}_{\substack{\text{Endogenous}\\ \text{cost of}\\ \text{labor}}}.$$

$\bar{k}(u(\ell))$ in location $\ell = (p,\, a)$ denotes average human capital. Online Appendix IV.H defines the constants $\mathcal{P} > 0$, $\mathcal{Q} > 0$ and the function C.

Equation (19) highlights that three additional channels determine the location decision of employers in the extended model. First, exogenous technological complementarities now

41. When $\gamma \to 0$, I recover the recruiting technology in Section III and the aggregate free entry condition (17). When $\gamma \to +\infty$, I recover a local free entry condition: the value of opening a job is equalized across locations, $\bar{J}(z(\ell), \ell) = c_v$. See equation (73) in Online Appendix IV.J for more details.

also depend on amenities a. Higher productivity still makes locations more lucrative for jobs. Yet higher amenities reduce profitability by bringing in more workers, raising housing prices, and driving up production costs with elasticity ψ. I identify a pair $\ell = (p, a)$ with the combined index of local advantage

$$\ell(p, a) \equiv p^{\mathcal{Q}} a^{-\psi \mathcal{P}}, \tag{20}$$

since I will show that it is a sufficient statistic for the location choice of employers.

Second, the housing-price channel also introduces an endogenous source of complementarity. The function $C(\underline{w}(\ell), z(\ell))$ encodes that local expenditures on housing increase with local wages, driving up housing prices and thus operation costs of employers.

Third, employers internalize human capital differences across locations. Localized scarring effects of unemployment imply that average human capital $\bar{k}(u(\ell))$ is proportional to $\frac{\mu+\Delta}{\mu+\Delta+\varphi u(\ell)}$ and thus decreases with the local unemployment rate $u(\ell)$. Human capital complements production, so that high-quality employers find it less profitable to enter in a location where workers have less human capital. There, only low-quality jobs open, further worsening unemployment in equilibrium. Human capital and scarring effects thus play two roles. They micro-found part of the production complementarities that were fully exogenous in Section III. They also add feedback effects linking unemployment and human capital in equilibrium.

Labor market pooling complementarities remain unchanged and still depend only on the local vacancy meeting rate. Similarly, the expected cost of labor continues to be summarized by local reservation wages $\underline{w}(\ell)$. Because the structure of the location choice of employers in equation (19) closely resembles its more stylized version in equation (15), virtually all the analytical results from Section III carry through.

PROPOSITION 6. (Characterization of the extended model) To a first order when the migration rate μ and the scarring effects of unemployment φ are not too large, Propositions 1, 2, 3, 4, and Corollary 1 obtain in the extended framework under the same conditions, with three modifications. First, replace the local unemployment rate by $u(\ell) = \frac{s(\ell)+\mu+\Delta}{s(\ell)+\mu+\Delta+f_R(\ell)}$. Second, replace ℓ with the combined index of local advantage $\ell(p, a)$. Third, population depends on the pair $(\ell(p, a), a)$: $L(p, a) \equiv L(\ell(p, a), a)$.

Proof. See Online Appendix IV.

Proposition 5 does not apply directly to the extended model because place-based corporate tax credits also affects job creation, which now responds elastically to local labor market conditions and taxes. Place-based corporate tax credits may still implement the first-best location decision for employers but possibly distort job creation. Yet, I find quantitatively that the distortion of job creation is minimal in equilibrium. As a result, Section V.B shows that place-based corporate tax credits deliver sizable employment and welfare gains.

Population cannot be summarized solely by the local advantage index $\ell(p, a)$ because workers value amenities directly, while employers value amenities through housing prices only. As a result, amenities generate variation in population conditional on the local advantage index $\ell(p, a)$. Online Appendix IV.I provides more details. With the extended framework at hand, I turn to the structural estimation.

IV.C. Identification

Despite its rich structure, the quantitative model is transparent enough to produce estimating equations for all but one of the parameters. No simulation is required until the last step, which estimates the entry cost. This section discusses how to recover recursively each parameter given the data I choose. This recursive scheme recovers parameters one after the other, so that parameters estimated early on do not depend on estimates of parameters estimated later on. A proposition at the end of this subsection summarizes the formal identification of the model. Different specific estimators are used for different parameters, but all can be nested into an overarching Generalized Methods of Moments (GMM) estimator.

In total, there are 19 parameters to be estimated: ρ, Δ, ω, ψ, δ, σ, β, b, Y, η, μ, ε, α, γ, c_v, m, λ, φ, c_e; together with two distributions F_z, $F_{p,a}$. I first recover these distributions nonparametrically. Then I estimate functional forms to simulate counterfactuals, adding another seven parameters.

The 26 parameters can be divided into three groups. Parameters in the first group—ρ, Δ, ω, ψ, μ, b, c_v, m—directly map into empirical counterparts or can be normalized, thus only requiring simple minimum distance estimators (MDEs). Parameters in the second group—δ, σ, β, Y, η, ε, α, γ, λ, φ—require more involved estimating equations, together with different estimators. The third group of parameters consists of distributional functional forms. The fourth group of parameters only contains the entry cost c_e, which is estimated by numerical search (method of simulated moments). Before describing how to estimate each group of parameters, I briefly discuss the data used to construct empirical targets.

1. *Data.* I use data from France for all years between 1997 and 2007. A quarter is the time period $[t, t+1)$. Most of the estimation uses averages over the entire period. For some parameters, I split the sample into two subperiods, with averages for 1997–2001 and for 2002–2007. I index locations (cities) in the data by c. I use aggregate data for the household housing expenditure share. I measure expenditures on real estate for firms in the firm-level balance sheet data. The DADS provide measures of local unemployment rates u_c, local job-losing rates for stayers s_c, local job-finding rates for stayers f_{Rc}, local average wages W_c, population shares L_c, and the aggregate mobility rate of workers. The DADS also enable finer disaggregation of job-losing rates and wages by tenure and location. I measure the average job offer acceptance probability in the LFS. I obtain housing prices r_c from the French notaries.

2. *First Group (Eight Parameters).* The mobility rate for individuals transitioning into unemployment at the same time directly identifies the moving opportunity rate μ.[42] The labor force exit rate identifies Δ. The interest rate identifies ρ through the effective discount rate of individuals $\rho + \Delta$.[43] The household housing expenditure share ω maps into the value reported by INSEE, 23%.[44] The employer real estate expenditure share out

42. In the model, unemployed and employed workers always change location and enter unemployment when they receive the moving opportunity at rate μ. With a continuum of locations, there is always a location with a high enough preference draw. The moving rate must be time-aggregated quarterly.

43. Although workers are not allowed to borrow or save in the model, $\rho + \Delta$ is their intertemporal marginal rate of substitution and would coincide with the interest rate in a complete-markets version of the model.

44. The calculations of INSEE reflect both renters and homeowners.

of value added ψ maps into my estimate of 11%.[45] The remaining parameters in this first group can be normalized: $b = c_v = m = 1$.[46]

3. *Second Group (10 Parameters).*

Productivity Process δ and σ. I use data on job-losing rates and wage growth by tenure to estimate (δ, σ). I leverage a closed-form solution for the job-losing rate in the first year in the model, which follows from an explicit solution to the time-dependent KF equation. The job-losing rate in the first year of a job in city c is $s_1(s_c, \hat{\delta})$, where $\hat{\delta} = \frac{\delta}{\sigma}$. The function s_1 depends on the average job-losing rate s_c that captures the initial productivity distribution. s_1 is decreasing in $\hat{\delta}$ given μ, Δ. Intuitively, if the volatility σ is much larger than the drift δ, many separations occur at early tenure. Details are in Online Appendix V.B. Denoting s_{1c} the measured job-losing rate in the first year in city c, I recover $\hat{\delta}$ directly by estimating

$$s_{1c} = s_1(s_c, \hat{\delta}) \tag{21}$$

with nonlinear least squares (NLLS), treating residuals as measurement error.

Given the estimated ratio $\hat{\delta} = \frac{\delta}{\sigma}$, the same solution to the time-dependent KF equation enables me to explicitly compute wage growth by tenure when β is not too large. Online Appendix V.C shows that it identifies the common scale of δ, σ. Intuitively, when productivity depreciates faster, wages at continuing jobs fall behind wages at new jobs at a faster pace. Thus, a regression similar to equation (21) estimates δ when β is small.[47]

Bargaining Power β. Wages relative to value added in location c are $\beta + \frac{1-\beta}{H(s_c)}$, where H only depends on δ and σ. I target aggregate wages relative to value added to identify β by MDE.

Learning and Scarring Rates λ and φ. Wage changes for workers coming out of unemployment reflect human capital

45. Balance sheet data lists all rental expenditures, as well as the book value of land, buildings, and structures owned by the firm. I annuitize the value of those properties using a 5% annual interest rate and add the annuitized value to rental expenditures. This defines expenditures on real estate.

46. The unemployment income parameter b is not separately identified from productivity ℓ. The shifter of the vacancy cost function c_v and the matching-function efficiency are not separately identified from the entry cost c_e.

47. When β is large, δ and β are estimated jointly. At the estimated bargaining power β however, the difference is negligible.

losses, which grow with unemployment duration. For worker i who loses their job at time t_0 and finds a new job at time t_1 in location c, wages satisfy

$$\log W_{ict_1} = (\lambda - \varphi)(t_1 - t_0) + \Phi_c + \log W_{ict_0} + \upsilon_{ic}, \tag{22}$$

where υ_{ic} is a mean-zero random variable that reflects draws from the local new job distribution, and Φ_c is a location fixed effect. Hence, OLS consistently estimates $\lambda - \varphi$ using equation (22) because new productivity draws are independent from unemployment duration. Aggregate real wage growth identifies λ directly. Thus, I recover φ. Details are in Online Appendix V.B.[48]

Local Quality and Threshold. For the remainder of the estimation, I recover estimates of the local job quality z_c and the local productivity threshold $\underline{y}_c$ in each city c. They are equilibrium outcomes, not fixed primitives of the economy. Given the estimate for δ, local job-losing and job-finding rates directly identify job quality and the threshold in each city as per Proposition 1,

$$z_c = \frac{\delta}{s_c}, \quad \underline{y}_c = \frac{b\underline{y}_0}{\hat{\rho}} \frac{\beta f_{Rc} \bar{S}(z_c)}{\hat{\rho} - \beta f_{Rc} \bar{S}(z_c)}, \tag{23}$$

where $\hat{\rho} = \rho + \Delta + \mu + \varphi - \lambda$, and $\underline{y}_0$ and the function $\bar{S}$ can be calculated from known parameters.

Lower Bound of Initial Productivity Draws Y. The success probability of a meeting for workers in city c is $(\frac{Y}{\underline{y}_c})^{\frac{1}{z_c}}$ in the model. I construct an empirical counterpart using data on job search behavior from the LFS in Online Appendix V.G. I estimate the average success probability for workers at 20.6% and find Y to match this target.[49]

48. In practice, mechanisms left out from the model may generate endogeneity issues. To address those concerns, Online Appendix Table A6 proposes several other specifications with more flexible controls (for instance, industry fixed effects, worker fixed effects, past wage controls, employed workers as control group). The point estimate of φ remains stable around 1% per quarter and statistically significant across specifications.

49. Faberman et al. (2017) suggest an acceptance probability of 29.6% in the United States. Only this worker success probability in the model maps transparently to data. Paying the entry cost c_e and the productivity draw z define a job in the model. Repeated draws of the same quality z after several unsuccessful meetings can correspond to situations where employers interview several candidates for a given position.

Housing Elasticity η. At this stage of the recursive scheme, housing prices in each city satisfy $\log r_c = r_1 + \frac{1}{1+\eta} \log r_0(W_c, L_c, u_c, z_c, \underline{y}_c)$, where Online Appendix V.H details the known function r_0. I then obtain η with OLS, assuming that measurement error is the only residual.[50]

Migration Elasticity $\frac{1}{\varepsilon}$. Migration shares by destination π_c satisfy

$$\log \pi_c = \pi_0 + \frac{1}{\varepsilon} \log \overline{U}_c + \log a_c, \tag{24}$$

where $\overline{U}_c = \frac{\overline{w}_c}{(1-\beta+\beta H(s_c))r_c^{\omega}}$ can now be computed in the model, and π_0 is a general-equilibrium constant. Unobserved amenities a_c are correlated with $\overline{U}_c$. Hence, I split the sample into two subperiods 0 and 1 and first-difference equation (24). Then, I use local productivity shocks based on shift-share projections of economy-wide industry shocks as instruments for the change $\log \frac{\overline{U}_{c,1}}{\overline{U}_{c,0}}$. I thus estimate $\frac{1}{\varepsilon}$ with 2SLS using equation (24) in first differences. I interpret the data in each subperiod as a different steady state of the model. The identification assumption is that economy-wide industry-level shocks are orthogonal to local changes in amenities. I further discuss how to map industry-level shocks into the model and the identification assumption in Online Appendix V.I.

Nonparametric Distributions of Local Productivity, Amenities, and Job Quality. Equation (112) in Online Appendix V.F shows that local productivity p_c follows from inverting the predictions of the model for local wages. Given the migration elasticity estimate, inverting the population equation (62) in Online Appendix IV.E then delivers an estimate of local amenities a_c in each city. Together, the estimates $(p_c,\ a_c)$ provide a nonparametric estimate of the distribution $F_{p,a}$.[51] Online Appendix V.J shows that the

50. Omitted factors like heterogeneous housing supply elasticities may be a source of endogeneity. With repeated cross sections of housing prices, difference-in-difference specifications using shift-share shocks as instruments could be used to correct for endogeneity. With only one cross section, these approaches are not possible.

51. Alternatively, amenities could be obtained as residuals from the migration share equation (24). Because the estimation relies on observed population shares, I choose to match population rather than migration shares. In practice, they are highly correlated.

density function of job-losing rates across locations identifies the density function of job quality f_z using equation (23).

Matching Function and Vacancy Cost Elasticities α and γ. I express local job-finding rates as a function of estimated location choices and estimated employer values $\hat{J}$:

$$\log\left(f_{Rc}\left(\frac{Y}{\underline{y}_c}\right)^{-\frac{1}{z_c}}\right) = f_0 + \frac{1-\alpha}{1+\alpha\gamma}\log\frac{F_z(z_c)-F_z(z_{c-1})}{(F_\ell(\ell_c)-F_\ell(\ell_{c-1}))\mathcal{U}_c} + \frac{(1-\alpha)\gamma}{1+\alpha\gamma}\log\hat{J}_c, \tag{25}$$

where $\hat{J}$ is defined in Online Appendix V.K, along with more details. I use a shift-share approach in first differences to estimate α, γ jointly with 2SLS, similarly to the estimation of the migration elasticity $\frac{1}{\varepsilon}$.

Together with details in Online Appendix V, the previous arguments prove Proposition 7.

PROPOSITION 7. (Identification) To a first order when μ, Δ, δ, and β are not too large, the parameters μ, Δ, ρ, ω, ψ, δ, σ, β, λ, φ, η, ε, Y, α, and γ, as well as the distribution of firms' qualities F_z, and the joint distribution of local productivities and amenities $F_{p,a}$, are exactly identified by an overarching GMM estimator. The other parameters can be normalized except the entry cost.

4. *Third Group (Seven Parameters).* I estimate a joint lognormal distribution for local amenities and productivities, with respective standard deviations σ_a, σ_ℓ, and correlation $c_{\ell,a}$. I estimate a beta distribution for the distribution of employer quality. Its shape parameters are g_1, g_2 and its support is $[\underline{z}, \overline{z}]$.

5. *Fourth group (One Parameter).* A numerical search finally estimates the entry cost c_e by targeting the aggregate unemployment rate.

IV.D. Parameter Estimates

Online Appendix Table A7 reports the parameter estimates. Overall, they are close to values found in the literature. The housing share for workers $\omega = 0.23$ is close to the commonly used value of 0.3 for the United States. Similarly, the housing share for firms $\psi = 0.11$ is in the range of estimates reported in

Desmet, Nagy, and Rossi-Hansberg (2018). The negative drift δ of the worker-level productivity process is close to the quarterly value of 0.5% implied by the estimates in Engbom (2018), and the volatility σ is somewhat smaller. The bargaining power β is 0.08, close to the estimate in Hagedorn and Manovskii (2008) and references therein. The housing supply elasticity η implies a price-to-population elasticity of 0.28, within the range reported in Saiz (2010) for the United States. The migration elasticity $\frac{1}{\varepsilon}$ is 4.72, within but toward the high end of the values reported in the literature between 0.5 and 5.[52] The matching-function elasticity α is 0.3, within the range reported in Petrongolo and Pissarides (2001). The inverse vacancy cost elasticity γ implies that the cost function is close to quadratic, in line with existing estimates. The scarring rate φ implies a 4% relative wage loss for workers who spend a year unemployed, consistent with Jarosch (2021).[53]

IV.E. Overidentification Exercises

1. *Job Loss in First Year.* With the estimated model at hand, I start with two exercises that support the estimates of the productivity process δ and σ. First, Figure V, Panel A shows that the model closely fits the full cross-sectional variation of job-losing rates in the first year, despite relying on a single degree of freedom $\frac{\delta}{\sigma}$ to predict them as per equation (21). Job loss is more frequent in the first year than on average. The persistence of productivity shocks in equation (4) is key to obtain this declining tenure profile of job loss.[54]

Second, I compute firm-level labor productivity growth relative to aggregate labor productivity growth with balance sheet data. I obtain a relative decline of 0.1% quarterly, close to the estimate of δ.[55]

52. The estimate for μ implies an annual migration rate of about 1%. The overall migration rate in my sample is about 3%. This discrepancy arises because many migrants are employed workers moving with a job in hand. However, in steady state, the migration elasticity is the key driver of population movements, not the migration rate.

53. Jarosch (2021) also includes negotiation capital losses that account for half of his overall 10% wage loss.

54. By contrast, with independently and identically distributed shocks as in Kuhn, Manovskii, and Qiu (2021), the tenure profile of job loss is counterfactually flat.

55. I focus on large and high labor productivity firms to minimize survival selection bias. These firms are the least likely to exit in the data and according to theories of firm dynamics with frictional labor markets such as Bilal et al. (2022).

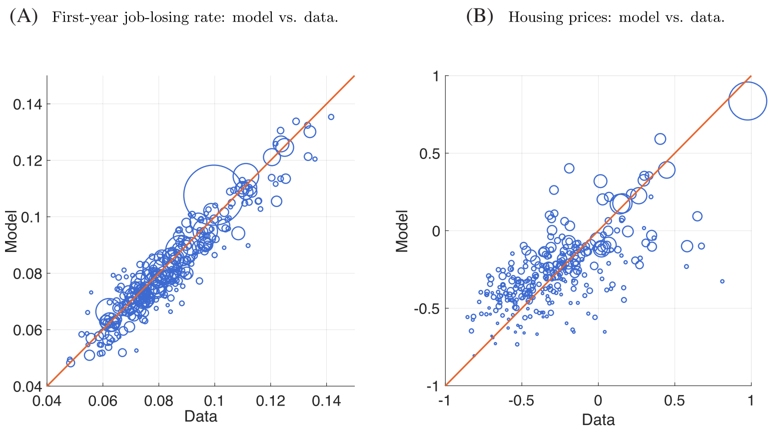

FIGURE V

First-Year Job-Losing Rates and Housing Prices across Cities

Panel A: annual job-losing rate in the first year of a job, model against data. Panel B: housing prices in the model against the data. Cities in the model are identified by their job-losing rate. Blue circles are proportional to city size.

2. *Housing Prices.* How well does the estimated housing supply elasticity account for cross-sectional dispersion in housing prices? Figure V, Panel B plots housing prices in the model against the data. Despite using a single parameter η, the predictions of the model are centered around the 45-degree line in orange with moderate residual dispersion.

3. *Amenities.* Unobserved local amenities allow the model to match the dispersion in city-level population. A natural check of the nonparametric amenity estimates a_c is to correlate them with local characteristics that should affect the value of living in a particular location. I correlate estimated log amenities on the log of sun hours per month, as well as the log density of residential service establishments of various kinds. Online Appendix Table A8 shows that more sun hours and a higher density of health or commercial services are all positively associated with higher amenities.[56] These results support the view that estimated amenities capture salient features of residential attractiveness.

56. For instance, doubling the number of sun hours per month raises the amenity value of a location by 12%. Doubling the density of health establishments increases amenities by 6.7%.

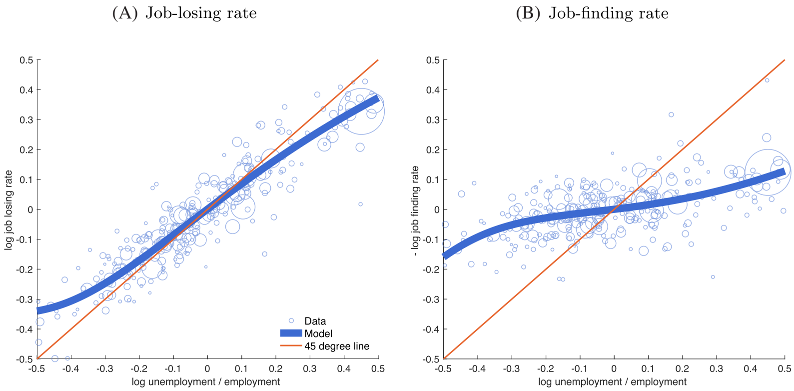

FIGURE VI

Local Job-Losing and Job-Finding Rates Against Unemployment-Employment Ratios in Model

Panel A plots the log of the job-losing rate against the log of the unemployment-employment ratio, across cities in the DADS data and in the estimated model. Panel B plots minus the log of the job-finding rate against the log of the unemployment-employment ratio, across cities in the DADS data and in the estimated model.

Having established the ability of the estimated model to speak to a number of targeted and nontargeted moments in addition to the validation exercises in Section III.F, I turn to the main structural results.

V. SPATIAL UNEMPLOYMENT GAPS AND PLACE-BASED POLICIES

This section shows that the model quantitatively accounts for spatial unemployment differentials and then discusses the employment and welfare effects of place-based policies.

V.A. *Spatial Job Loss Differentials and Unemployment*

The estimated model replicates closely the key role of job loss in the data. Figure VI plots the model equivalent of Figure II—the graphical decomposition of spatial unemployment gaps into job-losing and job-finding rates—together with the data for comparison. Job-losing rates account for most of the variation in local unemployment rates because employers sort strongly across locations, as per Proposition 2. The job-finding rate is nearly flat across locations because of the opposing forces highlighted in

TABLE I

AGGREGATE AND LOCAL UNEMPLOYMENT RATES IN THE DECENTRALIZED EQUILIBRIUM

	Data	Baseline	No pooling	Est. planner
Aggregate unemployment rate	0.097	0.096	0.083	0.097
St. dev. unemployment rate	0.025	0.019	0.003	0.003
St. dev. log unemp. / emp.	0.269	0.217	0.040	0.035
Job-losing rate, %	77	73	−33	45
Job-finding rate, %	23	27	133	55

Notes. All statistics are population weighted. The Data column reports moments in the data. The Baseline column reports moments in the estimated model. No pooling reports moments in the estimated model after shutting down the labor market pooling externality. Est. planner reports moments for a fully reestimated model under directed search. Its allocation coincides with the social planner's allocation. Fourth and fifth rows report the fraction of the variance of the log unemployment-to-employment ratio (standard deviation reported in third row) accounted for by the job-losing and job-finding rates.

Proposition 1. As a result, the unemployment rate largely follows the spatial patterns of the job-losing rate.

Neither the location decision of employers, nor the spatial variation in job-finding rates, are constrained by the estimation. The spatial variation in job-losing rates results from (i) the distribution f_z, which is constrained by the estimation, and (ii) the equilibrium assignment of employers to locations $z(\ell)$, which is left entirely free. The estimation does not limit the spatial variation in job-finding rates apart from the two coefficients that identify α and γ. The job-losing and job-finding variance shares are therefore useful moments to assess the ability of the model to speak to spatial unemployment differentials.

Does the model account quantitatively for spatial unemployment gaps? Table I reports the dispersion in local unemployment rates and its breakdown into job-losing and job-finding rates. The first two columns reveal that the model accounts for over 75% of the cross-sectional standard deviation of local unemployment rates, 0.019 against 0.025. The decentralized equilibrium also closely replicates the contribution of job-losing rates to spatial unemployment differentials. The job-losing share is 73% in the estimated model against 77% in the data.

I evaluate the role of labor market pooling complementarites in the third column of Table I. It reports the same decomposition as the second column after shutting down the labor market pooling externality. The labor market pooling externality is key in generating spatial differences in unemployment rates. The cross-sectional standard deviation of local unemployment rates drops to 0.003 without labor market pooling externalities, 15% of its baseline value and 12% of its value in the data. Hence, the pooling externality yields over a fivefold amplification of spatial unemployment gaps.

The labor market pooling externality matters quantitatively because it magnifies the spatial sorting of employers. It induces excess clustering of the most productive employers with stable jobs in the best locations. As a result, only employers that are not productive enough, with jobs that are too unstable, remain in high-unemployment locations. Consistently, the job-losing rate share plummets.[57]

I confirm the key role of the pooling externality by reestimating an efficient model without the externality. In the fourth column of Table I, I impose directed search instead of random search before estimating the model.[58] Even when reestimated, the efficient allocation falls short of replicating the empirical dispersion in local unemployment rates and the central role of job loss. The dispersion in local unemployment rates again drops to 12% of its value in the data, and the job-losing rate generates less than than half of this variation.

This comparison between the baseline and the reestimated efficient allocation confirms that the estimation does not place strong constraints on the dispersion in unemployment, job-losing, and job-finding rates. These moments therefore provide informative overidentification restrictions to evaluate the ability of the model to account for spatial unemployment gaps and discriminate between different sets of assumptions. Table I strongly favors the baseline version of the model that includes the labor market pooling externality, against the efficient economy that does not feature this amplification force.

Can the model also account for the comovement between labor market flows, wages, population, and vacancies? Table II displays the results from worker-level OLS regressions of job-losing and job-finding rates onto local wages and population. It compares results in the baseline model with the data.

57. As discussed in Section III.G, the labor market pooling externality affects spatial unemployment gaps because employers choose their location. If employer quality $z(\ell)$ in every location ℓ was exogenous instead of being determined in equilibrium by location decisions, there would be no pooling externality.

58. The directed search and planning allocations coincide under the same parameters as per Proposition 4. In practice, parameter estimates under the reestimated efficient allocation are close to estimates in the decentralized equilibrium.

TABLE II

OLS Regressions of Worker-Level Job Loss and Job-Finding Probabilities and City-Group-Level of Labor Market Tightness

	Job loss		Job finding		Log labor market tightness			
	Data	Model	Data	Model	Data		Model	
		Base		Base	JtJ adj.	No adj.	Base	$\gamma = 3$
Log city wage	−0.12***	−0.19	0.01	0.06				
	(0.03)		(0.02)					
Log city population	0.04	−0.06	0.02	0.00				
	(0.07)		(0.06)					
Log unemp.-emp. ratio					0.47*	−0.51*	0.31	−0.72
					(0.16)	(0.14)		
Ind.-year & worker FEs	√		√					
Obs.	2,825,413		394,678		8	8		
R^2	0.124		0.228		0.590	0.687		

Notes. Data for job loss and job finding: Dependent variables relative to unconditional mean. Independent variables are standardized to unit standard deviation. Worker-level regression. Standard errors are in parentheses, two-way clustered by city and three-digit industry. Quarterly frequency. 1997–2007. Movers only. Data for labor market tightness: Log of tightness. Standard errors in parentheses. City population density by km^2. City-group-level variation. Model: population moments. Wages net of human capital in the model. "Base" denotes model with baseline parameters. $\gamma = 3$ denotes a model with parameters equal to baseline values, except γ, which is set to 3. "JtJ adj." denotes labor market tightness in the data inclusive of the adjustment for job-to-job search as in Section III.F. "No adj." denotes labor market tightness in the data without the adjustment for job-to-job search.
$^{+}$ $p > .10$; * $p > .05$; ** $p > .01$; *** $p > .001$.

Wages correlate negatively with job loss both in the data (-0.12) and in the model (-0.19). This negative correlation reflects the spatial sorting of employers. Employers who offer stable jobs also pay high wages. Thus, cities with high wages are also those with low rates of job loss. Consistent with the moderate spatial variation in the job-finding rate in Figure VI, Panel B, the job-finding rate is not strongly correlated with wages or population in the model and in the data.

Job-losing and job-finding rates correlate more weakly with local population after controlling for local wages in the model and in the data. This weaker correlation reflects the difference in location decisions between workers and employers. Recall that Proposition 6 implies that labor market flows and wages are one-to-one with the local index $\ell(p, a)$, while population depends on amenities a conditional on $\ell(p, a)$ because of the residential choice of workers. Population thus exhibits additional dispersion relative to wages which drives the coefficient on population toward zero.

Can the model reproduce the comovement between unemployment and vacancies in the data? Section III.F highlighted that this comovement is ambiguous theoretically and empirically. Consistent with this ambiguity, Table II reveals that the comovement between labor market tightness and unemployment is quantitatively small and can take any sign depending on parameter values.

At baseline estimates, this comovement is positive and consistent with the empirical correlation between unemployment and tightness after adjusting for job-to-job search. Recall that this adjustment is required to align the measurement of labor market tightness with its counterpart in the model. However, with less elastic recruiting costs $\gamma = 3$, the comovement is negative and consistent with the empirical correlation between unemployment and tightness without the job-to-job adjustment. Online Appendix Figure A11(a) represents these results graphically. Similar conclusions hold for the vacancy meeting rate as shown in Online Appendix Figure A11(b).

The recruiting cost elasticity γ is key for the sign of the comovement between vacancies and unemployment because it determines how much local job creation responds to local labor market conditions. As emphasized in Section IV.C and in equation (25), the empirical comovement between job-finding rates, real wages, and population across locations identifies the recruiting cost elasticity $\gamma = 1.44$.

In a related setup that builds on the key elements of this study, Kuhn, Manovskii, and Qiu (2021) assume away the location decision of employers and thus the pooling externality. They also impose local free entry $\gamma = +\infty$ rather than estimating a recruiting cost elasticity. Finally, they target a measure of labor market tightness that does not adjust for job-to-job search. Under these strong assumptions, and consistent with the results from this article when γ is increased from its point estimate of 1.44 to 3, Kuhn, Manovskii, and Qiu (2021) find that tightness correlates negatively with unemployment.

V.B. Place-Based Policies

Having demonstrated that the model accounts for spatial unemployment and job loss gaps, this final section presents two policy counterfactuals. Both quantify the local and general-equilibrium welfare gains from place-based policies in the long run by comparing steady states. The first counterfactual studies the policy that corrects the labor market pooling externality. The second counterfactual contrasts this policy with the real-world French Enterprise Zone (EZ) program in France.

I start by examining the quasi-optimal policy that corrects the labor market pooling externality. Under this policy, the economy is not fully efficient since the Hosios (1990) condition needs not hold. Instead, the quasi-optimal policy is a second-best policy that focuses on the location choice of employers. The quasi-optimal policy takes the form of a corporate tax credit whose generosity rises with the local job-losing rate, consistent with Propositions 5 and 6. The policy is financed with a nondistortionary flat income tax.[59]

I contrast the effects of the quasi-optimal policy with a real-world example of an economy-wide set of place-based policies. Federal programs such as the Empowerment Zones program in the United States proposed considerable tax breaks for firms opening jobs in high-unemployment areas. In France, a similar EZ program was rolled out in 1996 and subsequently expanded—the Zones Franches Urbaines. The labor market pooling externality provides a theoretical basis for such policies. By changing incentives to open jobs across locations, the policies effectively relocate jobs and affect the general equilibrium of the economy.[60]

59. To compute welfare gains without taking a stand on distributional issues between owners and workers, I use the equivalent formulation where profits and rents are rebated to workers with a nondistortionary flat income subsidy.

60. Ideally, the estimation would account for the policy during the sample period. However, the necessary estimates of local policy expenditures are

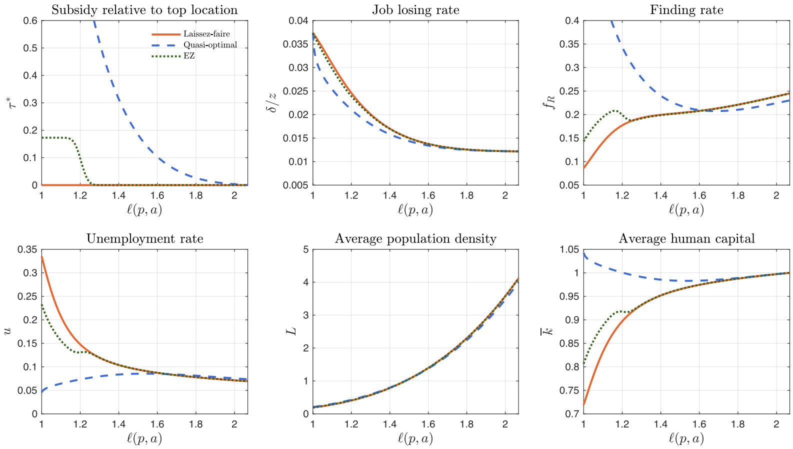

FIGURE VII

Outcomes under the Decentralized Equilibrium, Quasi-Optimal Policy, and the French EZ Program

Place-based corporate tax credit and allocations under the decentralized equilibrium, quasi-optimal policy, and the French EZ program. Locations are indexed by the combined index of local advantage $\ell(p, a)$ relative to the location with the lowest index. Equilibrium under the quasi-optimal policy is virtually identical to equilibrium under efficient location decisions and efficient vacancy creation.

Figure VII displays the cross-sectional patterns of the equilibrium under the laissez-faire, the quasi-optimal policy, and a budget-equivalent version of the French EZ program. The EZ subsidy is much smaller than the quasi-optimal one in scale and scope. However, it shares the same qualitative pattern. The leftward shifts in the job-losing rate indicate that both policies relocate more productive employers toward high-unemployment locations. Under the EZ program few marginal jobs change location, with minor effects on the job-losing rate. By contrast, the quasi-optimal policy heavily relocates productive jobs toward initially high-unemployment locations, resulting in a large drop in the job-losing rate.

The job-finding rate is more sensitive to policy than the job-losing rate because of the opposing forces highlighted in Proposition 1. The EZ program increases the job-finding rate

difficult to obtain. In practice, the policy is small and has modest local and general-equilibrium effects. Therefore, it is unlikely to affect parameter estimates and counterfactuals substantially.

because of a volume effect. Despite only a moderate decline in the job-losing rate, the EZ program attracts more jobs to high-unemployment locations. Hence, the unemployment rate declines in treated locations.

The employment response is broadly consistent with difference-in-difference evidence evaluating actual place-based policies. Mayer, Mayneris, and Py (2015) evaluate the French EZ program and find that employment increases by 23% in treated locations. Although less directly comparable, Busso, Gregory, and Kline (2013) find a 12% employment response for a similar EZ program in the United States. In the model, employment increases by a more modest 8% in treated locations.[61]

The quasi-optimal policy also strongly increases the job-finding rate in initially high-unemployment locations. There, the combined reduction in job-losing rates and increase in job-finding rates result in large drops in local unemployment rates that can exceed 10 percentage points. Consequently, spatial unemployment differentials plummet.

Mirroring the falling unemployment rate, average human capital $\bar{k}(u(\ell))$ steeply rises across locations in the laissez-faire. Localized scarring effects imply human capital gaps of over 25% between residents of the best and worst locations in the laissez-faire. The EZ program alleviates localized scarring effects due to the reduction in local unemployment rates in treated locations. In line with the drastic reduction in unemployment under the quasi-optimal policy, human capital accumulation improves dramatically in initially high-unemployment locations.

Figure VIII depicts the welfare gains for residents across all locations. Locations are ranked by their unemployment rate in the laissez-faire equilibrium and grouped into population-weighted quantiles to reflect how many workers experience a given welfare increase. The quasi-optimal policy achieves large welfare gains that exceed 10% in initially high-unemployment locations.

What is the role of localized scarring effects of unemployment? The different colored areas correspond to an exact welfare decomposition in equation (96), Online Appendix IV.O. The blue (dark gray) area represents direct gains to the average resident worker, conditional on unit human capital. It is equal to the

61. The discrepancy may arise for at least two reasons. First, the French EZ program is stylized in the model relative to its implementation in practice. Second, the model lacks a labor market participation decision.

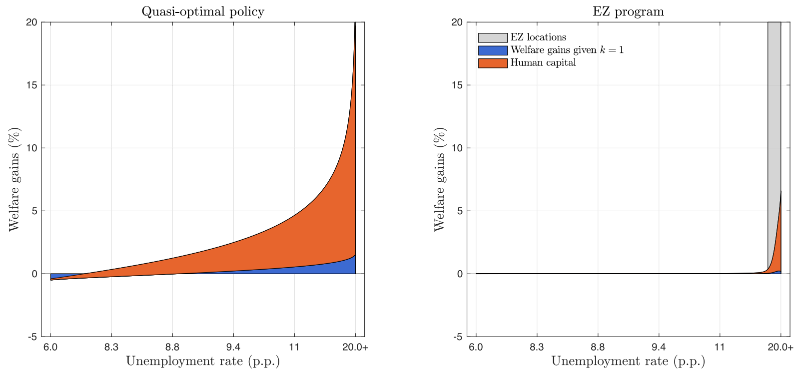

FIGURE VIII

Welfare Gains from the Quasi-Optimal Policy and the French EZ Program

Expected welfare gains of residents who never receive the moving opportunity, in consumption-equivalent percent changes. Split into the average gain to a worker conditional on $k = 1$, and human capital gain defined as changes in the $W^w(\ell)$ and $\bar{k}(\ell)$ components as per equation (96) in Online Appendix IV.O. Locations are ranked by their unemployment rate in the laissez-faire. The x-axis reflects population-weighted quantiles. Left: quasi-optimal policy. Right: French EZ program.

steady-state welfare gains of an unemployed worker who never received the moving opportunity and so stayed in the same location, with $k = 1$. Figure VIII shows that direct gains steadily rise with prepolicy local unemployment under both policies.[62]

Reductions in scarring effects of unemployment are central to welfare gains from place-based policies. By lowering local unemployment, both policies alleviate localized scarring effects and let workers accumulate more human capital. The orange (light gray) area in Figure VIII reveals that diminishing scarring effects account for the majority of welfare gains in most locations. Because the quasi-optimal policy relocates jobs away from the best locations, residents there experience welfare losses. By contrast, the EZ program has more modest effects, with welfare gains peaking around 5% and concentrated in treated, high-unemployment areas.

To highlight the spatial distribution of these local welfare gains, Figure IX, Panel A maps the welfare gains from the

62. The blue (dark gray) area also corresponds to the contribution of each location to the aggregate welfare gains for workers with $k = 1$.

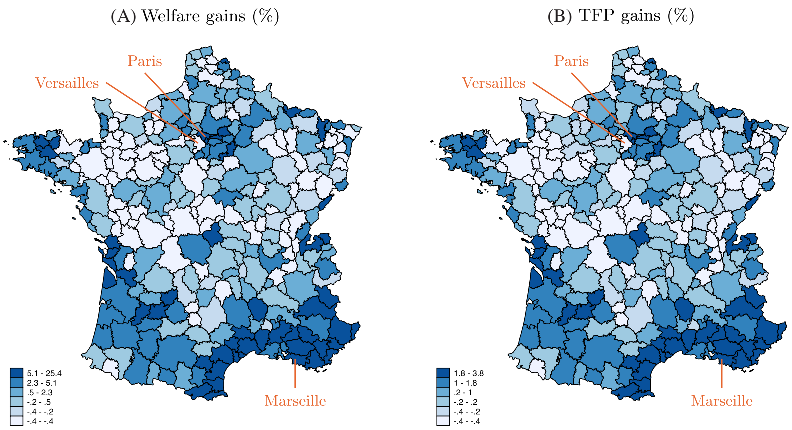

FIGURE IX

Local Gains from the Quasi-Optimal Policy

Panel A maps welfare gains from the quasi-optimal policy by commuting zone in mainland France. Panel B maps TFP gains from the quasi-optimal policy by commuting zone in mainland France. Corsica and overseas territories are omitted for exposition.

quasi-optimal policy across all French commuting zones. Because welfare gains are strongly correlated with the local unemployment rate, the southern Mediterranean coast benefits most. In suburban areas close to Paris, several high-unemployment commuting zones also benefit substantially. Local welfare gains are accompanied by substantial TFP improvements, as more productive employers relocate toward areas with more generous tax credits.

I aggregate local welfare gains and compute aggregate welfare gains from the quasi-optimal policy and the EZ program in Table III. The quasi-optimal policy achieves just over 2% aggregate welfare gains. The quasi-optimal policy also reduces spatial unemployment differentials more than fivefold as in Table I. Despite its relatively small size, the EZ program reduced spatial unemployment differentials by 19% and raised aggregate welfare by 0.14%. Reductions in scarring effects of unemployment account for the vast majority of overall welfare gains.[63]

63. Perhaps surprisingly, average direct gains to unemployed workers are negative because of the decline in the aggregate unemployment rate. This result arises because the policy does not enforce the Hosios condition. Given that I estimate $\beta < \alpha$ consistently with the literature, the well-known efficiency result by

TABLE III
AGGREGATE GAINS FROM PLACE-BASED POLICIES

	Laissez-faire	Quasi-optimal	EZ program
Aggregate unemployment rate (percentage points)	9.70	8.38	9.61
St. dev. unemployment rate (percentage points)	1.92	0.34	1.55
Aggregate welfare gains (%)		2.29	0.14
Unemployed		− 0.29	0.00
Employed		0.03	0.00
Human capital		2.55	0.13
Income tax (%)		0.78	0.01

Note. Unemployed, employed, and human capital gains are defined as change in the W^u, W^e, W^k components in equation (98) in Online Appendix IV.O, respectively.

It is not surprising that the EZ policy delivers smaller gains than the quasi-optimal policy since it consists of a much smaller subsidy scheme. Financing the EZ policy requires a flat income tax of 0.006%. The quasi-optimal policy requires an income tax of 0.78%. If scaling up the redistribution-efficiency ratio of the EZ policy was possible, welfare would rise by 18% for every percentage point of income tax. The quasi-optimal policy is eight times less efficient, indicating that decreasing returns rapidly kick in. Indeed, one should expect the planner's problem to be concave in the corporate tax credit around the quasi-optimal policy. Thus, the largest gains for a marginal increase in the corporate tax credit should arise close to the laissez-faire.

This comparison suggests that smaller place-based policies may be more efficient than larger ones in the presence of additional frictions. Although a full investigation is beyond the scope of this article, many economic forces left out of the model may generate deadweight losses that scale with the policy intervention. Fiscal optimization across establishments within firms, fiscal externalities, or political economy constraints are a few examples. In this case, interventions of the scale of the EZ program are likely to be more robust than the quasi-optimal policy.

Hosios (1990) implies that the planner would increase the aggregate unemployment rate in the first-best, not decrease it. The quasi-optimal subsidy still delivers aggregate gains because of reduced scarring effects.

VI. Conclusion

This article has proposed an alternative view of spatial unemployment differentials. I have shown that high localized unemployment arises because workers repeatedly lose their job, not because finding a job is particularly hard. Differences in job-losing rates emerge as employers with unstable jobs self-select into similar locations, while employers with stable jobs locate in others. I have developed a theory in which labor market pooling complementarities are a central driver of the location choice of heterogeneous employers. As a result, employers with stable jobs overvalue locating close to each other due to labor market pooling externalities. This view implies that redistributing from low-unemployment locations toward high-unemployment locations is welfare improving.

Of course, the idea that pooling externalities result in too much concentration in the best options available to workers and employers is more general than the particular spatial context put forward in this study. For instance, investigating the implications of pooling externalities for the allocation of workers and employers across occupations and industries could lead to interesting policy insights. Indeed, in the spatial context alone, pooling externalities quantitatively account for the lion's share of differences in unemployment across locations.

Consequently, this article emphasizes that spatial unemployment differentials are not an immutable characteristic of the economic landscape. Instead, place-based policies have the potential to dramatically reshape the spatial distribution of unemployment, and ameliorate employment prospects at the aggregate level. While a long tradition of research has found that agglomeration economies call for taxes on poor locations, the implications thereof have remained at odds with a range of real-world spatial policies. The view that labor market pooling externalities lie at the heart of the location decisions of employers helps reconcile theory with the intuition that incentivizing businesses to open in distressed areas may help rather than harm individuals. Yet the inherently local nature of many economic interactions gives rise to many other externalities. Therefore, any policy recommendation should account for as many sources of agglomeration and congestion as possible. As individuals who grow up and live in different places seem to face increasingly divergent economic opportunities, place-based policies appear more relevant than ever.

Harvard University and National Bureau of Economic Research, United States, and Centre for Economic Policy Research, United Kingdom

Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

Code replicating the tables and figures in this article can be found in Bilal (2023) in the Harvard Dataverse, https://doi.org/10.7910/DVN/SMPOYZ.

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