The Geography of Job Creation and Job Destruction*

Moritz Kuhn† Iourii Manovskii‡ Xincheng Qiu§

Abstract

Spatial differences in labor market performance are large and highly persistent. Using data from the United States, Germany, and the United Kingdom, we document striking similarities across these countries in the spatial differences in unemployment, vacancies, and job filling, finding, and separation rates. The novel facts on the geography of vacancies and job filling are instrumental in guiding and disciplining the development of a theory of local labor market performance. We find that a spatial version of a Diamond-Mortensen-Pissarides model with endogenous separations and on-the-job search quantitatively accounts for all the documented empirical regularities. The model also quantitatively rationalizes why differences in job-separation rates have primary importance in inducing differences in unemployment across space while changes in the job-finding rate are the main driver in unemployment fluctuations over the business cycle.

Keywords: Local Labor Markets, Unemployment, Vacancies, Search and Matching
JEL Codes: J63, J64, E24, E32, R13

*We thank participants at NBER Summer Institute, Barcelona GSE Summer Forum, SITE Macroeconomics and Inequality workshop, Annual Search and Matching conference, EM3C workshop, Oxford NuCamp PhD workshop, Washington University in St. Louis EGS conference, ifo Conference on Macroeconomics and Survey Data, Society of Labor Economics Annual Meeting, RIDGE Labor workshop, NASM Econometric Society, EEA-ESEM, UPenn Macro Lunch, PKU GSM, IIES Stockholm, and University of Zurich for helpful comments. We thank the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/1 – 390838866 and the CRC TR 224 (Project A03) and NSF Grant SES–1824520 for financial support.

†University of Bonn, Department of Economics. Email: mokuhn@uni-bonn.de.
‡University of Pennsylvania, Department of Economics. Email: manovski@econ.upenn.edu.
§University of Pennsylvania, Department of Economics. Email: qiux@sas.upenn.edu.

1 Introduction

Large and persistent differences in unemployment rates across regional labor markets in the United States are well documented (Topel, 1986; Elhorst, 2003; Kline and Moretti, 2013). Regardless of whether regional labor markets are considered at the commuting zone, county, or metropolitan area level, there are many regions with unemployment rates that are more than double or less than half of the national average, and these deviations persist for decades. As we document, the persistent differences across regional labor markets are not limited to unemployment but are also a feature of numerous other labor market variables. Moreover, they are not unique to the United States, with strikingly similar patterns observed in other countries. Differences in regional labor market outcomes are important contributors to inequality and receive significant attention in policy-making. Many billions of dollars are spent annually in the United States alone on local labor market policies. Yet, perhaps surprisingly, these large and persistent spatial differences have received only scant attention in the academic literature,[1] in contrast to the voluminous literature studying the variation in unemployment over the business cycle. There is little consensus to date about the origins of these persistent differences in local unemployment rates and whether they call for particular policy actions. Answering these questions requires a quantitative theory of spatial unemployment differences which we endeavor to provide in this paper.

The development of such a theory must be guided by the empirical regularities characterizing regional labor markets and the quantitative performance of the model must be assessed based on its ability to match those facts. Clearly, local unemployment is an equilibrium outcome determined by both employers' and employees' actions, and it is thus vital to collect the facts describing differences across locations on both sides of the labor market. While many facts on the worker flows between employment and unemployment have been documented in recent literature, the crucial missing piece is the spatial differences in the properties of job creation and job filling by employers. We aim to fill this empirical gap in this paper.[2]

To characterize these differences empirically, we use administrative and survey microdata from the United States, Germany, and the United Kingdom to document striking similarities of regional labor market patterns across countries. We leverage these similarities and exploit the unique strengths of the available data across countries to provide a comprehensive picture of regional labor market differences that guide our development of a theoretical framework.

The first novel fact that we document is that labor markets with lower unemployment rates

[1]Existing studies include Beaudry, Green, and Sand (2012, 2014), Bilal (2021), Head and Lloyd-Ellis (2012), Kline and Moretti (2013), Lkhagvasuren (2012), Hoffmann, Piazzesi, and Schneider (2019), Martellini (2021).

[2]Following Mortensen and Pissarides (1994), we use terms "job creation" and "job destruction" to describe creating and terminating job matches. This is different from another common usage of these terms following Davis, Haltiwanger, and Schuh (1996) which refers to the establishment-level employment reallocation.

are also tighter, i.e., have more vacant jobs per unemployed worker. The fact that potential employers tend to create more jobs in locations where the number of unemployed workers is low rationalizes our second key finding that it takes potential employers longer to fill vacant jobs in low unemployment locations.

Turning to the worker side of the market, we find that the job-finding rates, i.e., the flow rates from unemployment to employment, are higher in low unemployment locations. At the same time, the job-separation rates, i.e., the flow rates from employment to unemployment, are lower in low unemployment locations. We confirm recent findings in Bilal (2021) and Jung, Korfmann, and Preugschat (2021) that differences in separation rates across locations are the most important driver of geographic differences in unemployment rates.[3] The latter fact is surprising, because it is diametrically opposed to well-known findings regarding the drivers of aggregate unemployment over the business cycle, where the fluctuations in the job-finding rate play the dominant role (Fujita and Ramey, 2009; Shimer, 2012). Thus, an important challenge to a quantitative theory of unemployment is to rationalize the contrasting roles that job-finding and job-separation rates play in determining unemployment differences across locations and over the business cycle.

Taken together, the empirical patterns that we document point to the Diamond-Mortensen-Pissarides (DMP) framework (see Pissarides, 2000, for a textbook treatment) as a natural starting point in interpreting local unemployment differences. Kline and Moretti (2013) have already noted that this framework can potentially rationalize differences in unemployment rates across locations and can give rise to inefficiencies that may be corrected through place-based policies. Their analysis is theoretical and they do not assess the theory's quantitative ability to account for the data. However, even at the theoretical level, their modeling approach rationalizes differences in unemployment across locations solely through differences in job-finding rates while the data attribute a dominant role to separation rates in accounting for unemployment differences across local labor markets. To account for this empirical observation, Bilal (2021) adopts a different modeling strategy based on assortative matching between jobs and locations. Upon creating a job, employers in his model have to decide to which local labor market to send it. High productivity jobs have a higher opportunity cost of being unfilled and are sent to the locations where vacant jobs are filled faster. These locations also feature low equilibrium unemployment rates due mainly to lower separation rates. Thus, the core implication of this estimated model is that low unemployment (and high productivity) locations feature low tightness and high vacancy filling rate. We document the opposite relationship in the data.[4]

[3] Similarly large differences in job-finding and separation rates over the life cycle have been documented and studied in Choi, Janiak, and Villena-Roldán (2015); Menzio, Telyukova, and Visschers (2016); Gervais et al. (2016); Jung and Kuhn (2019).

[4] While we only mention the key mechanism that leads to the inconsistency between the estimated model in Bilal (2021) and the vacancy filling data that we document in this paper, we provide a more detailed discussion

Building on the insights gained from the respective successes and failures of these two modeling approaches, we begin by endogenizing the separation rate in the standard DMP model along the lines of Den Haan, Ramey, and Watson (2000). In the model, geographic locations differ in their productivity while workers and firms are freely mobile across locations. Unemployed workers and firms with vacant jobs search for each other in local labor markets. Once they meet, an idiosyncratic match productivity is drawn that then evolves stochastically over time. Matched workers and firms dissolve the match when its idiosyncratic productivity falls below an endogenous location-specific threshold. The model's spatial equilibrium is sustained by differences in local costs of living as in Rosen (1979) and Roback (1982). The local productivity and cost of living differences reflect what Fujita and Thisse (2013) label the "fundamental tradeoff of urban economics."

Qualitatively, the model provides a natural interpretation of all the empirical patterns that we document. Highly productive locations feature tight labor markets, i.e., have high ratios of vacancies to unemployed workers, because firms enjoy a higher profit flow from filled jobs in these locations. At the same time, the spatial equilibrium condition restricts the supply of unemployed workers in highly productive locations because the equilibrium costs of living are also higher. Tighter labor markets imply that it takes longer for firms to fill a vacant position while unemployed workers find jobs faster. Because of a higher average productivity, idiosyncratic productivity shocks render fewer matches unprofitable so that separation rates are lower. Lower separation rates and higher job-finding rates imply lower unemployment rates in higher productivity locations as the equilibrium outcome.

To assess whether the model matches the empirical facts quantitatively, we calibrate the model by targeting job-finding, separation, and vacancy-filling rates at the U.S. local labor market with median unemployment, and the differences in productivity between local labor markets with highest and lowest unemployment rates. To assess the model's quantitative performance, we then compare how spatial unemployment and the relative importance of job-finding and separations vary with productivity across locations. We find that this simple model is able to match all the described facts quantitatively including the relationships of labor market tightness, vacancy-filling rates, job-finding and separation rates with unemployment rates. Moreover, we demonstrate that the implied differences in wages and cost of living in the spatial equilibrium align closely to the empirically observed differences across local labor markets.

While this baseline model is consistent with key spatial labor market facts and captures all the main trade-offs in an intuitive and highly transparent way, it does have two limitations. First, as is often the case in models with endogenous separations, it yields a counterfactually upward sloping Beveridge Curve. Second, it does not generate the asymmetry between the role

of his model and contribution to the literature in Kuhn, Manovskii, and Qiu (2022).

of job-finding and separation rates in accounting for differences in the sources of unemployment variation across time and space. To address these shortcomings, we introduce on-the-job search into the model, which is a prominent feature of the data. We calibrate the extended model following the same calibration strategy but add the empirically observed spatial dispersion of job-to-job rates, which hardly vary with local unemployment in the data, as an additional calibration target. We find that the extended model overcomes the two shortcomings of the baseline model but preserves its success along the other dimensions. Quite remarkably, the model not only matches the dispersion of unemployment and vacancies in the cross-section and their volatility over the business cycle, it also correctly attributes the different roles of job-finding and separations in the cross-section and over time.

To understand the mechanics of how on-the-job search reconciles theory with data, it is instructive to consider the comparative statics with respect to productivity. In the cross section, the model implies that differences in productivity across locations induce larger changes in separation rates than in job-finding rates, making the changes in separation rates more important in determining unemployment rate differences across space. Thus, a cross-sectional increase in productivity results in a significant decline in the separation rate and only a muted increase in job-finding rate. However, over the business cycle, a similar change in productivity has to result in a stronger reaction of the job-finding rate and a muted response of separation rate. Procyclical worker mobility provides a natural resolution to this tension. While the rate of job-to-job mobility is virtually constant in the cross-section, it is as volatile as the job-finding rate over the business cycle. Procyclical job-to-job mobility implies that after an aggregate productivity increase, more workers are willing to move to a new job. The larger pool of searchers stimulates vacancy creation by employers, as vacancies now become easier to fill. At the same time, a higher number of vacancies implies that it becomes easier for unemployed workers to find a job so that the job-finding rate increases. A higher job-finding rate reduces the surplus of current matches, thereby, increasing the endogenous separation threshold of existing matches. This induces a procyclical component to the separation rate that counteracts the dominant countercyclical effect of the aggregate productivity increase. In total, the separation rate still declines in booms but the decline is dampened. Hence, procyclical job-to-job mobility amplifies the cyclicality of the job-finding rate and mutes the volatility of the separation rate. As a result, matching the empirically observed degree of worker reallocation through job-to-job transitions reconciles the asymmetric importance of separation and job-finding rates across time and across space.[5]

[5]Procyclical worker reallocation is a much broader phenomenon in the data (Carrillo-Tudela and Visschers, 2020). For example, it is also well known that geographic mobility in the United States is procyclical. Thus, more workers leave their jobs in booms to look for jobs in different locations, muting the countercyclicality of the separation rate over the business cycle relative to the cross-section. Empirically, such regional migration and its cyclical fluctuations alone are, however, much too small to align model and data quantitatively.

A convenient feature of the DMP framework that we built upon is that its efficiency properties are well understood and boil down to the well-known Hosios (1990) condition. For our calibration of the baseline model, we purposefully impose this condition so that job creation is efficient in each local labor market despite vastly different labor market outcomes. Separation decisions are efficient, too, as matches only separate when the match surplus turns negative. Moreover, the Rosen-Roback spatial equilibrium framework implies an efficient labor allocation across local labor markets. Hence, the equilibrium of this model does not require any local labor market policies to achieve efficiency of job creation or job destruction. Labor market tightness that differs across locations is an efficient equilibrium outcome and is not a sign of mismatch that a social planner would like to address through policy, as is often assumed in the literature. To put it differently, the model provides a benchmark for labor market conditions that might be expected to prevail in a given location. Thus, it is not the deviations of labor market tightness from, say, the national average that could signal mismatch and suggest a role for policy, but the deviations from the prediction of the model. Moreover, labor market performance in some individual locations in the data deviates from the predictions of the model, sometimes considerably. It is these deviations from the model predictions that can be used to assess the effects of local economic policies.

The rest of the paper is organized as follows. In Section 2, we describe the relevant labor market facts using the data from Germany, the United States, and the United Kingdom. In Section 3, we present the baseline model, which we take to the data and show that its quantitative implications are in line with the regional U.S. labor market data. In Section 4, we extend the baseline model to allow for the incidence of job-to-job transitions and contrast the cross-sectional implications and business-cycle implications of the model. Section 5 concludes.

2 Facts

This section characterizes differences across local labor markets using microdata from Germany, the United States, and the United Kingdom. Although data sources are country-specific, they are generally consistent in terms of labor market concepts. Some details of variable construction and additional results are relegated to Appendix I. We aim at describing steady states of labor market dynamics and therefore pool data over time. Overall, we find strikingly similar patterns of the geography of job creation and job destruction across countries. The close alignment suggests that these patterns represent robust facts characterizing local labor market differences. We start our analysis with Germany where the available data are the most comprehensive.

2.1 Germany

Data for Germany come from three administrative data sources. Regional labor market data on vacancies, unemployment, and labor force are obtained as monthly time series from the statistics division of the German employment office for the time period from December 1999 to April 2020.[6] The German employment office administers all unemployed workers and registered vacancies in Germany so that regional data statistics are based on the universe of these data for Germany.

We construct regional worker flows based on IAB social security data from the sample of integrated employment biographies (SIAB).[7] The data constitute a 2% sample of all workers covered by social security legislation. Employment spells are reported at the location of work and we impute the location of the last employer to unemployment spells.[8] We follow Hartung, Jung, and Kuhn (2018) in constructing monthly worker flows from daily social security records and construct worker flow rates using annual averages of monthly flows from 2000 to 2017.[9] We always refer to the share of workers who transition from employment to unemployment (EU rate) as separation rate and the share of workers who transition from unemployment to employment (UE rate) as job-finding rate. Using the SIAB data, we also construct measures of the local labor market composition by age, gender, education, occupations, and industries as annual average employment shares of the respective groups. Annual local productivity data (real GDP per worker) come from the working group of the state statistical offices (*Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder*).

We use commuting zones to represent local labor markets. All data are available at the district (*Kreis*) level – analogous to U.S. counties – and we aggregate districts to 194 commuting zones based on 2018 commuting zone definitions. We use the crosswalk provided by the Federal Office for Building and Regional Planning to map district definitions over time. We use employment weights in the aggregation if districts are split between different commuting zones.

2.1.1 Geography of Unemployment in Germany

We begin by documenting the dispersion and persistence of differences in unemployment rates over time. The left panel of Figure 1 shows the unemployment rates across German commuting

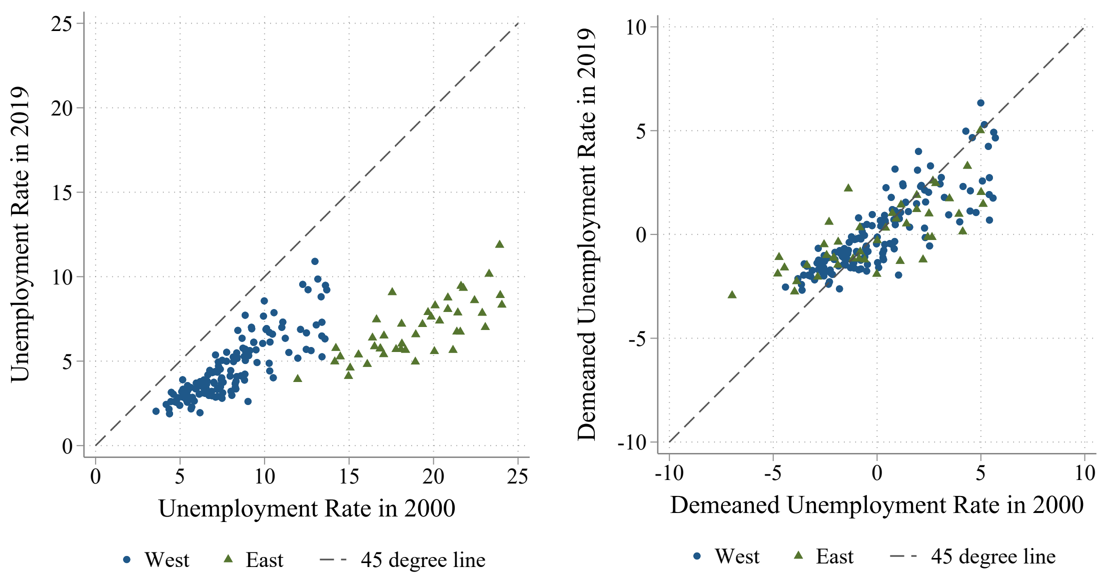
[6] These data have been obtained as special data request number 301063.

[7] Sample of Integrated Labour Market Biographies of the Institute for Employment Research (IAB) (version 1975 2017). Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the IAB (Antoni, Ganzer, and vom Berge, 2019).

[8] For cases where no previous employment spell exists, we use the next employment spell to assign the location to unemployment spells.

[9] There is no information on unemployment spells for years 2005 and 2006 so that these years are missing in our analysis.

Figure 1: Dispersion and Persistence of Unemployment across German Local Labor Markets

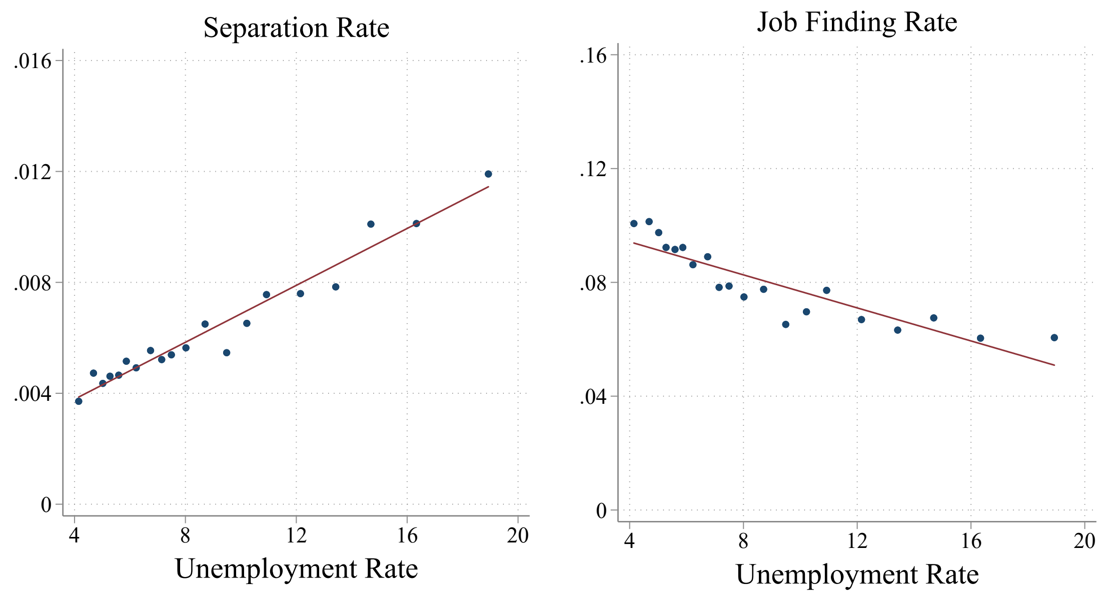


Notes: Unemployment rates across commuting zones in Germany in 2000 and 2019. Blue dots show commuting zones in West Germany and green triangles commuting zones in East Germany. The left panel shows unemployment rates and the right panel demeaned unemployment rates within East and West Germany. The dashed line in both panels is the 45-degree line.

zones in 2000 and 19 years later in 2019. Unemployment rates measured almost two decades apart show a striking positive correlation. All observations are below the 45-degree line indicating that unemployment rates declined substantially across all local labor markets between 2000 and 2019. The decline is particularly salient in East German labor markets that are marked as green triangles. To remove the aggregate labor market trend of falling unemployment rates over time, we remove the average unemployment rate in both years separately for East and West German labor markets and plot the results in the right panel of Figure 1. The observations now align closely with the 45-degree line indicating a high degree of persistence. The correlation of local unemployment rates over this 19-year time period is 0.84 (0.77) among labor markets in West (East) Germany. Hence, the high persistence does not stem from differences between East and West Germany but holds within the two regions. Appendix Figure A-1 demonstrates that the persistence of local unemployment rates does not depend on the particular time period or the specific years considered in Figure 1.

The dispersion of unemployment rates is not only very persistent but also very large. In 2000 and 2019, we find unemployment rates to vary by around 5 percentage points above and below the mean unemployment within each region. In 2000, unemployment rates are as low as 3.6% in Ebersberg (Bavaria) and as high as 24.0% in Oberspreewald (Brandenburg). This dispersion also prevails if we only consider the 81 non-rural commuting zones where the unemployment rate

Figure 2: Separation and Job-Finding Rate across German Local Labor Markets



Notes: This figure plots bin-scatter data of the separation rate (the left panel) and the job finding rate (the right panel) against the unemployment rate across German local labor markets. The red line is the linear fit.

varies between 3.6% and 21.4%. In 2019 after unemployment rates have been trending down for 15 years, unemployment rates still differ substantially from 1.9% in Donau-Ries (Bavaria) to 11.9% in Uckermark (Brandenburg).

To explore the sources of these large and persistent spatial unemployment rate differences, we plot in Figure 2 the spatial disparity in separation rate, i.e., the transition probability from employment to unemployment, and in job-finding rate, i.e., the transition probability from unemployment to employment, across German local labor markets. There are two important results apparent from Figure 2. First, as we move from low- to high-unemployment locations, the separation rate rises and job-finding rate falls. Second, the elasticity of the separation rate to local unemployment is larger than the corresponding elasticity of the job-finding rate. Separation rates increase by a factor of three whereas job-finding rates are only cut in half when we go from low- to high-unemployment local labor markets. These different elasticities suggest that differences in separation rates account for a larger fraction of spatial unemployment differences than differences in job-finding rates.

We quantify the latter observation through a formal variance decomposition. To this end, we apply the standard business-cycle decomposition of unemployment rate fluctuations (e.g., Fujita and Ramey, 2009) to the cross section of local labor markets, as in Bilal (2021). The decomposition is based on the steady-state condition for unemployment rates from a two-state labor market model within each location j

$$(1-u_j) \times s_j = u_j \times f_j \Longrightarrow \log \frac{u_j}{1-u_j} = \log s_j + (-\log f_j)\,,$$

where u_j, s_j, and f_j denote the steady-state unemployment rate, separation rate, and job-finding rate at location j, respectively.[10] To account for the approximation error of the two-state steady-state formulation, we further include an approximation error term ϵ_j

$$\log \frac{u_j}{1-u_j} = \log s_j + (-\log f_j) + \epsilon_j,$$

and arrive at a spatial application of the well-known unemployment decomposition:

$$\mathrm{var}\left(\log \frac{u}{1-u}\right) = \mathrm{cov}\left(\log \frac{u}{1-u}, \log s\right) + \mathrm{cov}\left(\log \frac{u}{1-u}, -\log f\right) + \mathrm{cov}\left(\log \frac{u}{1-u}, \epsilon\right), \quad (1)$$

where the variance and covariances are taken across local labor markets. The left-hand side of the decomposition captures observed unemployment rate dispersion and the first two terms on the right-hand side decompose this dispersion into a component from variation in separation rates and a component from job-finding rates, both of which are also observed in the data. The decomposition yields that the separation rate, job-finding rate, and the residual term account for 62.4%, 33.2%, and 4.4%, respectively, of the cross-sectional variation in unemployment rates in Germany. Appendix Figure A-2 visualizes this decomposition for German local labor markets.

2.1.2 Geography of Job Creation in Germany

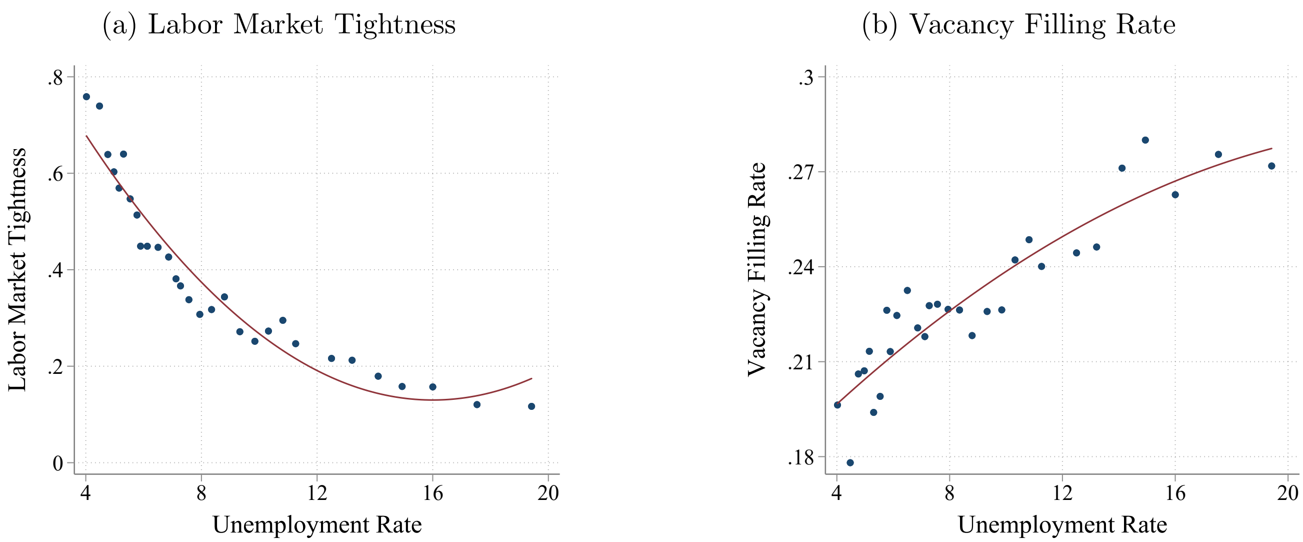
To characterize the differences in hiring prospects and vacancy creation across local labor markets, we first document the properties of labor market tightness, defined as the ratio of vacancies posted in a local labor market to the number of unemployed workers in that market. Figure 3a shows that there is a systematic negative relationship between tightness and unemployment rates across local labor markets.[11] Thus, labor markets with lower unemployment rates are tighter, i.e., there are more vacancies per unemployed worker in lower unemployment regions.

While the definition and measurement of tightness as the ratio of vacancies to unemployment is most common in the literature, it can also be defined as the ratio of vacancies to the sum of all searchers, unemployed and employed. The latter definition is rarely implemented as the search intensity of employed workers is difficult to measure. Fortunately, we are able to measure

[10] In Appendix I.1.3, we consider a three-state decomposition incorporating flows to and from nonparticpation and find that this has no material effect on our findings.

[11] The level of labor market tightness is adjusted using the Institute for Employment Research (IAB) estimates for the total number of vacancies, including those not registered with employment offices.

Figure 3: Tightness and Vacancy Filling Rate across German Local Labor Markets



Notes: Local labor market tightness and vacancy filling rates across German commuting zones. The left panel shows bin-scatter data of local labor market tightness against local unemployment rates. The right panel shows binscatter data of vacancy filling rates against local unemployment rates. The red line in both panels shows the quadratic fit to the raw data.

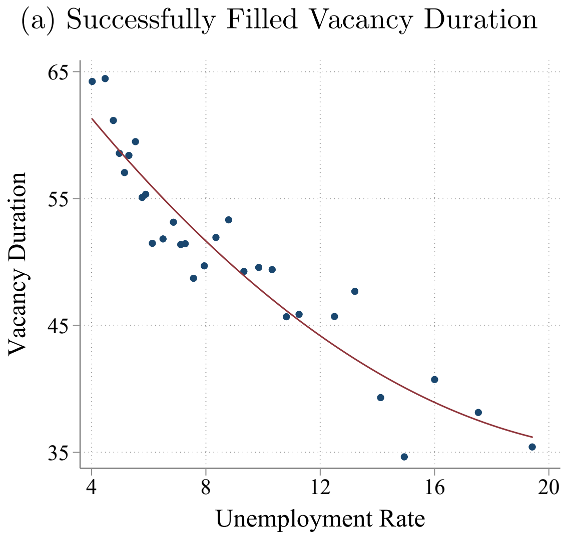
search by employed workers across local labor markets in Germany using additional microdata from the IAB vacancy survey. Using this measurement, we show in Appendix I.1.5 that local labor markets with low unemployment remain tighter after accounting for on-the-job search.

We next consider whether the differences in local labor market tightness translate into systematic differences in job-filling rates.[12] While vacancy posting initiates the recruiting process, job-filling rates are its end result. They reflect the combined effects of all intermediate factors, including potential heterogeneity in the prevalence of on-the-job search across locations or potential heterogeneity in match acceptance decisions. Thus, job-filling rates provide the most revealing measure of geographic differences in the speed with which firms recruit workers. Figure 3b shows that the probability to fill a vacancy within a month is about 50% higher in high-unemployment labor markets compared to low-unemployment labor markets. Thus, there are fewer vacancies per unemployed worker in higher unemployment labor markets and firms fill those vacancies faster. In labor markets with low unemployment, firms post more vacancies per unemployed worker and it takes firms much longer to fill them.

The richness of the German data allows us to explore the relationship between local unemployment rates and hiring prospects of firms in even greater detail. The left panel of Figure 4

[12]The German data allow to identify vacancy outflows that result in an employment relationship. Job-filling rates are computed as the outflow of such successfully filled vacancies over the sum of the stock of existing vacancies from the previous period and the inflow of new vacancies during the current period, as in Manning and Petrongolo (2017).

Figure 4: Vacancy Duration and Share of Filled Vacancies across German Local Labor Markets



Notes: Vacancy duration and share of successfully filled vacancies across local labor markets in Germany. The left panel shows bin-scatter data on vacancy duration (in days) of successfully filled vacancies against local unemployment rates. The right panel shows bin-scatter data of the share of successfully filled among all withdrawn vacancies against local unemployment rates. The red line in both panels shows the quadratic fit to the raw data.

shows a direct measure of the average completed vacancy duration of successfully filled vacancies.[13] This direct evidence on completed vacancy duration corroborates the findings based on job-filling rates: vacancies are filled faster in high-unemployment locations. The differences are large, varying from 65 days in low-unemployment locations to 35 days in high-unemployment locations. However, not all vacancies are successfully filled and some end up being retracted without hiring a worker. In the right panel of Figure 4, we plot the share of successfully filled vacancies among all unlisted vacancies against local unemployment. Evidently, not only are vacancies filled faster in higher unemployment locations, but also a higher fraction of posted vacancies in those markets ends up being successfully filled with a worker.

An important outstanding question is whether the systematic differences in vacancy posting and filling across local labor markets are simply a reflection of the differences in worker or firm composition across these markets. Table 1 contains the results of a regression of labor market tightness and vacancy filling rates on local unemployment rates and local labor market composition controls, including age, gender, education, occupation, and industry shares for each local labor market derived from the IAB microdata together with year fixed effects to account for macroeconomic trends.[14] The results reveal that the relationship between tightness

[13] Average duration does not coincide with the inverse of job-filling rates if vacancy durations differ. See Kuhn and Ploj (2020) for the case of worker flow rates.

[14] Estimated coefficients in the time fixed-effect specification are equivalent to the average cross-sectional coefficients over different years.

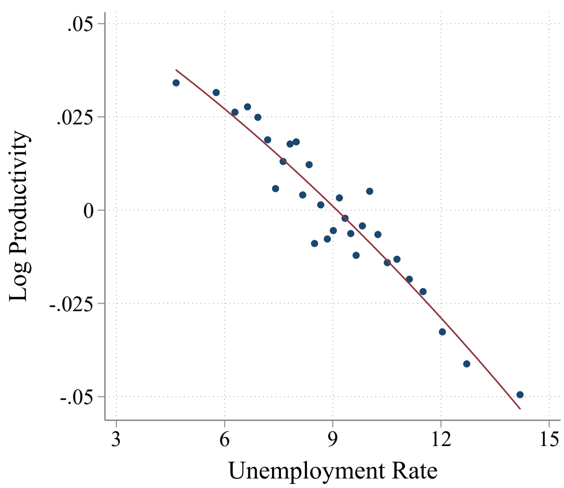
Table 1: Tightness and Vacancy Filling Rate across German Local Labor Markets

	Labor Market Tightness		Vacancy Filling Rate	
	(1)	(2)	(3)	(4)
Unemployment Rate	-3.410***	-2.455***	0.631***	0.345***
	(0.491)	(0.424)	(0.081)	(0.070)
Year FE	Yes	Yes	Yes	Yes
Controls		Yes		Yes
Observations	3492	3492	3492	3492
R-squared	0.64	0.72	0.61	0.67

Clustered standard errors (at the state level), *** $p < 0.01$

Notes: Regression estimates of local labor market tightness and vacancy filling rates on local unemployment rate and additional labor market composition controls across commuting zones in Germany. All regressions include year fixed effects. Controls for local labor market composition include age, gender, education, occupation, and industry shares of employment. Standard errors are clustered at the state level.

Figure 5: Productivity Dispersion across German Local Labor Markets



Notes: Dispersion of residual (log) productivity across local labor markets in Germany. Productivity is real GDP per worker. Data on productivity and unemployment are shown as bin-scatter data residualized for local labor market composition controlling for age, gender, education, occupation, and industry composition of employment, and year fixed effects. We add the mean to residualized unemployment rate on the horizontal axis to ease interpretation.

or job filling and local unemployment remains highly statistically and economically significant. In Appendix I.1.6, we document further that even at the 3-digit occupation level a strong relationship between local unemployment rates and local occupation-specific vacancy duration holds.[15]

Finally, we document the relationship between local unemployment and local productivity, an

[15]We thank Giuseppe Moscarini for suggesting this additional robustness analysis.

important connection to guide the development of a theoretical framework below.[16] Using the same specification and control variables underlying Table 1, we construct residualized output per worker as our measure of local productivity. Figure 5 reveals a systematic negative relationship between the unemployment rate and log productivity with low-unemployment labor markets being more productive. Note that the dispersion of unemployment rates on the horizontal axis is reduced as some of the unemployment rate dispersion is accounted for by observable differences in worker and firm composition across local labor markets.

2.2 United States

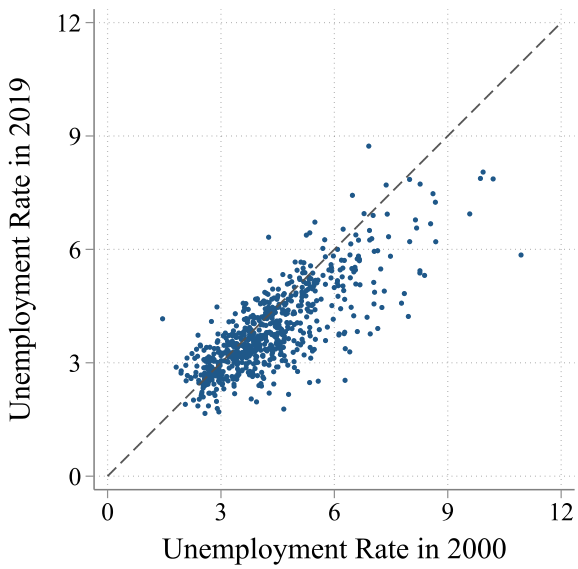
For the United States, we define local labor markets as commuting zones whenever possible, but some variables are only available at the MSA level forcing us to occasionally use that definition instead. We obtain unemployment rates for 2000-2019 from the Local Area Unemployment Statistics program of the U.S. Bureau of Labor Statistics and aggregate county-level statistics to the commuting zone level.[17] We construct worker flows using data from the Current Population Survey (CPS) (Flood et al., 2021). Due to its limited sample size for regional studies, not many counties can be identified in CPS, so we construct worker flows for metropolitan areas instead. To improve the accuracy of estimates, we average monthly worker flow rates over the 20-year period from 2000 to 2019.[18] For vacancy data, we use the Job Openings and Labor Turnover Survey (JOLTS) estimates for 18 largest MSAs with 1.5 million or more employees each for the time period from February 2001 (when the available series starts) to December 2019. These MSAs cover local labor markets with roughly 40% of the entire U.S. labor force in 2019. We construct data for local labor market composition using the Quarterly Workforce Indicators, which is in turn tabulated from the underlying microdata of the Longitudinal Employer-Household Dynamics program. We extract the age, gender, education, and industry composition of employment for each local labor market from these data. Local real GDP per employment data for 2001-2018 come from the Bureau of Economic Analysis Regional Economic Accounts.

[16] Duranton and Puga (2004) thoroughly review theoretical microfoundations of local productivity differences and Papageorgiou (2021) provides a recent quantitative evaluation.

[17] We focus on the 691 commuting zones in the continental United States, which cover all areas in the 48 adjoining U.S. states and the District of Columbia but excludes non-contiguous states of Alaska and Hawaii and other territories such as Puerto Rico.

[18] The Census Bureau warns that estimates for individual metropolitan areas produced from CPS microdata files should be treated with caution, especially for smaller metropolitan areas with populations under 500,000, because of large sampling variability. This small sample issue is especially stark when we compute the outflows from unemployment. To avoid the small sample bias, we pool the whole 20-year sample period of CPS data from 2000 to 2019 to get the worker flows at the MSA level. We focus on MSAs with observations throughout the 20 years and have 181 MSAs in the sample.

Figure 6: Dispersion and Persistence of Unemployment across U.S. Local Labor Markets



Notes: Unemployment rates across U.S. commuting zones in 2000 and 2019. Each dot shows a commuting zone. The horizontal axis shows unemployment rates in 2000 and the vertical axis shows unemployment rates in 2019. The dashed gray line is the 45-degree line. Yuma (AZ) is dropped as an outlier with extremely high unemployment rates of 16.9% in 2000 and 17.2% in 2019.

2.2.1 Geography of Unemployment in the United States

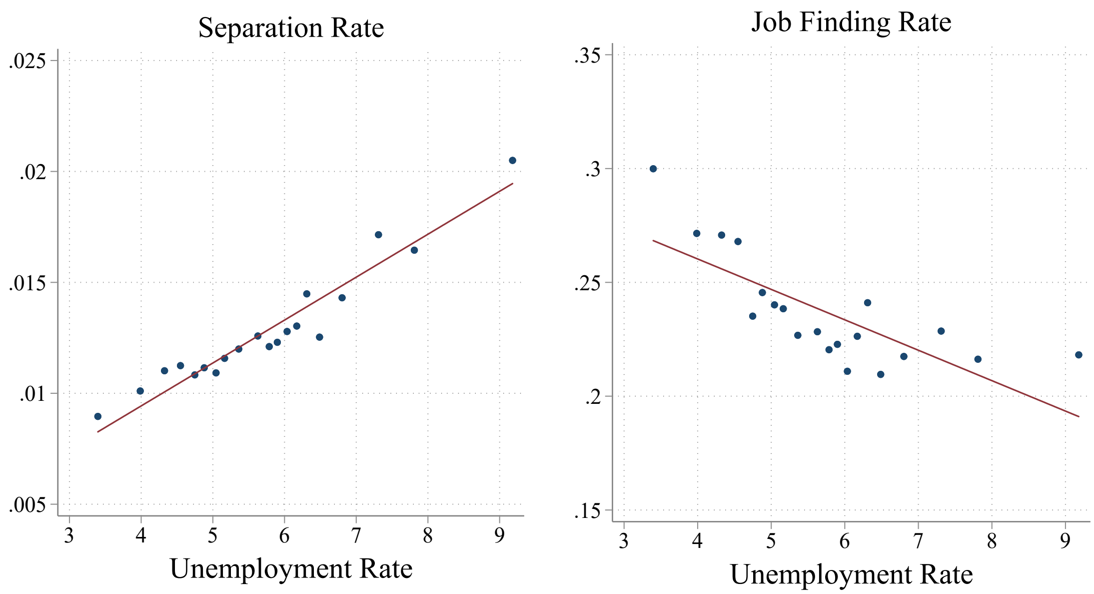
Figure 6 plots local unemployment rates in 2000 against local unemployment rates 19 years later together with the 45-degree line. We observe a large dispersion of unemployment rates across local labor markets. For example, in 2000, the (unweighted) average unemployment rate across commuting zones is 4.3%, with a standard deviation of 1.5%, but we also observe unemployment rates as low as 1.5% and as high as 16.9%.[19] These large local unemployment differences persist even after two decades: local labor markets with high unemployment rates in 2000 are still at the top of the unemployment rate distribution almost 20 years later despite a long labor market boom and the Great Recession in between.[20] Overall, the correlation between unemployment rates in 2000 and 2019 is 0.81. In Appendix I.2.1, we show that this high correlation is not induced by the choice of these two particular years and that the same patterns arise if we use MSAs as the unit of observation for local labor markets.

Figure 7 illustrates that separation rates are increasing and job-finding rates are decreasing

[19]These two locations are not the only extreme lows or highs. Although the highest unemployment commuting zone (where Yuma County, AZ is located) could be treated as an outlier and hence is dropped in Figure 6, the second to the sixth highest CZ-level unemployment rates are 10.9%, 10.2%, 9.9%, 9.9%, and 9.6%. The second to the sixth lowest CZ-level unemployment rates are 1.8%, 1.9%, 2.0%, 2.1%, 2.1%.

[20]Amior and Manning (2018) also document the persistence of local joblessness in the United States, although they focus on the employment-population ratios and do not study spatial differences in job and worker flows. Persistent local joblessness and the migration patterns that are the focus of their paper are consistent with the equilibrium model with free mobility that we develop below.

Figure 7: Separation and Job-Finding Rate across U.S. Local Labor Markets



Notes: This figure plots bin-scatter data of the separation rate (the left panel) and the job finding rate (the right panel) against the unemployment rate across U.S. local labor markets. The red line is the linear fit.

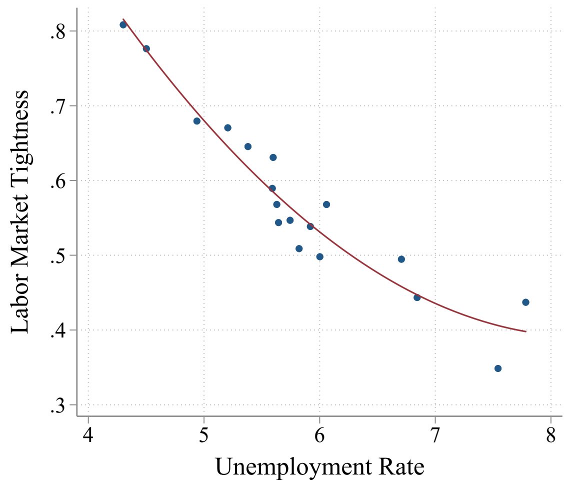
in the local unemployment rate. In addition, the percentage variation in separation rates dominates that in job-finding rates. We find separation rates to double across space, whereas job-finding rates decline by roughly one-third. A formal decomposition in Equation (1) reveals that separation rate differences account for 72.0% of the spatial variation of unemployment in the U.S. labor market and job-finding rate differences account for 32.8% with a residual component of -4.8%. Appendix Figure A-10 visualizes their relative importance in accounting for local unemployment differences.[21]

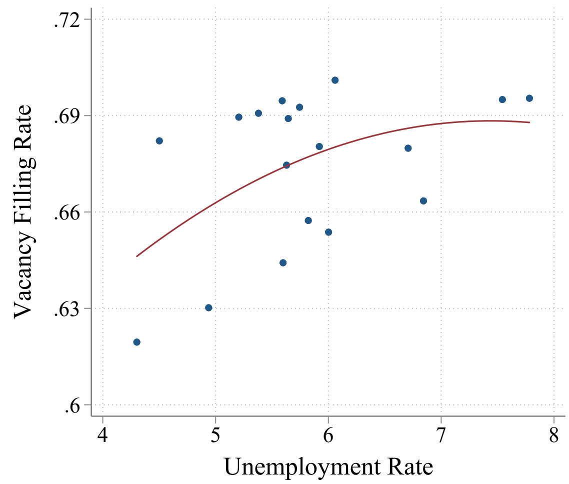
2.2.2 Geography of Job Creation in the United States

Using the newly released JOLTS data for the 18 largest MSAs, Figure 8a illustrates a clear negative relationship between unemployment rates and labor market tightness indicating that there are more open positions per unemployed worker in low-unemployment labor markets. Hence, local labor markets with lower unemployment rates are tighter. The large unemployment dispersion even among these 18 MSAs is notable. To construct the vacancy filling rate, we follow Davis, Faberman, and Haltiwanger (2013) by posing a model of vacancy dynamics at the daily frequency. We then aggregate the daily model to the monthly frequency, at which corresponding data are collected in JOLTS, thus making possible the identification of daily vacancy filling rates

[21] These decomposition results for the United States align closely with those reported in Bilal (2021).

Figure 8: Tightness and Vacancy Filling Rate across U.S. Local Labor Markets





Notes: Labor market tightness and vacancy filling rate across the 18 largest MSAs in the United States. The left panel shows labor market tightness of each MSA against the local unemployment rate. The right panel shows the local vacancy filling rate each MSA against local unemployment rates. The red line in both panels shows the quadratic fit to the raw data.

from data on monthly hires. The resulting daily filling rate q is then transformed to its monthly counterpart $1-(1-q)^D$, where D is the number of working days per month (set to 26), in order to get a comparable variable to the monthly filling rate as in the previous section. Despite the limited number of observations in the JOLTS MSA data, Figure 8b clearly indicates that the vacancy filling rate is increasing in local unemployment.

To control for the effect of differences in the worker and employer composition on labor market tightness and vacancy filling rates across local labor markets, we once again run a set of linear regressions with local labor market composition controls. The results in Table 2 indicate that even after accounting for local labor market composition, the unemployment rate remains highly significant in its relationship to labor market tightness and the vacancy filling rate.[22]

Finally, Figure 9 documents a clear negative relationship between local productivity (output per worker residualized using the year fixed effects and local labor market composition controls as in Table 2) and local unemployment in the United States.

[22]The result is robust to an alternative measure, the vacancy yield, defined as the number of monthly hires per vacancy, which has been used by Gavazza, Mongey, and Violante (2018). The vacancy yield compares the stock of vacancies at one moment in time with the flow of all new hires during a month. The faster vacancies are filled, the fewer vacancies will be recorded in the stock of vacancies on the reference day during the month. Thus, a higher vacancy yield is also indicative of a shorter vacancy duration, despite not dealing with time aggregation.

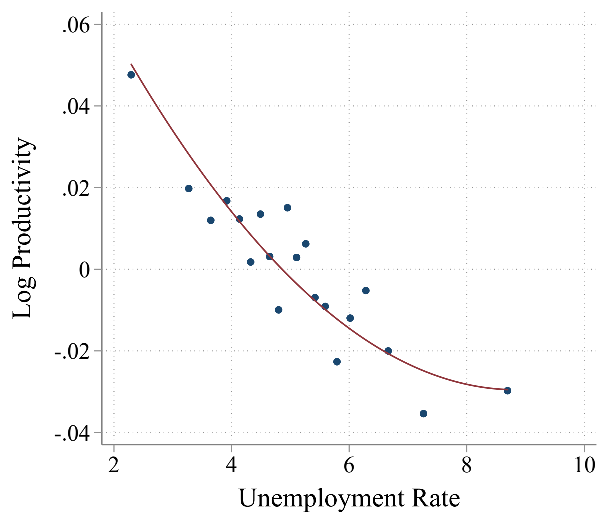
Table 2: Tightness and Vacancy Filling Rate across U.S. Local Labor Markets

	Labor Market Tightness		Vacancy Filling Rate	
	(1)	(2)	(3)	(4)
Unemployment Rate	-8.678***	-6.187***	0.890**	0.652***
	(1.118)	(1.615)	(0.361)	(0.161)
Year FE	Yes	Yes	Yes	Yes
Controls		Yes		Yes
Observations	337	337	337	337
R-squared	0.87	0.89	0.81	0.88

Clustered standard errors (at the MSA level), ** $p < 0.05$, *** $p < 0.01$

Notes: Regression estimates of local labor market tightness and vacancy filling rates on local unemployment rate and additional labor market composition controls across the 18 largest U.S. MSAs. All regressions include year fixed effects. Controls for local labor market composition include age, gender, education, and industry shares of employment. Standard errors are clustered at the MSA level.

Figure 9: Productivity Dispersion across U.S. Local Labor Markets



Notes: Dispersion of residual (log) productivity across commuting zones in the United States. Productivity is real GDP per worker. Data on productivity and unemployment are shown as bin-scatter data residualized for year fixed effects and local labor market composition using controls for age, gender, education, and industry composition of employment. We add the mean to residualized unemployment rate on the horizontal axis to ease interpretation.

2.3 United Kingdom

For the United Kingdom, we obtain local labor market data from Nomis labor market statistics that are provided by the Office for National Statistics (ONS).[23] The unit of observation for local labor markets is the Local Authority District (LAD) and there are 378 districts with non-missing data.[24] We rely on the official estimates for district-level unemployment from 2004 (when the available series starts) to 2018 by the ONS and Ray Chambers.[25] To compute the stocks and flows of vacancies, we rely on administrative Jobcentre Plus data of the U.K. Public Employment Service between April 2004 and April 2006.[26] During this time period all vacancies were followed up with employers until they were filled through any recruitment channel.[27] We calculate the vacancy filling rate as outflows of successfully filled vacancies divided by the stock of vacancies.[28] We measure local labor market composition by age, gender, occupation and industry from tabulations of the Annual Population Survey by Nomis. We construct local productivity as local gross value added obtained from ONS divided by local employment.

To construct local labor market separation and job-finding rates, we start from the observation that unemployment benefit claims data is a good predictor of local unemployment in the United Kingdom (see Footnote 25). We therefore combine the Job Seekers Allowance (JSA) data with information on local unemployment. The JSA data are provided by ONS at the local labor market level with information on stocks of benefit recipients as well as data on in- and outflows of workers receiving JSA benefits. We adjust the JSA data to be consistent with local unemployment data based on the assumption that the share of JSA-covered workers as a fraction of the stock of unemployed workers is the same for the flow data on in- and outflows from unemployment. We take the average worker flow rates from 2004 to 2015. In Appendix I.3.2, we provide details of the method and evidence of its accuracy.

2.3.1 Geography of Unemployment in the United Kingdom

Figure 10 reports the dispersion and persistence of regional unemployment rates for the United Kingdom. We find that unemployment rates vary strongly in the cross section ranging from

[23]See https://www.nomisweb.co.uk.

[24]The average size of a LAD is 77,681 persons in 2005 and the Isles of Scilly and the City of London have missing data because of data disclosure.

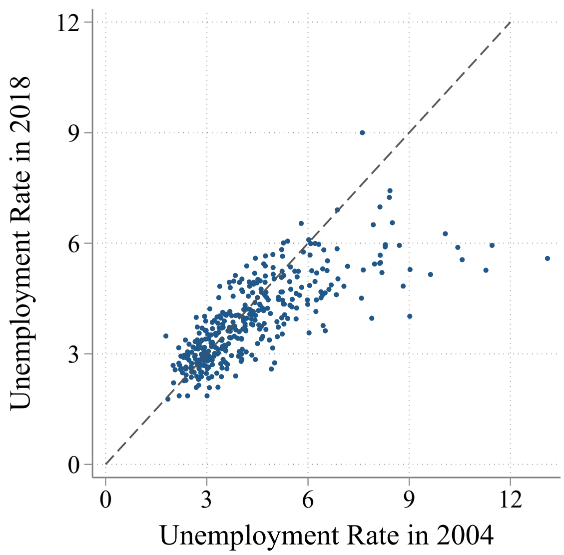
[25]To deal with the limited sample size of the UK Labor Force Survey (LFS), the key element of their methodology is to combine the employment status from the LFS with the unemployment benefit claimant count data, which is a strong predictor for unemployment though not a direct measure for unemployment. These estimates are now accredited as the official ones for local authority districts.

[26]The vacancy data do not cover Northern Ireland.

[27]In subsequent years, vacancies are automatically withdrawn according to an ex ante closure date agreed with the employer regardless of whether they are filled or not.

[28]Manning and Petrongolo (2017) impute outflows as the difference between the monthly variations in vacancy stocks including contemporaneous inflows. We get similar results using their imputation.

Figure 10: Dispersion and Persistence of Unemployment across U.K. Local Labor Markets

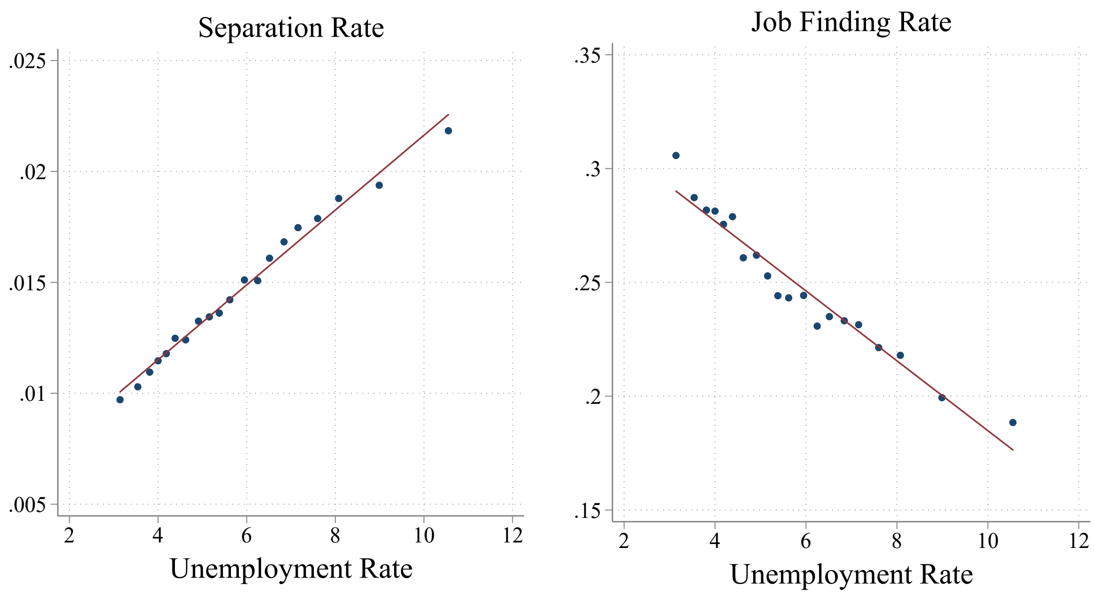


Notes: Unemployment rates across local authority districts in the United Kingdom in 2004 and 2018. Each blue dot shows one local authority district. The horizontal axis shows data in 2004 and the vertical axis data in 2018. The dashed gray line is the 45-degree line.

1.8% to 13.1% in 2004 and from 1.8% to 9.0% in 2018. Although we observe a decline in unemployment rates for high unemployment labor markets between 2004 and 2018, we still find high-unemployment labor markets in 2004 at the top of the unemployment rate distribution in 2018. Overall, the correlation of local unemployment rates in these two years is 0.76. Appendix I.3.1 documents that this correlation is not restricted to these two years.

Using the local worker flow data that we constructed for the United Kingdom, we decompose local unemployment rate differences into contributions from differences in separation and job-finding rates. Figure 11 illustrates that separation rates are increasing with local unemployment rates and job-finding rates are decreasing with local unemployment rates. As is evident in the figure, the percentage decline of separation rates is roughly twice as large as the increase of job-finding rates, indicating that differences in separation rates across local labor markets are the dominant driver of local unemployment rate differences. The formal decomposition attributes 64.3% of the unemployment variation across space to differences in separation rates, 35.8% to job-finding rates, and -0.1% to the residual. Appendix Figure A-13 visualizes this decomposition result.

Figure 11: Separation and Job Finding Rate across U.K. Local Labor Markets



Notes: This figure plots bin-scatter data of the separation rate (the left panel) and the job finding rate (the right panel) against the unemployment rate across U.K. local labor markets. The red line is the linear fit.

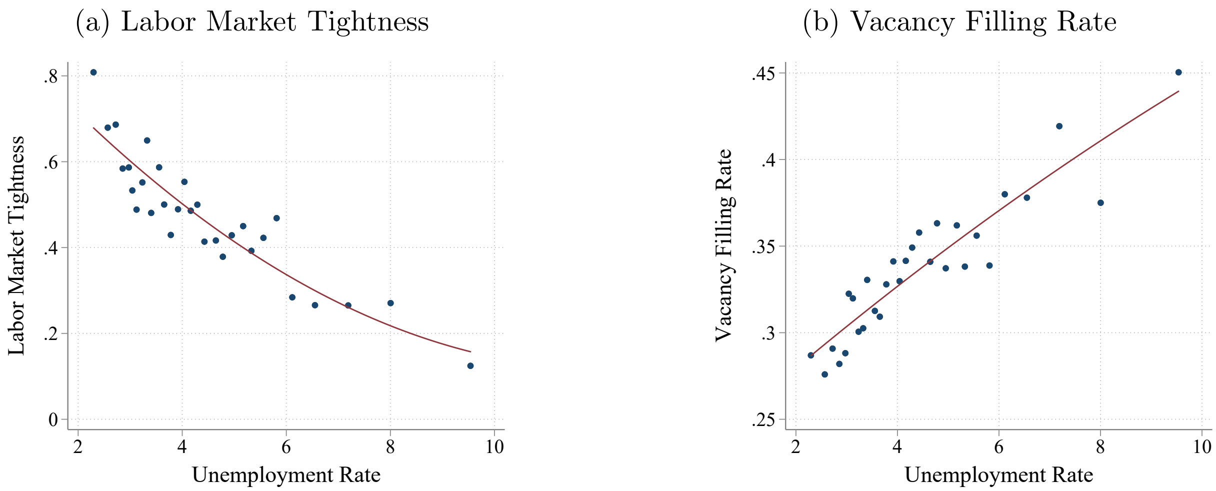
2.3.2 Geography of Job Creation in the United Kingdom

In Figure 12, we plot the labor market tightness and the vacancy-filling rate across labor markets with different unemployment rates. Figure 12a corroborates the finding that locations with lower unemployment rates are tighter with more vacancies per unemployed worker. Figure 12b shows that having more vacancies per unemployed worker in a labor market makes it harder for employers to fill their vacancies resulting in a lower job-filling rate.

To control for the influence of differences in worker and employer composition across local labor markets, we regress local labor market tightness and vacancy-filling rates on local unemployment and control for the age, gender, occupation, and industry composition of local labor markets. For the United Kingdom, the time span of vacancy data is short so that no controls for macroeconomic trends are needed in the regression. Table 3 reports the coefficients on the local unemployment rate. We find that the relationship of labor market tightness and vacancy-filling rates with unemployment remains almost unaffected after including local labor market controls and is strongly statistically and economically significant.

Finally, Figure 13 shows local labor market productivity in the United Kingdom for different levels of unemployment controlling for local labor market characteristics as in Table 3. We find a clear negative correlation with high-unemployment labor markets being on average less productive.

Figure 12: Tightness and Vacancy Filling Rate across U.K. Local Labor Markets



Notes: Local labor market tightness and vacancy filling rates across local authority districts in the United Kingdom. The left panel shows bin-scatter data of local labor market tightness against local unemployment rates. The right panel shows bin-scatter data of vacancy filling rates against local unemployment rates. The red line in both panels shows the quadratic fit to the raw data.

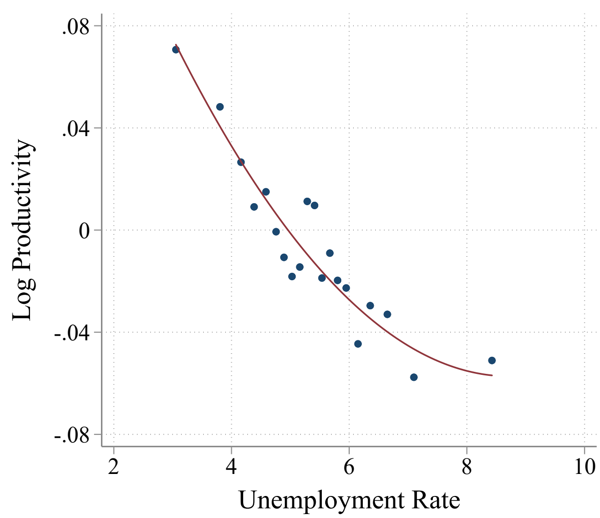
Table 3: Tightness and Vacancy Filling Rate across U.K. Local Labor Markets

	Labor Market Tightness		Vacancy Filling Rate	
	(1)	(2)	(3)	(4)
Unemployment Rate	-7.594***	-9.386***	2.138***	2.393***
	(1.198)	(1.510)	(0.371)	(0.345)
Controls		Yes		Yes
Observations	378	378	378	378
R-squared	0.28	0.43	0.33	0.51

Clustered standard errors (at the region level), *** $p < 0.01$

Notes: Regression estimates of local labor market tightness and vacancy filling rates on local unemployment rate and additional labor market composition controls across U.K. local authority districts. Controls for local labor market composition include age, gender, occupation, and industry shares of employment. Standard errors are clustered at the region level (9 regions in England, one each in Scotland and Wales. Data for Northern Ireland are not available.).

Figure 13: Productivity Dispersion across U.K. Local Labor Markets



Notes: Dispersion of residual (log) productivity across local authority districts in the United Kingdom. Productivity is real GDP per worker. Data on productivity and unemployment are shown as bin-scatter data residualized using year fixed effects and local labor market composition using controls for age, gender, occupation, and industry shares of employment. We add the mean to residualized unemployment rate on the horizontal axis to ease interpretation.

2.4 Summary of Empirical Findings and Modeling Implications

In this section, we provided a comprehensive analysis of the geography of job creation and job destruction. Our empirical analysis for Germany, the United States, and the United Kingdom uncovered a consistent picture of local labor market differences.

In all three countries, unemployment rate differences across local labor markets are large and highly persistent. Moreover, unemployment rates and productivity are negatively correlated with high-unemployment labor markets being less productive on average.

Considering worker flows, in all three countries job-finding rates decline and separation rates increase in the local unemployment rate. About two-thirds of unemployment differences across local labor markets are accounted for by differences in separation rates, with differences in job-finding rates accounting for the remaining one-third. The latter fact represents the key theoretical challenge to the spatial DMP model of Kline and Moretti (2013), in which differences in local unemployment are induced only by differences in job-finding rates.

On the hiring side of the labor market, we find that in all three countries local labor markets with lower unemployment rates are tighter, i.e., have more vacancies per unemployed worker. Moreover, it takes longer to fill a vacancy in local labor markets with lower unemployment rates. The spatial job sorting model in Bilal (2021) is inconsistent with this fact because its core sorting mechanism leads high productivity firms to locate in areas where both unemployment and tightness are low and vacancy filling rates are high.

3 Baseline Model

Having documented the key empirical regularities characterizing local labor markets, we now turn to searching for the theoretical framework that can be used to jointly account for these facts and lay the foundation for the analysis of local labor market policies. Our objective in this paper is to identify the main elements of this framework that we expect to be essential to match the prominent patterns in the data and that we hope will form the backbone of the more elaborate models used for policy analysis in practice. Thus, we strive for simplicity and transparency of the model that would allow us to isolate the key mechanisms.

In this section, we develop the baseline version of the model that identifies the role of endogenous job creation and destruction for spatial unemployment rate differences. Qualitatively, the empirical regularities documented above clearly point to a model based on the DMP framework. Equilibrium unemployment arises because each local labor market is frictional and the local labor markets differ in their level of aggregate productivity. Firms create jobs in each market until the value of a vacancy falls to zero in each of them. The surplus of a match between a worker and a firm is larger in more productive locations, and this induces higher vacancy creation and tightness there. As there are more vacancies per unemployed worker in such markets, the probability to fill each vacancy declines while the probability of an unemployed worker to find a job increases. In addition, job matches between workers and firms are characterized by stochastic idiosyncratic productivity. When idiosyncratic productivity becomes sufficiently low, the match separates.[29] In more productive locations, the match surplus is higher, so that matches can tolerate a wider range of idiosyncratic productivity realizations, and as a result job separations are lower. Higher job-finding and lower separation rates imply lower unemployment in high-productivity locations. To sustain the equilibrium with multiple local labor markets heterogeneous in their productivity, we assume that the costs of living vary across locations, making unemployed workers indifferent between them. In other words, we embed frictional heterogeneous local labor market into the classic Rosen (1979)-Roback (1982) spatial equilibrium framework. The rest of this section formalizes this setting and explores its quantitative ability to match the facts. Subsequently, we will add additional mechanisms to this baseline model and assess their role.

There are N local labor markets indexed by $j = \{1, 2, \ldots, N\}$. Each location j is characterized by its exogenous productivity A_j and a local cost of living c_j. At each location, there is a positive mass of risk-neutral, infinitely lived workers and of profit-maximizing firms. Workers and firms are *ex ante* homogeneous and discount the future at a common discount factor $\beta \in (0, 1)$. Time is discrete.

A worker can be either employed or unemployed. Regardless of the employment status, each worker incurs the local cost of living c_j. Employed workers receive a local wage and unemployed workers receive flow utility z. Unemployed workers can freely move between locations and firms can freely decide in which local labor market to post a vacancy at per-period cost κ. Firms operate constant returns to scale technologies so that firm size remains undetermined and we consider single worker-firm matches.[30] In the baseline model, only unemployed workers search for vacant jobs (we will introduce on-the-job search in Section 4). Contacts between workers and firms are governed by a constant-returns-to-scale matching function in each local labor market $M(U_j, V_j)$, where U_j denotes unemployed workers and V_j denotes the vacancies in local labor market j. We use lower case letters for corresponding rates normalized by the labor force, i.e., u_j denotes the unemployment rate and v_j the vacancy rate. We denote by $\theta_j = v_j/u_j$ labor market tightness. The contact rate for searching workers is $f(\theta_j) = M(1, \theta_j)$ and for vacant firms it is $q(\theta_j) = M\left(\theta_j^{-1}, 1\right)$, with $f(\theta_j) = \theta_j q(\theta_j)$.

[29] Den Haan, Ramey, and Watson (2000) and Merz (1999) provide business-cycle models to study the role of endogenous separations for aggregate unemployment dynamics.

[30] Models with frictional labor markets and firm size determined through decreasing returns include Elsby and Michaels (2013), Kaas and Kircher (2015), and Schaal (2017).

Each worker-firm match produces period output $y_j = A_j\varepsilon$ that is the product of the location-specific productivity A_j and an i.i.d. match-specific stochastic productivity ε distributed according to $F(\varepsilon)$. Idiosyncratic productivity shocks realize at the end of the period and each worker-firm pair (including the newly created matches) decides whether to continue the match in the next period. If they decide to separate, the worker enters next period as unemployed. The separation decisions are privately efficient and occur when the joint match surplus becomes negative given the realization of ε. In addition, there are exogenous separations with probability δ that capture separations in the data that are independent of idiosyncratic match productivity, e.g., plant closures, mass layoffs, etc. Wages, $w_j(\varepsilon)$, are determined through state-contingent generalized Nash bargaining with worker bargaining power $\eta \in (0,1)$. Firms retain the remaining output $A_j\varepsilon - w_j(\varepsilon)$.

The value functions for unemployed and employed workers in local labor market j have the following recursive representation

$$V_j^u = z - c_j + \beta \left\{ V_j^u + f(\theta_j)(1-\delta)\,\mathbb{E}_{\varepsilon'}\left[V_j^e(\varepsilon') - V_j^u\right]^+ \right\}, \tag{2}$$

$$V_j^e(\varepsilon) = w_j(\varepsilon) - c_j + \beta \left\{ V_j^u + (1-\delta)\,\mathbb{E}_{\varepsilon'}\left[V_j^e(\varepsilon') - V_j^u\right]^+ \right\}, \tag{3}$$

where $\mathbb{E}_{\varepsilon'}[\bullet]^+$ denotes the expectation over the max $\{\bullet, 0\}$ with respect to future productivity ε'. This maximum operator over continuation values represents the optimal separation decision. The value of a matched firm V_j^p and a firm with a vacancy V_j^v in local labor market j have the following recursive representations

$$V_j^p(\varepsilon) = A_j\varepsilon - w_j(\varepsilon) + \beta(1-\delta)\,\mathbb{E}_{\varepsilon'}\left[V_j^p(\varepsilon')\right]^+, \tag{4}$$

$$V_j^v = -\kappa + \beta q(\theta_j)(1-\delta)\,\mathbb{E}_{\varepsilon'}\left[V_j^p(\varepsilon')\right]^+. \tag{5}$$

where we already impose that in equilibrium the continuation value of the firm after separation is zero. The optimal endogenous separation decision is characterized by a cutoff value ε_j^R so that matches separate if idiosyncratic productivity falls short of this cutoff value and produce otherwise. We derive in Appendix II.1 that the cutoff value ε_j^R, the local labor market tightness θ_j, and the wage $w_j(\varepsilon)$ at each location can be characterized as

$$0 = A_j\varepsilon_j^R - z + \beta(1-\delta)(1-\eta f(\theta_j))\,\mathbb{E}_{\varepsilon'}\left[S_j(\varepsilon')\right]^+, \tag{6}$$

$$\kappa = \beta q(\theta_j)(1-\delta)(1-\eta)\mathbb{E}_{\varepsilon'}\left[S_j(\varepsilon')\right]^+, \tag{7}$$

$$w_j(\varepsilon) = (1-\eta)z + \eta A_j\varepsilon + \eta\kappa\theta_j. \tag{8}$$

The resulting separation rate π_j^{eu}, job-finding rate π_j^{ue}, and job-filling rate π_j^{vp} within each local labor market are

$$
\begin{aligned}
\pi_j^{eu} &= 1-(1-\delta)\left(1-F\left(\varepsilon_j^R\right)\right), && (9)\\
\pi_j^{ue} &= f\left(\theta_j\right)(1-\delta)\left(1-F\left(\varepsilon_j^R\right)\right), && (10)\\
\pi_j^{vp} &= q\left(\theta_j\right)(1-\delta)\left(1-F\left(\varepsilon_j^R\right)\right). && (11)
\end{aligned}
$$

Since each individual local labor market is described by essentially a textbook DMP model with endogenous separations, the definition of within-location equilibrium is standard (Pissarides, 2000). The key condition is free entry into vacancy creation which implies that there are zero profits from posting a vacancy ($V_j^v = 0$) in each market making firms indifferent between posting vacancies in different local labor markets. For the spatial equilibrium, we follow Rosen (1979)-Roback (1982) and assume that the cost of living c_j adjust so that unemployed workers are indifferent between local labor markets, $V_j^u = \underline{V}$ for all $j = 1, 2, \ldots, N$. As vacancies and unemployed workers are freely mobile across locations and are indifferent between them and given constant returns to scale in each location, the distribution of location sizes is not a state variable of the model. The literature typically endogenizes c_j by assuming that local housing price is convex in the number of workers in a location. This gives rise to a relationship between a location's productivity and size. Any deviations from this relationship in the data are then rationalized by unobserved amenity values offered by individual locations. For our purposes in this paper, introducing this additional structure is straightforward but unnecessary. Thus, without loss of generality, we consider a stationary equilibrium where location sizes are positive but otherwise undetermined, noting that the model could replicate observed spatial mobility patterns if we were to introduce idiosyncratic preference shocks over locations for workers.

3.1 Calibration

We calibrate the model at monthly frequency to the U.S. economy. We set the discount factor $\beta = 0.997$ to match an annual interest rate of 4%. We set the exogenous separation probability $\delta = 0.004$ to replicate the average separation rate of workers with at least 10 years of job tenure.[31] To facilitate the discussion of efficiency below, we impose the Hosios condition. The remaining parameters are calibrated internally. We assume a Cobb-Douglas matching function $M(u, v) = mu^{\alpha}v^{1-\alpha}$ where m denotes matching efficiency and α determines the elasticity of the matching function with respect to unemployment. As in Pissarides (2000), we assume

[31] We follow the large literature on displacement effects following Jacobson, LaLonde, and Sullivan (1993) which builds on the idea that separations for high-tenure workers are largely due to exogenous layoff events rather than shocks to idiosyncratic match productivity. We estimate δ from basic CPS with tenure supplements for the period from 2000 and 2019. An exogenous separation rate of 0.4% implies expected job duration of 21 years, conditional on not separating endogenously.

that each period a new productivity shock $\varepsilon \sim \mathcal{U}[0, 2]$ is drawn with probability λ. While uniform distribution is particularly analytically transparent, we show in Appendix II.4 that all our quantitative findings are not sensitive to other common distributional assumptions in the literature, such as lognormal, Pareto, etc. The separation decision depends on the discounted present value of the match, so that a persistent shock over several periods is identical to a one-time shock with the same discounted value. In line with this interpretation, productivity takes its expected value if no new shock is drawn.[32] Thus, there are five parameters that remain to be calibrated: the probability of receiving an idiosyncratic shock λ, matching efficiency m, bargaining power η, flow utility z, and vacancy posting cost κ.

We have two sets of targets to calibrate these parameters. First, we consider the location with median unemployment rate in the United States and normalize the fundamental productivity of that location in the model to $A = 1$. We then find among the metropolitan areas identified in the CPS that the median unemployment location has a separation rate of $\pi^{eu} = 0.0128$ and a job-finding rate of $\pi^{ue} = 0.2368$. We cannot measure job-filling rate in that location from public JOLTS data, and instead use an average job-filling rate $\pi^{vp} = 0.7365$ derived from microdata estimates in Davis, Faberman, and Haltiwanger (2013).[33]

Our second set of targets is based on the systematic productivity differences associated with local unemployment differences. We restrict attention to unemployment rates from 2% to 9%, where the majority of local labor markets fall in (see Figure 6). Based on the bins in Figure 9, we target that the lowest-unemployment location (5th percentile) with an unemployment rate that is 2.8 percentage points lower than the median location has a productivity that is 4.8% higher than the median location, and the highest-unemployment location (95th percentile) with an unemployment rate that is 3.6 percentage points higher than the median location has a productivity 3.0% lower than the median location. Because of the different selection of viable matches across locations, output per worker measured in the data differs from fundamental location productivity A_j. This implies that we also need to calibrate the fundamental productivity levels in those two locations, labeled $\underline{A}$ and $\overline{A}$.

While all parameters are determined jointly, the mapping between data moments and model parameters is quite intuitive. Naturally, the target for the separation rate informs the frequency of idiosyncratic productivity shocks (λ). The matching efficiency (m) is informed by the job-

[32]The formulation allows to match a leptokurtic idiosyncratic shock distribution for which Bachmann and Bayer (2014) provide empirical support.

[33]Davis, Faberman, and Haltiwanger (2013) report that the average daily job-filling rate for nonfarm sectors is 5%, which we convert to monthly frequency as $1-(1-0.05)^{26}$, where 26 is the average number of working days per month. Our empirical analysis of job-filling rate data suggests that the relationship between unemployment rates and job-filling rates is close to linear so that for a symmetric distribution of unemployment rates mean and median job-filling rates are close to each other. Robustness analyses showed that results remain largely unaffected when calibrating to other job-filling rates within a reasonable range.

Table 4: Calibration

	Symbol	Value
Discount factor	β	0.997
Exogenous separation	δ	0.004
Idiosyncratic shock	λ	0.0814
Matching efficiency	m	0.4371
Vacancy posting cost	κ	0.3070
Flow nonmarket value	z	0.9072
Matching elasticity	α	0.4711
Worker bargaining power	η	0.4711

Notes: Calibrated parameters and calibrated values for the baseline model.

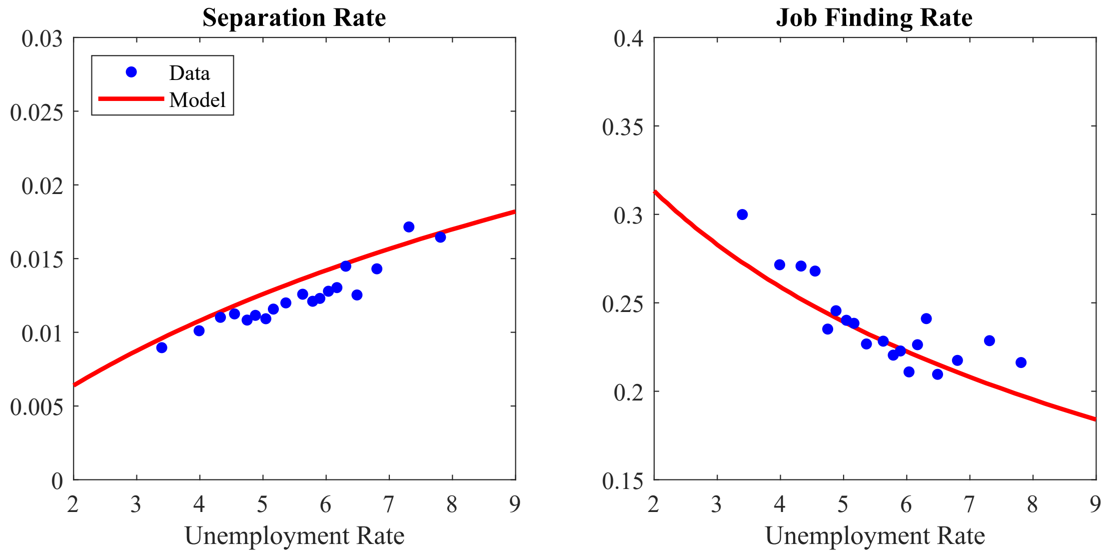
finding rate. The job-filling rate helps disentangle matching efficiency and vacancy posting costs (κ) because a higher matching efficiency increases job-finding and job-filling rates, but higher vacancy posting costs reduce vacancy posting and thereby move job-finding rate and job-filling rates in opposite directions. There is a direct link between $\{\underline{A}, \overline{A}\}$ to output per worker in the lowest and highest unemployment locations. Furthermore, the outside option z is related to the unemployment level in the least productive location. If the outside option approaches $\underline{A}$ from below, the separation rate in the location increases and the job-finding rate decreases, both leading to a higher unemployment rate, although the calibration procedure does not target the relative importance of the two mechanisms. A lower bargaining power of workers η implies higher vacancy creation in all locations. Separation rates depend on the total surplus rather than its split and will therefore be only indirectly affected by changes in the bargaining power. More vacancy creation will lower the unemployment rate in all locations including the most productive one and therefore allow us to match the unemployment rate in the most productive location.

Table 4 contains the calibrated parameter values. The fact that the calibrated model matches the targets nearly exactly will become apparent when we present the results.

3.2 Quantitative Experiment and Results

In the calibrated model, we vary the fundamental productivity A to trace out differences in labor market outcomes across local labor markets which we compare to their empirical counterparts. Note that our calibration procedure targeted worker flows at the median unemployment

Figure 14: Separation and Job-Finding Rate across Local Labor Markets



Notes: Separation rates and job-finding rates from the model and data. The left panel shows separation rates. The right panel shows job-finding rates. The horizontal axis shows local unemployment rate in both panels. Model predictions are shown as red lines and data as blue dots.

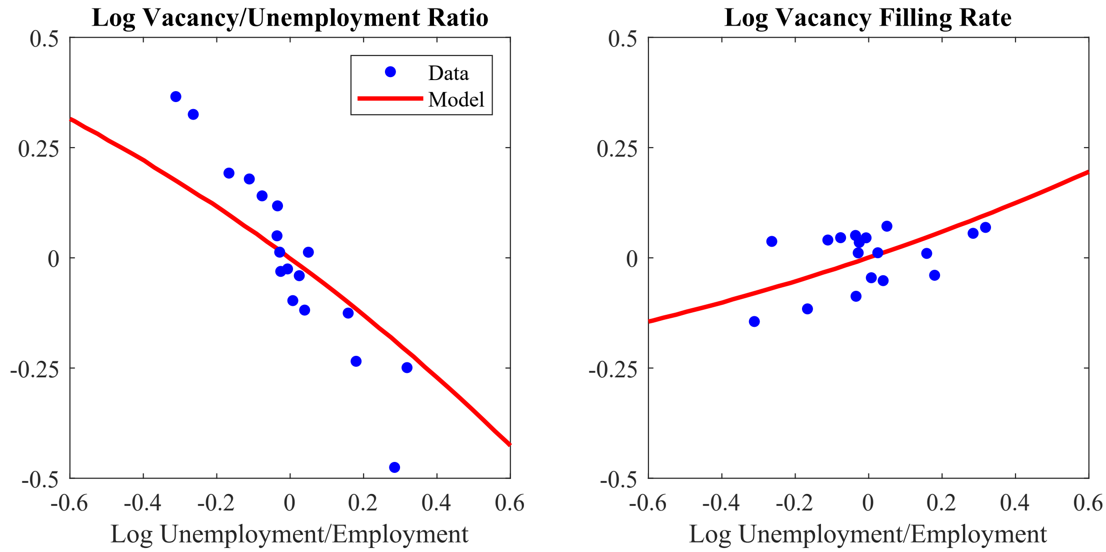
location, the dispersion of productivity between the most and least productive locations, and unemployment rates in those locations. We targeted neither the role of job-finding and separation rates in determining unemployment differences across locations nor differences in vacancy filling or tightness.

In Figure 14, we plot the separation and job-finding rates across local labor markets. The left panel shows that separation rates increase in the model when we move from locations with low unemployment to locations with high unemployment. The right panel indicates that job-finding rates fall with local unemployment. Despite not being targeted, the model closely matches both aspects of the data not only qualitatively but also quantitatively. Comparing the variation across locations, we find that job-finding rates vary substantially less than separation rates. The formal decomposition highlights a tight match between theory and empirical evidence with job-finding rates accounting for 33.5% of the cross-sectional variation in unemployment rates in the model compared to 32.8% in the data. The fact that the model is successful in replicating the relative importance of job-finding and separation rates in determining the spatial variation in unemployment is visualized in Figure A-15.

It is well understood that the elasticity of labor market tightness with respect to productivity in the DMP model depends on the size of the surplus.[34] In our spatial setting, the surplus covaries positively with productivity across locations but is relatively large on average. Thus, despite the high dispersion and persistence of local productivity (as compared to its business

[34]See Hagedorn and Manovskii (2008); Ljungqvist and Sargent (2017).

Figure 15: Tightness and Vacancy Duration across Local Labor Markets



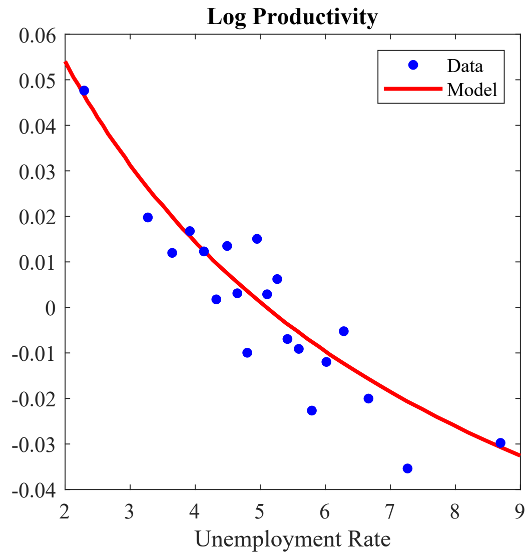
Notes: Differences in labor market tightness and vacancy filling rates across local labor markets from model and data. The left panel shows (demeaned) dispersion in log labor market tightness from the data on the 18 largest MSAs in the United States (blue dots) and the model prediction (red line). The right panel shows (demeaned) dispersion in log vacancy filling rates from the same data (blue dots) and the model prediction (red line). The horizontal axes in both panels show the log deviation of the unemployment-employment ratio for local labor markets.

cycle properties), the job-finding rates do not vary dramatically across space. However, the fraction of viable matches, and thus the separation rate depends negatively on surplus. The larger the surplus, the smaller is the share of idiosyncratic shocks that will make the surplus negative, inducing a separation. This effect is sufficiently strong to assign the major role to separations in accounting for the dispersion of local unemployment rates.

In Figure 15, we show the relationship of local unemployment with labor market tightness and vacancy filling rates in the model. The left panel indicates that, as expected, labor market tightness in the model declines with local unemployment. This is qualitatively consistent with the pattern of the data, but quantitatively the slope of the relationship is slightly weaker in the model. The extended model in the next section will eliminate this discrepancy and explain its origins. The right panel shows that the vacancy filling rate rises with local unemployment in the model, reproducing the corresponding relationship in the data.

Figure 16 shows the log deviation of average output per worker from the median location. The calibration targeted the endpoints of the productivity support but we see that the variation in productivity with unemployment is also matched closely in the interior of the productivity grid. Note that this is not a mechanical outcome. While we vary the fundamental location productivity A_j across locations in the quantitative experiment, the figure plots a different object – output per worker, which is affected both by A_j and the differences in the idiosyncratic

Figure 16: Productivity and Unemployment across Local Labor Markets



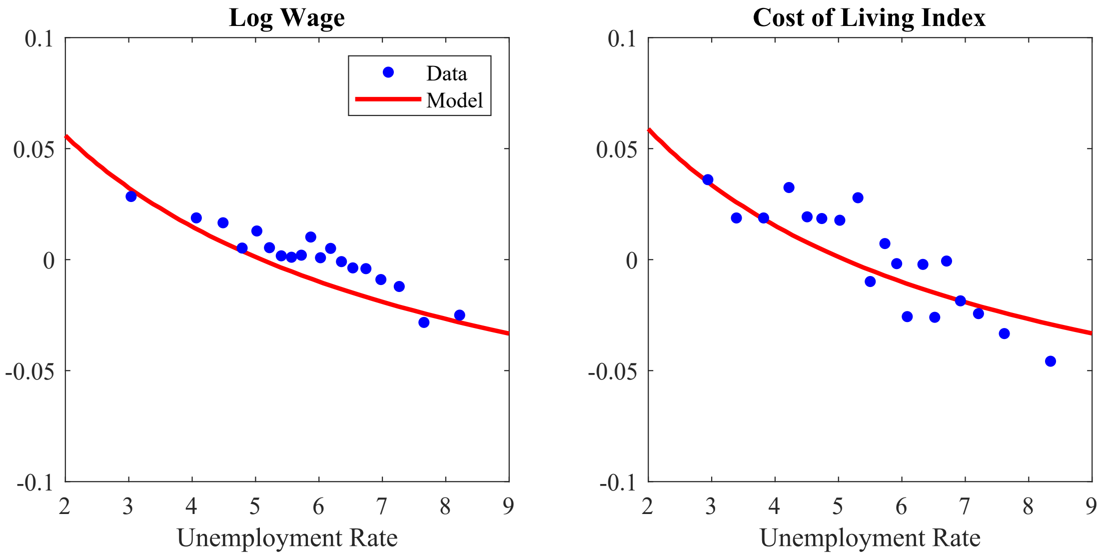
Notes: Average output per worker dispersion in the model and in the data across local labor markets. Model predictions are shown as red line. Data are shown as blue dots. Horizontal axis shows the local unemployment rate.

productivity distributions across locations induced by the very different separation thresholds described above.

In the model, the key determinant of vacancy creation is the relationship between productivity and wages. Yet, we have not targeted the properties of wages when calibrating the model. Thus, it is useful to verify how well the model replicates the relationship between wages and local unemployment. We plot this relationship in the model and in the data in the left panel of Figure 17. Wage and salary income data come from the American Community Surveys (ACS) (Ruggles et al., 2021). We aggregate average wages from the Public Use Microdata Area level, which is effectively the smallest identifiable geographic unit in ACS, to the commuting zone level. We remove year fixed effects and local labor market composition. The match between model and data is very tight.

Finally, the cost of living in different locations is the key spatial equilibrium object in the model. We did not target local costs of living when calibrating the model but instead backed them out as the values required to support the spatial equilibrium. Thus, it is natural to ask how the equilibrium variation in the cost of living in the model compares to the data. We obtain empirical measures of local costs of living from Economic Policy Institutes Family Budget Calculator that provides estimates for a two-parent, two-child family across U.S. counties covering costs for housing, food, child care, transportation, health care, and other necessities. Notably, it compares the costs of a fixed consumption basket across space. Note that the model only pins down the relative difference of costs of living, but not the levels. Therefore, we construct the

Figure 17: Average Wage and Cost of Living across Local Labor Markets



Notes: Average wage and cost of living differences across local labor markets in model and data. The left panel shows differences in average log wages from the model (solid red line) against the data (blue dots). The right panel shows differences in cost of living from the model (solid red line) against the data (blue dots). The horizontal axes show local unemployment rates. See text for details on wage and cost of living data.

relative index $\tilde{c}_j = (c_j - c_{med})/w_{med}$ to capture the relative difference in cost of living measured in the unit of the wage at the median location. The right panel of Figure 17 illustrates the close quantitative match between the model and the data showing that cost of living is clearly negatively correlated with the local unemployment rate so that it is less expensive to live in high-unemployment locations.[35]

3.3 Efficiency

A first objective of developing a theory of local labor markets is to identify the drivers of differences in local labor market outcomes. Another objective is to assess the scope for and the design of welfare-improving policy interventions. According to estimates by Bartik (2004) discussed in Manning and Petrongolo (2017), the U.S. federal, state, and local governments spend about 50 billion dollar a year on local development policies but the rationale for these policies remains rather illusive (see Moretti, 2011; Neumark and Simpson, 2015, for surveys).

We have just seen that our very simple quantitative model provides a surprisingly close fit to the data. Thus, it seems relevant to consider the role it assigns to place-based policies. Extending the arguments in Kline and Moretti (2013), we prove in Appendix II.2 that despite

[35]Appendix I.1.8 shows that qualitatively and quantitatively similar relationships of wages and costs of living with unemployment hold across German local labor markets.

significant variation in labor market outcomes across locations, the competitive equilibrium of our model is efficient and a social planer will not be able to improve welfare through policy. There are two key elements necessary to understand this result. First, job creation and job destruction are efficient in any individual labor market because the Hosios condition equating the unemployment elasticity of the matching function and workers' bargaining weight is satisfied.[36] The condition optimally trades off the resource costs of vacancy creation with the cost of unemployment in every labor market. Separation decisions are efficient as they only occur if the joint match surplus turns negative. Second, the allocation of workers and jobs across markets is also efficient. Both vacancies and unemployed workers are freely mobile across locations and are indifferent between them in equilibrium. The key here is that the cost of living in every market is determined in a way such that a potential gain in terms of expected earnings from moving any unemployed worker to any location is exactly offset by the change in the cost of living. Similarly, the expected gain in profits from moving a vacancy is exactly offset by the change in the job-filling probability. A social planner who is subject to the same labor market frictions faces exactly the same trade-offs and cannot improve on the competitive allocation.

The key take-away then is that large differences in labor market outcomes (unemployment, vacancies, tightness, wages, etc.) across local labor markets are not necessarily an indication of inefficiency, as is often assumed in the literature, (see, for example, Şahin et al., 2014, and the discussion therein). Instead, the model highlights that the relevant statistic to assess efficiency is not the dispersion of, e.g., tightness across space but the deviation of tightness from its efficient level conditional on local labor market productivity. This policy benchmark is not observed in the data and must be informed by an empirically successful theoretical framework. For example, it is possible that in a labor market with high labor market tightness and low unemployment, vacancy creation is nevertheless too low compared to the efficient benchmark if tightness in this labor market – despite being higher than the average – is below the efficient outcome predicted by the model.

4 Model with On-the-Job Search

While our baseline spatial version of the DMP model with endogenous separations successfully accounts for key empirical facts on local labor market differences, it generates an upward sloping Beveridge curve, which is counterfactual. It also does not account for the empirically large worker reallocation through job-to-job transitions. To address both limitations, we add on-the-job search to the baseline model. We aim to add on-the-job search without changing the baseline model in any other way. This allows to preserve the high transparency afforded by the

[36] Our choice to impose this condition is supported by the observed fit of the model to untargeted data series.

streamlined baseline model and to isolate cleanly the role played by on-the-job search.

We assume that in addition to the unemployed, a fraction ϕ of employed workers is searching each period. The inputs of the constant returns to scale matching function $M(S_j, V_j)$ in each local labor market j are then all searching workers S_j, the sum of all unemployed workers U_j and a share ϕ of employed workers E_j, and vacancies V_j. Using again lower case letters for corresponding rates normalized by the labor force, labor market tightness is $\theta_j = v_j/s_j$. The contact rate for searching workers is $f(\theta_j) = M(1, \theta_j)$ and for vacant firms it is $q(\theta_j) = M\left(\theta_j^{-1}, 1\right)$.

We assume that matches are experience goods so that an employed searcher meeting a new firm has to give up the option of preserving the existing match before observing the productivity of the new match. Because productivity shocks are i.i.d., a new job is *ex ante* the same as the old one so that workers are indifferent between them. While all unemployed workers accept a job upon a meeting, we assume that only a fraction χ_j of on-the-job searchers accept an offered job for non-pecuniary reasons.[37] Thus, the probability that the contact between a vacant firm and a job applicant will be turned into a match is

$$\varphi_j(u_j) = \frac{u_j + \chi_j \phi (1 - u_j)}{u_j + \phi (1 - u_j)}$$

and the expressions for vacancy filling rate, π^{vp}, and job-to-job rate, π^{j2j}, become

$$\begin{aligned} \pi_j^{vp} &= q(\theta_j)(1-\delta)\varphi_j\left(1 - F\left(\varepsilon_j^R\right)\right) = \frac{\varphi_j}{\theta_j}\pi_j^{ue}, && (12) \\ \pi_j^{j2j} &= \phi\chi_j f(\theta_j)(1-\delta)\left(1 - F\left(\varepsilon_j^R\right)\right) = \phi\chi_j \pi_j^{ue}, && (13) \end{aligned}$$

while the expressions for the separation rate π_j^{eu} and job-finding rate π_j^{ue} are still given by equations (9) and (10), respectively.

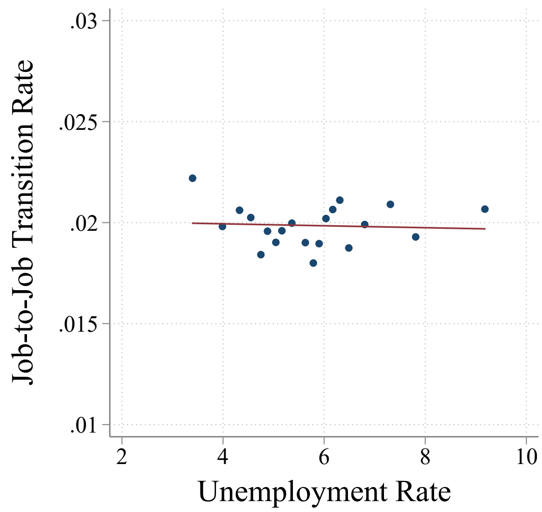
Except for adding job-to-job transitions, everything else remains the same as in the baseline model. The adjustments to value functions, free entry, and wage bargaining are straightforward and are relegated to Appendix II.5.

To calibrate the extended model, we follow the same calibration strategy and add two targets to discipline job-to-job transitions. We calibrate the share of searching employed workers to $\phi = 0.12$ using estimates in Faberman et al. (2017).[38] Second, we calibrate the location-specific

[37] Our choice to fix ϕ and let χ_j vary across space was guided by the data in the Survey of Consumer Expectations (SCE) Job Search Supplement, see Faberman et al. (2017). Using state level variation and controlling for aggregate conditions, we find that acceptance rates of searching employed workers increase by 4 percentage points for each percentage point increase in unemployment, while the share of searching workers is virtually flat at approximately 12%.

[38] We take the number of applications sent as a measure of the relative search intensity. In October 2013-17 waves of the SCE Job Search Supplement sample, 74.2% are employed and account for 59.1% of the total

Figure 18: Job-to-Job Rate across U.S. Local Labor Markets



Notes: Monthly job-to-job transition rates across metropolitan statistical areas in the United States. The horizontal axis shows local unemployment rates. Blue dots show bin-scatter data and the solid red line shows linear fit to raw data.

parameter χ_j to match the empirical pattern of job-to-job transition rates across local labor markets. Figure 18 shows estimated local job-to-job rates from CPS data. Evidently, job-to-job rates are virtually constant in the cross section of local labor markets.[39] Thus, we calibrate the parameters χ_j by targeting a constant job-to-job rate of 2% across all local labor markets.[40] Table 5 summarizes the calibrated parameters for the model with on-the-job search.

4.1 Results

We perform the same quantitative experiment of varying fundamental location productivities and tracing out the relationship between economic variables across local labor markets. We find that the model with on-the-job search preserves all the quantitative successes of the baseline

applications, whereas 6.2% are unemployed and account for 39.6% of the total applications. This implies a relative search intensity of the employed $\phi = \frac{59.1}{74.2} / \frac{39.6}{6.2} = 0.12$.

[39] Bilal (2021) also reports virtually constant job-to-job transition rates across French local labor markets. Appendix Figure A-6 also documents for Germany that the job-to-job transition rate is constant across local labor markets with different unemployment rates. Fujita, Moscarini, and Postel-Vinay (2020) point to a measurement problem of job-to-job transitions in CPS over time due to a survey methodology change starting in 2008. We have verified that the same pattern holds if we consider pre-2008 CPS data only.

[40] While we treat χ_j as a location-specific parameter in our simple model, it naturally captures the equilibrium outcome in an explicit job-ladder model. Such a model gives rise to the following trade-off. In low unemployment locations, vacancies are plentiful, allowing workers to move frequently between jobs, but as a result, they quickly sort into good matches leading to lower job-to-job mobility in steady state. This is reinforced by the lower separation rate so that fewer workers restart their job search. In contrast, in high unemployment locations, the steady-state job-to-job rate is relatively high despite low availability of vacant jobs because workers are on average less well matched and have to restart their search more often due to high separation rates. Such a model naturally gives rise to approximately constant steady-state job-to-job rates across locations.

Table 5: Calibrated Parameters for Model with On-the-Job Search

Parameter	Value	Parameter	Value
β	0.997	m	0.5508
δ	0.004	κ	0.2955
ϕ	0.12	z	0.9279
χ_j	$[0.56, 0.94]$	α	0.3901
λ	0.0508	η	0.3901

Notes: Calibrated parameters and calibrated values for the model with on-the-job search.

model while overcoming its limitations. For brevity, we discuss only the key results in this section and present the remaining findings in Appendix II.5.2.

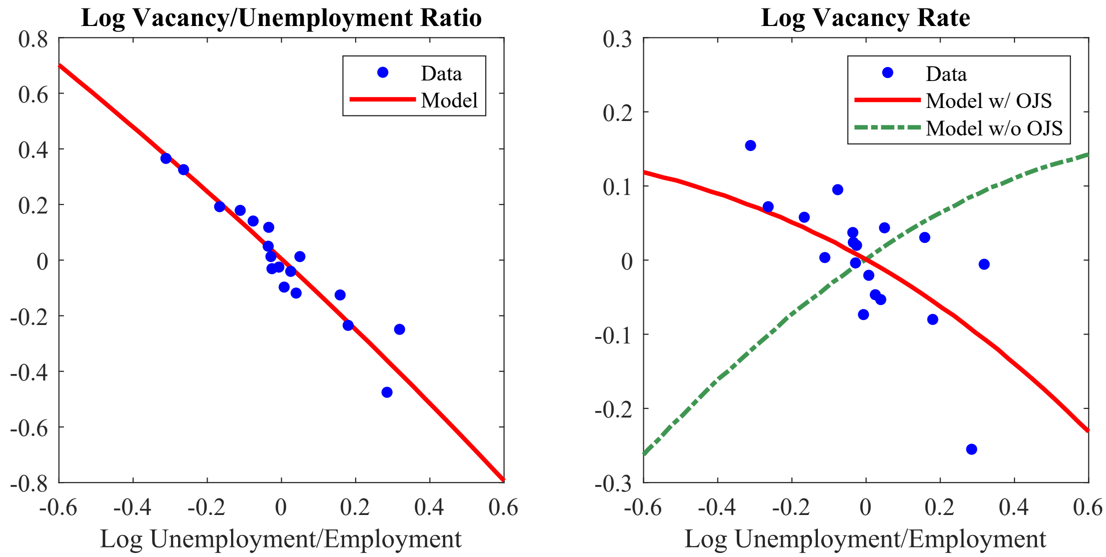
The model continues to match closely the empirical relationships of separation and job-finding rates with unemployment across local labor markets (see Appendix Figure A-19). This implies that the model with on-the-job search also accounts very well for the cross-sectional decomposition of the sources of unemployment rate differences as shown in Figure A-18. As in the data, separation rates vary much more across local labor markets and account for the bulk of unemployment rate differences across space. In fact, the formal decomposition indicates that the fit is nearly exact: with on-the-job search, job-finding rates account for 32.7% of spatial differences of unemployment rates, as compared to 32.8% from the decomposition in the data.

The left panel of Figure 19 shows the dispersion of log labor market tightness in the model and data around its mean. The addition of on-the-job search to the model clearly improves the model's fit to the cross-sectional dispersion of tightness. The reason for this improvement is that the addition of on-the-job search allows the model to match the relationship between vacancies and unemployment across locations – the spatial Beveridge curve, as is shown in the right panel of Figure 19.

4.2 Business-Cycle Analysis

A salient property of the data and our spatial DMP model with endogenous separations and on-the-job search is that the differences in job-finding rates account for only about 30% of the cross-sectional variation in unemployment rates. This fact is in stark contrast to the established finding on unemployment variation over the business cycle. Specifically, in their detailed analysis of business-cycle dynamics of U.S. labor market flows, Fujita and Ramey (2009) find that between 50% and 60% of unemployment variation is accounted for by variation in job-finding

Figure 19: Model Predictions on Tightness and Spatial Beveridge Curve



Notes: Differences in labor market tightness across local labor markets and spatial Beveridge curve from model and data. The left panel shows (demeaned) dispersion of log labor market tightness from the data (blue dots) and the model prediction (red line). The right panel plots the spatial Beveridge curve (log deviations of local vacancy rate against unemployment) in the baseline model (dotted green line), in the extended model with on-the-job search (solid red line), and in the data (blue dots). The horizontal axes in both panels show the log deviation of the unemployment-employment ratio for local labor markets.

rates, about twice as much as for the spatial variation. Thus, although the focus of this paper is on the geography of job creation and job destruction, it would be a highly desirable feature of the spatial theory if it were able to match the role of job-finding and separation rates over the business cycle. In this section, we put the theory to such a test.

To study business-cycle dynamics, we extend the model by introducing time-varying fundamental productivity p_t. Specificallly, each worker-firm match produces period output $y_{jt} = p_t A_j \varepsilon$ that is the product of the aggregate productivity p_t, the location-specific productivity A_j, and the match-specific stochastic productivity ε. Over time, the aggregate productivity fluctuates according to an AR(1) process

$$\log(p_t) = \rho \log(p_{t-1}) + \xi_t,$$

with i.i.d. shocks ξ_t that are normally distributed with mean zero and standard deviation σ_ξ. The model is otherwise unchanged. Of course, economic agents take into account stochastic productivity so the model equations change. But the changes are straightforward and we relegate them to Appendix II.6.

We keep all the model parameters fixed at their calibrated values in the previous section and use the parameters of the productivity process from Hagedorn and Manovskii (2008).

Table 6: Business-Cycle Statistics

	u	v	v/u	π^{ue}	π^{eu}	p
Data	0.125	0.139	0.259	0.083	0.060	0.013
Model	0.138	0.133	0.243	0.099	0.075	0.013

Notes: The table reports business-cycle statistics for unemployment rates (u), vacancy rates (v), labor market tightness (v/u), job-finding rates (π^{ue}), separation rates (π^{eu}), and (log) productivity p in the data and in the model. All values refer to the standard deviation of de-trended log quarterly series (HP Filter, smoothing parameter 1,600). Data for u, v, v/u, and p are taken from Hagedorn and Manovskii (2008). Data for π^{ue} and π^{eu} are calculated from the job-finding and separation rate series constructed by Shimer (2012).

For simplicity, we focus on the labor market dynamics over the business cycle in the median unemployment location.[41]

In Table 6, we report the standard deviation of unemployment rates, vacancies, tightness, job-finding rates, separation rates, and the shocks to aggregate productivity over the business cycle. In the first row, we report values in the data. In the second row, we report the corresponding values in the model. The standard deviation of productivity is matched by construction.

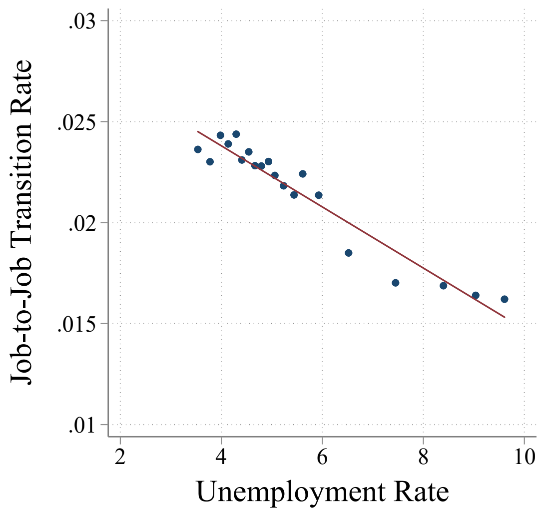
The results indicate that the model features large amplification so that unemployment and vacancy rates are an order of magnitude more volatile than productivity shocks, in line with the data. The model also matches the fact that labor market tightness is about twice as volatile as the unemployment rate. Most importantly, however, the model also yields a highly volatile job-finding rate that is about a third more volatile than the separation rate closely matching the empirical volatility differences. Performing Fujita and Ramey's (2009) decomposition of the unemployment volatility in the model reveals that job-finding rates explain 54.4% of the business-cycle fluctuation of the unemployment rate, which is right in the middle of the 50% to 60% range of estimates in the data reported by Fujita and Ramey (2009). Thus, the model is able to match the business-cycle dynamics while still being consistent with the persistent spatial labor market differences as demonstrated above.[42]

At first glance, this result may appear surprising. The model accounts for the fact that most of the spatial unemployment differences are explained by the differences in separation rates, whereas the variation of unemployment over the business cycle is largely driven by the

[41] We have verified that this is indeed a good guide to the dynamics of the aggregate economy. We focus on the median location just for simplicity and transparency, as otherwise we have to match location sizes for correct aggregation, which unnecessarily complicates the model.

[42] Pizzinelli, Theodoridis, and Zanetti (2020) argue that a DMP model with on-the-job search and endogenous separations can rationalize the state dependence in unemployment and job-separation rates.

Figure 20: Job-to-Job Rate over the Business Cycle



Notes: Monthly job-to-job transition rates over the business cycle for different unemployment rates. Blue dots show bin-scatter data of monthly job-to-job transition rates calculated from the Current Population Survey against the aggregate unemployment rate. Red line shows a linear fit to raw data.

variation in the job-finding rate. Yet, both types of variation are induced by symmetric changes in productivity. Key to understanding the difference is the role played by on-the-job search.

Job-to-job transitions are a major source of worker reallocation. However, properties of this reallocation differ over time and across space. As discussed above, job-to-job rates are constant across space but they are strongly procyclical over the business cycle, as illustrated in Figure 20. Over the business cycle, job-to-job rates are high when unemployment is low (booms) and low when unemployment is high (recessions). The model matches the empirical procyclicality of job-to-job rates which inherit their cyclical properties from worker contact rates that themselves are a direct function of labor market tightness. The additional procyclicality of the mass of on-the-job searchers spurs additional vacancy creation by firms and thereby amplifies the elasticity of vacancies and tightness with respect to productivity over the business cycle compared to the cross section of local labor markets. Hence, once the model matches the empirically observed procyclical worker reallocation, the model jointly accounts for labor market differences across time and space.

In summary, we find that the DMP framework with endogenous separations and on-the-job search is successful in jointly matching the spatial variation in unemployment rates, worker flow rates, vacancy posting, and the sources of unemployment variation. Additionally, the model with aggregate fluctuations also accounts for the cyclical variation in labor market dynamics with strong amplification of productivity shocks and an important role of job-finding rates for unemployment variation over the business cycle.

5 Conclusion

There are large and very persistent differences in unemployment rates across local labor markets. Policymakers are concerned about such large differences in labor market outcomes within countries and spend billions of dollars on a wide variety of policies in an attempt to reduce these differences. However, the policy-making is constrained by the lack of economic theory that is quantitatively consistent with local labor market facts. Part of the problem is that some of the facts crucial for the development of the theory have themselves not been documented yet.

We attempt to make progress on both the empirical and theoretical aspects of the problem in this paper. We first document the key facts characterizing local labor markets. We take a broad approach and study local labor market data from three different countries – Germany, United States, and United Kingdom. This allows us to exploit advantages of country-specific data sources, but overall we find strikingly similar relationships between key variables across local labor markets in all three countries. This leads us to suspect that we uncover some fundamental economic relationships useful for guiding the development of economic theory.

Specifically, we find that local labor markets with lower unemployment are more productive and tighter, i.e., have more job vacancies per unemployed worker. In these tighter labor markets, unemployed workers find jobs more quickly whereas employers fill vacant positions slower and average vacancy duration is longer. This is reminiscent of the standard relationships in the DMP model as in e.g., Kline and Moretti (2013), but is in contrast to the key model mechanism in Bilal (2021).[43] All three countries also reveal a robust relationship between worker flow rates and local unemployment. Differences in job-separation rates across local labor markets account for two-thirds of the differences in unemployment, with the differences in job-finding rates accounting for the remaining one-third. The standard DMP model with exogenous separations as, for example, in Kline and Moretti (2013), fails to account for this fact and this lead Bilal (2021) to explore an alternative model.

We take a different route in this paper. We consider a version of DMP model with endogenous separations embedded in the classic Rosen-Roback spatial equilibrium framework and find that it is able to match all the relevant empirical facts both qualitatively and quantitatively. We purposefully work with the simplest version of the model because of the pedagogical value of its minimalist structure. It allows us to isolate and understand the role of the key mechanisms in a very transparent manner. Moreover, it lends itself to a clear analysis of efficiency. The decentralized equilibrium of our baseline model is efficient, a choice we make to illustrate that spatial variation in unemployment, vacancies, and tightness is not necessarily a sign of ineffi-

[43]The pooling externality at the core of Bilal's theory implies that more productive firms sort into lower-unemployment locations because they enjoy a lower tightness and a higher vacancy filling rate there. In contrast, in the data, lower-unemployment locations feature higher tightness and lower vacancy filling rates.

ciency, as is commonly assumed in the literature and equalizing these variables across space will not constitute sound policy advice.

Although our baseline model is sufficient to highlight the key elements around which we expect future more elaborate models for detailed policy analysis can built, it has a shortcoming in its ability to generate a downward sloping spatial Beveridge curve observed in the data. Moreover, it cannot address a fundamental challenge facing the literature: while separations rates are more important than job-finding rates in accounting for the variation of unemployment across space, it is well known that the opposite is true over the business cycle. We show that introducing on-the-job search in our baseline model allows to address both challenges and explain the economics behind this finding. The resulting model is consistent with all the evidence we document on the geography of unemployment, job creation, and job destruction but in addition, it also matches the observed labor market dynamics over the business cycle. These empirical successes of the model make us hopeful that it will form the foundation on which future literature will be built.

References

Amior, Michael and Alan Manning. 2018. “The Persistence of Local Joblessness.” *American Economic Review* 108 (7):1942–70.

Antoni, Manfred, Andreas Ganzer, and Philipp vom Berge. 2019. “Sample of Integrated Labour Market Biographies Regional File (SIAB-R) 1975-2017.” Tech. rep., FDZ-Datenreport, Nuremberg.

Bachmann, Rüdiger and Christian Bayer. 2014. “Investment Dispersion and the Business Cycle.” *American Economic Review* 104 (4):1392–1416.

Bartik, Timothy J. 2004. “Evaluating the Impacts of Local Economic Policies On Local Economic Outcomes: What Has Been Done and What is Doable?” In *Evaluating Local Economic and Employment Development: How to Access What Works Among Programmes and Policies*. Paris: Organisation for Economic Co-Operation and Development, 113–142.

BBSR. 2009. *Regionaler Preisindex*. Bonn: Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR).

Beaudry, Paul, David A. Green, and Benjamin M. Sand. 2012. “Does Industrial Composition Matter for Wages? A Test of Search and Bargaining Theory.” *Econometrica* 80 (3):1063–1104.

———. 2014. “Spatial Equilibrium with Unemployment and Wage Bargaining: Theory and Estimation.” *Journal of Urban Economics* 74 (C):2–19.

Bilal, Adrien. 2021. “The Geography of Unemployment.” Tech. Rep. 29269, National Bureau of Economic Research.

Bossler, Mario, Hermann Gartner, Alexander Kubis, Benjamin Küfner, and Thomas Rothe. 2019. “The IAB Job Vacancy Survey: Establishment Survey on Labour Demand and Recruitment Processes, Waves 2000 to 2016 and Subsequent Quarters 2006 to 2017.” Tech. rep., Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg.

Carrillo-Tudela, Carlos and Ludo Visschers. 2020. “Unemployment and Endogenous Reallocation over the Business Cycle.” mimeo, Univ. of Edinburgh and Essex.

Choi, Sekyu, Alexandre Janiak, and Benjamín Villena-Roldán. 2015. “Unemployment, Participation and Worker Flows Over the Life-Cycle.” *The Economic Journal* 125 (589):1705–1733.

Davis, Steven J, R Jason Faberman, and John C Haltiwanger. 2013. “The Establishment-Level Behavior of Vacancies and Hiring.” *The Quarterly Journal of Economics* 128 (2):581–622.

Davis, Steven J, John C Haltiwanger, and Scott Schuh. 1996. *Job Creation and Destruction*. MIT Press.

Den Haan, Wouter J, Garey Ramey, and Joel Watson. 2000. “Job Destruction and Propagation of Shocks.” *American Economic Review* 90 (3):482–498.

Duranton, Gilles and Diego Puga. 2004. “Microfoundations of Urban Agglomeration Economies.” In *Handbook of Urban and Regional Economics, Vol. 4*, edited by J. V. Henderson and J.-F. Thisse. Amsterdam: Elsevier-North Holland, 2063–2117.

Elhorst, J Paul. 2003. “The Mystery of Regional Unemployment Differentials: Theoretical and Empirical Explanations.” *Journal of Economic Surveys* 17 (5):709–748.

Elsby, Michael W. L. and Ryan Michaels. 2013. “Marginal Jobs, Heterogenous Firms, and Unemployment Flows.” *American Economic Journal: Macroeconomics* 5 (1):148.

Faberman, R Jason, Andreas I Mueller, Ayşegül Şahin, and Giorgio Topa. 2017. “Job Search Behavior among the Employed and Non-Employed.” Tech. rep., National Bureau of Economic Research.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2021. *Integrated Public Use Microdata Series, Current Population Survey: Version 9.0 [dataset]*. Minneapolis, MN: IPUMS.

Fournier, Juliette. 2021. “Spatial Mismatch.” *Unpublished manuscript* .

Fujita, Masahisa and Jacques-François Thisse. 2013. *Economics of Agglomeration: Cities, Industrial Location, and Globalization*. Cambridge University Press, 2^{nd} ed.

Fujita, Shigeru, Giuseppe Moscarini, and Fabien Postel-Vinay. 2020. “Measuring Employer-to-Employer Reallocation.” Tech. rep., National Bureau of Economic Research.

Fujita, Shigeru and Garey Ramey. 2009. “The Cyclicality of Separation and Job Finding Rates.” *International Economic Review* 50 (2):415–430.

Gavazza, Alessandro, Simon Mongey, and Giovanni L Violante. 2018. “Aggregate recruiting intensity.” *American Economic Review* 108 (8):2088–2127.

Gervais, Martin, Nir Jaimovich, Henry E. Siu, and Yaniv Yedid-Levi. 2016. “What Should I Be When I Grow Up? Occupations and Unemployment over the Life Cycle.” *Journal of Monetary Economics* 83:54–70.

Hagedorn, Marcus and Iourii Manovskii. 2008. “The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited.” *American Economic Review* 98 (4):1692–1706.

Hartung, Benjamin, Philip Jung, and Moritz Kuhn. 2018. “What Hides Behind the German Labor Market Miracle? Unemployment Insurance Reforms and Labor Market Dynamics.” *CEPR Discussion Paper No. DP13328* .

Head, Allen and Huw Lloyd-Ellis. 2012. “Housing Liquidity, Mobility, and the Labour Market.” *Review of Economic Studies* 79 (4):1559–89.

Hoffmann, Eran B, Monika Piazzesi, and Martin Schneider. 2019. “Jobs at Risk, Regional Growth, and Labor Market Flows.” Working paper, Stanford University.

Hosios, Arthur J. 1990. “On the Efficiency of Matching and Related Models of Search and Unemployment.” *The Review of Economic Studies* 57 (2):279–298.

Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan. 1993. “Earnings Losses of Displaced Workers.” *American Economic Review* 83 (4):685–709.

Jung, Philip, Philipp Korfmann, and Edgar Preugschat. 2021. “Optimal Regional Labor Market Policies.” Tech. rep., Institute of Labor Economics (IZA).

Jung, Philip and Moritz Kuhn. 2014. “Labour Market Institutions and Worker Flows: Comparing Germany and the US.” *The Economic Journal* 124 (581):1317–1342.

———. 2019. “Earnings Losses and Labor Mobility over the Life Cycle.” *Journal of the European Economic Association* 17 (3):678–724.

Kaas, Leo and Philipp Kircher. 2015. “Efficient Firm Dynamics in a Frictional Labor Market.” *American Economic Review* 105 (10):3030–3060.

Kline, Patrick and Enrico Moretti. 2013. “Place Based Policies with Unemployment.” *American Economic Review, Papers and Proceedings* 103 (3):238–243.

Kuhn, Moritz, Iourii Manovskii, and Xincheng Qiu. 2022. “The Geography of Worker and Job Flows: A Rejoinder to Bilal (2022).” Tech. rep., University of Bonn and University of Pennsylvania.

Kuhn, Moritz and Gašper Ploj. 2020. “Job Stability, Earnings Dynamics, and Life-Cycle Savings.” Tech. rep., CESifo Working Paper.

Ljungqvist, Lars and Thomas J. Sargent. 2017. “The Fundamental Surplus.” *American Economic Review* 107 (9):2630–65.

Lkhagvasuren, Damba. 2012. “Big Locational Unemployment Differences Despite High Labor Mobility.” *Journal of Monetary Economics* 59 (8):798–814.

Manning, Allan and Barbara Petrongolo. 2017. “How Local Are Labor Markets? Evidence from a Spatial Job Search Model.” *American Economic Review* 107 (100):2877–2907.

Martellini, Paolo. 2021. “Local Labor Markets and Aggregate Productivity.”

Menzio, Guido, Irina A Telyukova, and Ludo Visschers. 2016. "Directed Search over the Life Cycle." *Review of Economic Dynamics* 19:38–62.

Merz, Monika. 1999. "Heterogeneous Job-Matches and the Cyclical Behavior of Labor Turnover." *Journal of Monetary Economics* 43 (1):91–124.

Moretti, Enrico. 2011. "Local Labor Markets." In *Handbook of Labor Economics, Vol. 4B*, edited by David Card and Orley Ashenfelter. Amsterdam: Elsevier-North Holland, 1237–1313.

Mortensen, Dale T. and Christopher Pissarides. 1994. "Job Creation and Job Destruction in the Theory of Unemployment." *Review of Economic Studies* 61 (3):397–415.

Neumark, David and Helen Simpson. 2015. "Place-Based Policies." In *Handbook of Urban and Regional Economics, Vol. 5*, edited by Gilles Duranton, J. Vernon Henderson, and William C. Strange. Amsterdam: Elsevier, 1197–1287.

Papageorgiou, Theodore. 2021. "Occupational Matching and Cities." *American Economic Journal: Macroeconomics* Forthcoming.

Pissarides, Christopher. 2000. *Equilibrium Unemployment Theory.* 2^{nd} ed., Cambridge, MA: MIT Press.

Pizzinelli, Carlo, Konstantinos Theodoridis, and Francesco Zanetti. 2020. "State Dependence in Labor Market Fluctuations." *International Economic Review* 61 (3):1027–1072.

Roback, Jennifer. 1982. "Wages, Rents, and the Quality of Life." *Journal of Political Economy* 90 (6):1257–1278.

Rosen, Sherwin. 1979. "Wage-Based Indexes of Urban Quality of Life." *Current Issues in Urban Economics* :74–104.

Ruggles, Steven, Sarah Flood, Sophia Foster, Ronald Goeken, Jose Pacas, Schouweilerm Megan, and Matthew Sobek. 2021. *IPUMS USA: Version 11.0 [dataset].* Minneapolis, MN: IPUMS.

Şahin, Ayşegül, Joseph Song, Giorgio Topa, and Giovanni L Violante. 2014. "Mismatch Unemployment." *American Economic Review* 104 (11):3529–64.

Schaal, Edouard. 2017. "Uncertainty and Unemployment." *Econometrica* 85 (6):1675–1721.

Shimer, Robert. 2012. "Reassessing the Ins and Outs of Unemployment." *Review of Economic Dynamics* 15 (2):127–148.

Topel, Robert H. 1986. "Local Labor Markets." *Journal of Political Economy* 94 (3, Part 2):S111–S143.

I Details of Empirical Analysis and Additional Results

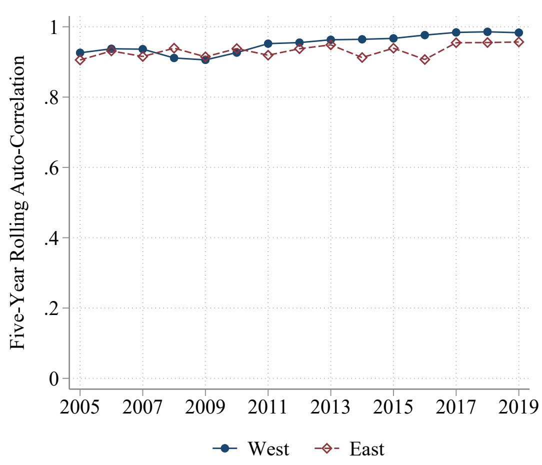
In this section, we provide further empirical results, sensitivity and robustness checks. Following the presentation in the main text, we organize the discussion by country: Germany (Section I.1), the United States (Section I.2), and the United Kingdom (Section I.3).

I.1 Germany

I.1.1 Local Unemployment Persistence

Figure 1 in the main text shows a high persistence of local unemployment rate differences between 2000 and 2019. Such a high persistence is not a particular feature of these two years but applies to other years and shorter time periods. Figure A-1 shows the five-year auto-correlation of local unemployment rates over the entire sample period.[44] We compute the correlation in each year as the correlation of local unemployment rates in that year with local unemployment rates five years ago. We find the auto-correlation to be very stable and to always exceed 0.9 in East and West Germany. We conclude that a high persistence of local unemployment rates is a robust feature of the German labor market over the past two decades.

Figure A-1: Persistence of Local Unemployment Rates in Germany



Notes: Auto-correlation of local unemployment rates in Germany from 2000 to 2019. Each dot shows the correlation of local unemployment rates in that year with local unemployment rates five years ago. The first 5-year correlation estimate exists in 2005. Blue dots show data for West Germany, red diamonds show data for East Germany.

[44] The time series starts in 2005 because the first data point to compute 5-year auto-correlations is 2000–2005.

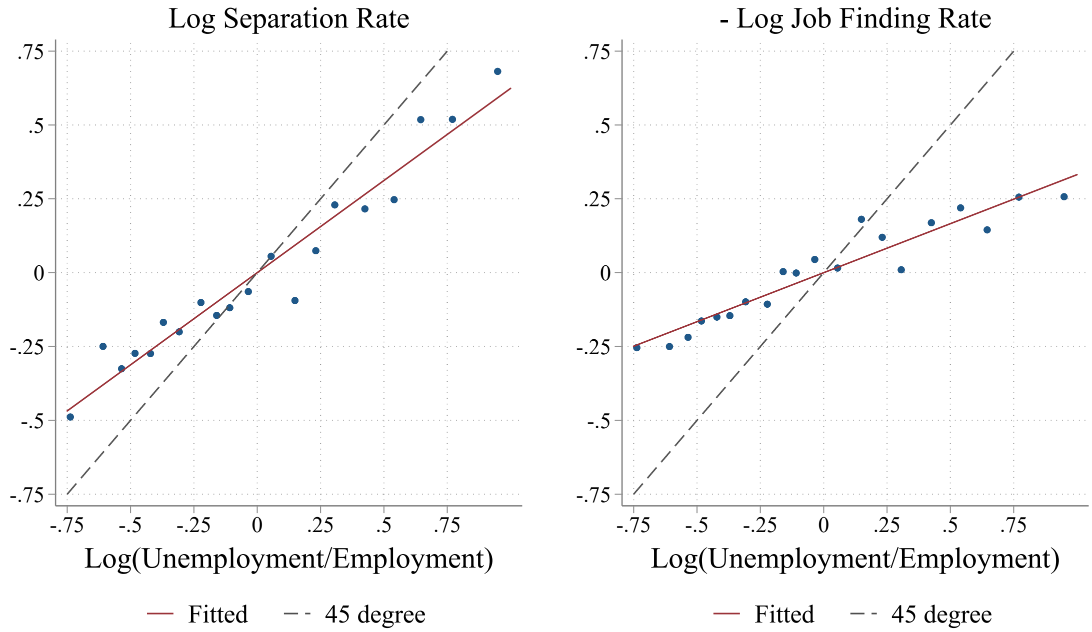
I.1.2 Unemployment Decomposition

Figure A-2 visualizes the unemployment variance decomposition across German local labor markets. The horizontal axis in both panels shows the log deviations of unemployment-to-employment ratios. The vertical axis in the left panel shows the log deviations of separation rates while in the right panel it shows the negative of the log deviations of job-finding rates. The figure also includes the 45-degree line and a linear fit with a bin-scatter plot of commuting-zone data. The closer the linear fit of the respective worker-flow rate data aligns with the 45-degree line, the more of the cross-sectional unemployment dispersion is accounted for by the deviation in that worker-flow rate.

First, as we move from low- to high-unemployment locations, the separation rate rises and job-finding rate falls (note that in the right panel we plot the negative of the job-finding rate deviations so that a positive slope indicates falling job-finding rates with rising unemployment rates). Second, the slope of the fitted line for separation rates is much closer to the 45-degree line than that for job-finding rates. Hence, more of the cross-sectional variation in unemployment rates is accounted for by the variation in separation rates compared to job-finding rates. For example, if we consider the location with a log unemployment rate deviation of -0.75, the log separation rate deviation is almost -0.5 whereas the log job-finding rate deviation is around -0.25. This suggests that around two thirds of the cross-sectional variation in unemployment rates stem from differences in separation rates.

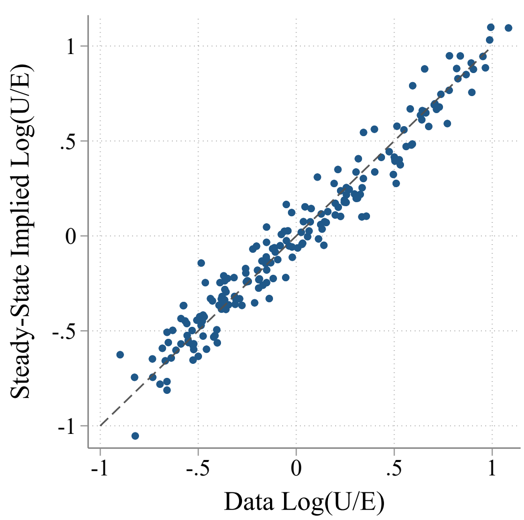
The decomposition of local unemployment rate differences in the main text relies on a two-state steady state approximation of unemployment dynamics. The decomposition in Section 2.1 finds only a small residual component suggesting that the two-state steady state approximation describes local unemployment dynamics in Germany well. Figure A-3 demonstrates this fact explicitly by comparing the demeaned empirical log unemployment-employment ratio ($\log(U/E)$) to the demeaned steady state log unemployment-employment ratio implied by estimated worker flow rates ($\log(s/f)$). We find that the data align closely around the 45-degree line implying that the two-state steady-state approximation provides a good fit to the observed data.

Figure A-2: Decomposition of Unemployment Differences across German Local Labor Markets



Notes: Decomposition of local unemployment rate differences in Germany into differences of separation and job-finding rates. The left panel plots bin-scatter data of the (demeaned) log separation rate (vertical axis) against the (demeaned) log unemployment-employment ratio (horizontal axis). The right panel plots bin-scatter data of the negative (demeaned) log job-finding rate (vertical axis) against the (demeaned) log unemployment-employment ratio (horizontal axis). In both panels, the blue dots show the raw data, the solid red line is the linear fit to the raw data, and the dashed gray line shows the 45-degree line.

Figure A-3: Steady-State Approximation of Local Unemployment Rates in Germany



Notes: Empirical unemployment and steady state approximation based on worker-flow rates for Germany. The horizontal axis shows (demeaned) local unemployment-to-employment ratio against steady-state approximation based on flow rates ($\log(s/f)$). Blue dots show data and the dashed gray line shows 45 degree line.

I.1.3 Three-State Decomposition

As a further robustness check, we consider a three-state model of unemployment dynamics such that $e + u + n = 1$, where e, u, n refer to the share of the population in employment, unemployment, and nonparticipation, respectively. The steady state conditions for u and n are

$$0 = e \times \pi^{eu} - u \times \pi^{ue} + n \times \pi^{nu} - u \times \pi^{un},$$

and

$$0 = e \times \pi^{en} - n \times \pi^{ne} + u \times \pi^{un} - n \times \pi^{nu},$$

where π^{od} denotes the transition rate between the origin state o and the destination state d. Shimer (2012) derives an expression for steady state unemployment rate in such three-state model:

$$\tilde{u} := \frac{u}{u+e} = \frac{\pi^{en}\pi^{nu} + \pi^{ne}\pi^{eu} + \pi^{nu}\pi^{eu}}{(\pi^{en}\pi^{nu} + \pi^{ne}\pi^{eu} + \pi^{nu}\pi^{eu}) + (\pi^{un}\pi^{ne} + \pi^{nu}\pi^{ue} + \pi^{ne}\pi^{ue})}.$$

Thus,

$$\frac{\tilde{u}}{1-\tilde{u}} = \frac{\pi^{en}\pi^{nu} + \pi^{ne}\pi^{eu} + \pi^{nu}\pi^{eu}}{\pi^{un}\pi^{ne} + \pi^{nu}\pi^{ue} + \pi^{ne}\pi^{ue}}.$$

Define the following term that captures the overall contribution from flows into or out of non-participation

$$\pi^{n} := \frac{\pi^{en}\pi^{nu} + \pi^{ne}\pi^{eu} + \pi^{nu}\pi^{eu}}{\pi^{un}\pi^{ne} + \pi^{nu}\pi^{ue} + \pi^{ne}\pi^{ue}} \Big/ \frac{\pi^{eu}}{\pi^{ue}},$$

so that by construction

$$\log \frac{\tilde{u}}{1-\tilde{u}} = \log \pi^{eu} - \log \pi^{ue} + \log \pi^{n}$$

holds in steady state. We introduce an residual term ϵ to the above equation to incorporate approximation errors and evaluate the following three-state decomposition:

$$\begin{aligned} \operatorname{var}\left(\log \frac{\tilde{u}}{1-\tilde{u}}\right) &= \operatorname{cov}\left(\log \frac{\tilde{u}}{1-\tilde{u}}, \log \pi^{eu}\right) + \operatorname{cov}\left(\log \frac{\tilde{u}}{1-\tilde{u}}, -\log \pi^{ue}\right) \\ &+ \operatorname{cov}\left(\log \frac{\tilde{u}}{1-\tilde{u}}, \log \pi^{n}\right) + \operatorname{cov}\left(\log \frac{\tilde{u}}{1-\tilde{u}}, \varepsilon\right). \end{aligned}$$

Using this decomposition, we find that the separation rate accounts for 60.6%, the job-finding rate accounts for 32.8%, nonparticipation for 0.6%, and the residual for 5.9% of the spatial dispersion of unemployment rates in Germany.

I.1.4 Construction of Labor Market Composition Controls

We construct the control variables for labor market composition from the IAB microdata. For each year, we construct employment shares for worker groups by occupation, industry, education, age, and sex. For occupation shares, we rely on the 1988 occupation classification (KldB1988) that is consistently available over the sample period to group workers into 17 broad occupation groups.[45] We construct five industry groups (agriculture, forestry, fishing, and mining; manufacturing and construction; wholesale, transportation, accommodation, and other services; information, communication, and financial services; public administration, education, and health). We construct three education groups for no apprenticeship, completed apprenticeship, and college. For age groups, we construct four age groups for workers age 20 to 25 years, 26 to 40 years, 41 to 55 years, and 56 years and older. Employment spells are reported daily throughout the year and we compute total annual employment in each group weighted by spell duration for each local labor market and year.

I.1.5 Labor Market Tightness and On-the-Job Search

In Section 2 of the main text, we use the standard definition of labor market tightness as the ratio of vacancies to unemployed workers. In the data, a sizable share of new hires comes directly from other employers. Thus, we consider as a robustness check an alternative notion of tightness defined as the ratio of vacancies to all searchers (employed and unemployed). We demonstrate that if we account for employed job seekers in the data, we still find that local labor markets with lower unemployment are tighter.

In Section 2, we construct tightness as the ratio of vacancies to unemployed workers

$$\theta = \frac{v}{u}.$$

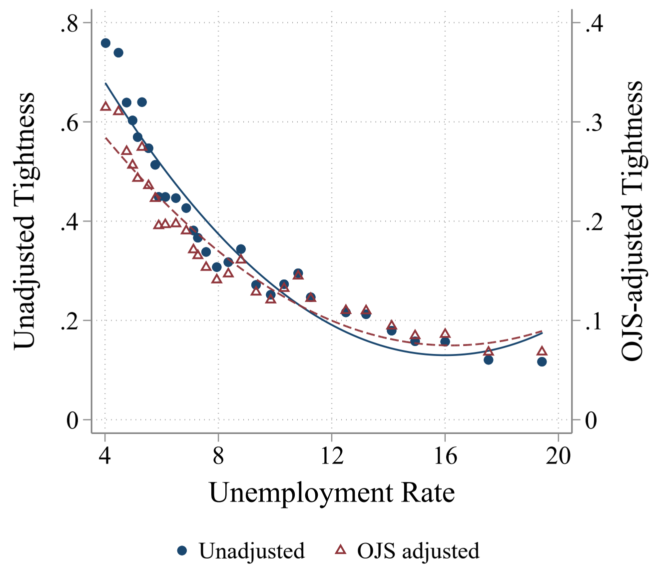
Including employed searchers increases the pool of searching workers, and tightness becomes

$$\tilde{\theta} = \frac{v}{u + s \times e} = \theta \frac{u}{u + s \times e},$$

where e denotes the number of employed workers and s the share of workers searching on the job. To adjust θ for on-the-job search, we multiply it by the share of unemployed searchers among all searchers, measured as the share of total hires that come from unemployment. We estimate the latter share and its relationship to the local unemployment rate using microdata from the

[45] We use the following grouping of semi-aggregated occupation groups in the SIAB data (See Table A6 in Antoni, Ganzer, and vom Berge (2019)): 1-3, 4-11, 12-37, 38-41, 42-58, 59-70, 71-79, 80-86, 87-89, 90-95, 96-98, 99-101, 102-110, 111-113, 114, 115-116, and 117-120.

Figure A-4: Tightness with On-the-Job Search Adjustment across German Local Labor Markets



Notes: Local labor market tightness with and without adjustment for on-the-job search across local labor markets. Blue dots show local labor market tightness as the vacancy-unemployment ratio at different local unemployment rates from Figure 3. The blue solid line shows quadratic fit to the data. The level is shown on the left axis. Red triangles show local labor market tightness adjusted for on-the-job search. The red dashed line shows quadratic fit to the data. The level is shown on the right axis. The horizontal axis shows local unemployment rates.

German IAB vacancy survey.[46] Using the estimated share, we can then construct an estimate for $\tilde{\theta}$ that takes the local unemployment rate into account. The IAB vacancy survey provides information on vacancies and the hiring behavior of establishments in Germany. Specifically, the survey asks each establishment about the previous labor market status of the last worker it hired within the preceding 12 months. We restrict the sample to hires from unemployment and other employers and create a dummy variable that is one if the last hire came from unemployment and zero if from employment.[47] The sample size does not allow us to construct results at the local labor market level, so that we estimate an aggregate relationship using the local unemployment rate as a regressor.

We run the regression of the dummy variable on local unemployment rates in a pooled sample of last hires for the period from 2007 to 2016 with year fixed effects. Local unemployment rates are at the commuting zone level that we merge in using district identifiers that become available

[46]We use data from the German Job Vacancy Survey of the IAB, version 2000-2017. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access. See Bossler et al. (2019) for details on the data.

[47]Last hires could also be previous apprentices, temporary help workers, self-employed, or coming from out of the labor force.

in the microdata in 2007. Specifically, we estimate

$$\mathbf{1}_{i,t} = \beta_0 + \beta_1 u_{c(i),t} + \gamma_t + \varepsilon_{i,t}, \tag{A1}$$

where γ_t denotes the year fixed effect and $u_{c(i),t}$ the unemployment rate of commuting zone c where the establishment i is located. Running this regression, we get a constant share $\beta_0 = 0.370$ and a positive coefficient $\beta_1 = 1.110$. The positive β_1 coefficient implies that there is a higher fraction of vacancies filled by unemployed job seekers in high-unemployment locations.[48] We use these estimated coefficients to impute for each commuting zone and year the share of unemployed searchers based on its unemployment rate. Using the imputed share, we construct $\tilde{\theta}$, labor market tightness adjusted for on-the-job search, from our local labor market data for θ. On average, we find the share of unemployed job seekers among all searchers to be 47.4% implying that the level of tightness adjusted for on-the-job search ($\tilde{\theta}$) is on average about one half of the level of tightness when considering only unemployed job seekers (θ).

Figure A-4 shows labor market tightness θ from Section 2 (blue dots) together with labor market tightness adjusted for searchers on the job $\tilde{\theta}$ (red triangles) across local labor markets. We find that the level of adjusted tightness is lower but that the variation across local labor markets remains very similar. We still find local labor market tightness to be declining in local unemployment rates and that the lowest unemployment location has an almost 4-times higher tightness compared to the highest unemployment locations even after adjusting for on-the-job search. Hence, we conclude that the result of lower unemployment locations being tighter is qualitatively and quantitatively robust to including on-the-job search.

I.1.6 Commuting Zone-Occupation Level Vacancy Duration

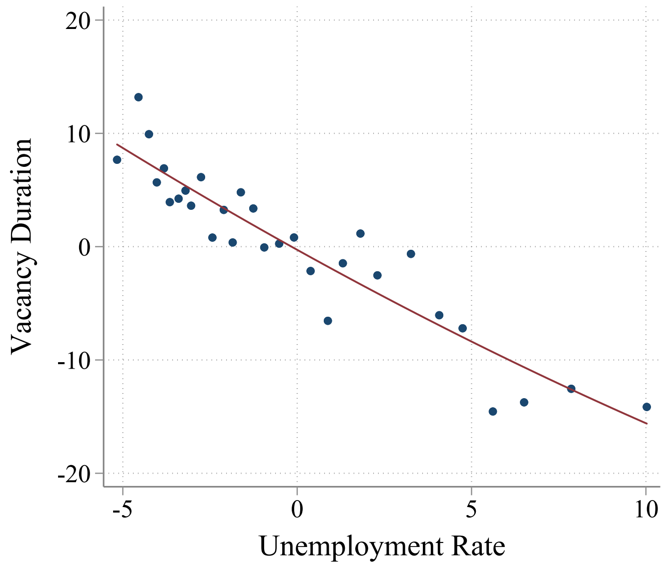
Table 1 shows that differences in labor market tightness and job-filling rates across local labor markets remain highly statistically and economically significant even after controlling for the local labor market composition. For the German data, we provide a further robustness check to control for local labor market composition. We look at the occupation-specific vacancy duration at the 3-digit level across local labor markets.[49] The occupation-specific vacancy duration data correspond to the data shown in Figure 4 but have been disaggregated within each local labor market by occupation and averaged over a 10-year period to get reliable estimates.[50] The final sample has 13,586 observations for average vacancy duration of 134 occupations at the

[48] Both coefficients are statistically significant at the 1-percent level.

[49] These data have been obtained as special data request no. 332811 from the statistics division of the German employment office.

[50] We aggregate the data again from districts to commuting zones weighted by vacancy outflows. The minimum number of filled vacancies for estimates to be reported at the district level over the 10-year period is 60. Data start in 2012 to rely on a consistent occupational coding scheme (KldB 2010).

Figure A-5: Commuting Zone-Occupation Level Vacancy Duration



Notes: This figure shows the relationship between vacancy duration and local unemployment after controlling for occupation fixed effects.

commuting-zone level.

These occupation-level local labor market data allow us to control non-parametrically for the occupational composition of local labor markets when comparing vacancy duration across space. Specifically, we consider the following regression

$$y_{c,o} = \beta u_c + \eta_o + \varepsilon_{c,o},$$

where $y_{c,o}$ is the average vacancy duration of occupation o in commuting zone c, u_c is the average unemployment rate of commuting zone c, η_o denotes the fixed effects associated with each occupation o, and $\varepsilon_{c,o}$ is the residual. The coefficient β is the coefficient of interest as it captures the relationship between occupation-specific vacancy duration and the local unemployment rate after removing occupation fixed effects. We find a statistically significant coefficient of -1.65 with a t-statistic of -28.54. Hence, we find that in labor markets with higher unemployment rates, employers fill their vacancies faster, even if we look within fine-grained 3-digit occupations across local labor markets. Quantitatively, the coefficient implies that the vacancy duration in the labor market with the highest unemployment rate is on average a month shorter than that with the lowest unemployment rate (Figure A-5).

To compare the results for the occupation-specific data to the regression evidence in Table 1, we also run the regression with log vacancy duration and log unemployment rates. Column (3) of Table A-1 reports the elasticity of vacancy duration with respect to the local unemployment rate when we rely on the occupation-specific vacancy duration and control for occupation fixed

Table A-1: (Log) Vacancy Duration across German Local Labor Markets

	CZ Level Regression		CZ-Occ Level Regression
	(1)	(2)	(3)
(Log) Unemployment Rate	-0.205***	-0.213***	-0.191***
	(0.022)	(0.020)	(0.032)
Year FE	Yes	Yes	-
Controls	All Controls	Occ Controls	Occ FE
Observations	3,492	3,492	13,586
R-squared	0.75	0.73	0.56

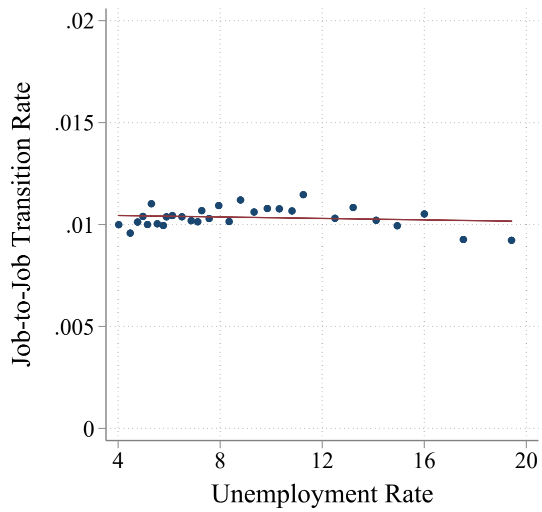
Notes: Regression estimates of (log) vacancy duration and on (log) local unemployment rate. Column (1)-(2) are CZ level regressions and Column (3) the CZ-Occupation level regression. Controls in addition to occupation compositions include age, gender, education, and industry shares of employment. Standard errors are clustered at the state level.

effects. The estimated elasticity of -0.19 is highly statistically significant. Columns (1) to (2) of Table 1 show the corresponding estimated coefficients for regression specifications using occupation shares to control for the occupation composition as also done in Table 1. Column (1) shows the estimate for the specification with the full set of local labor market composition controls and column (2) shows the specification with only the occupation composition controls. We find the estimated coefficient of -0.21 in column (2) to be very close to the coefficient from the more flexible specification with occupation fixed effects in column (3). Comparing column (1) with column (2) suggests that, once occupations are controlled for, including additional controls has little impact on the estimated elasticity.

I.1.7 Job-to-Job Rates

In this section, we construct job-to-job transition rates from the SIAB social security records, following Jung and Kuhn (2014), to estimate job-to-job transition rates at the local labor market level. To improve accuracy of the local labor market estimates, we construct worker flows using annual averages of worker flows and stocks. We consider commuting zones as unit of analysis for local labor markets. Figure A-6 shows job-to-job transition rates by local unemployment rates. As in the case of the United States, we find virtually no systematic variation in job-to-job rates across local labor markets.

Figure A-6: Job-to-Job Rate across German Local Labor Markets



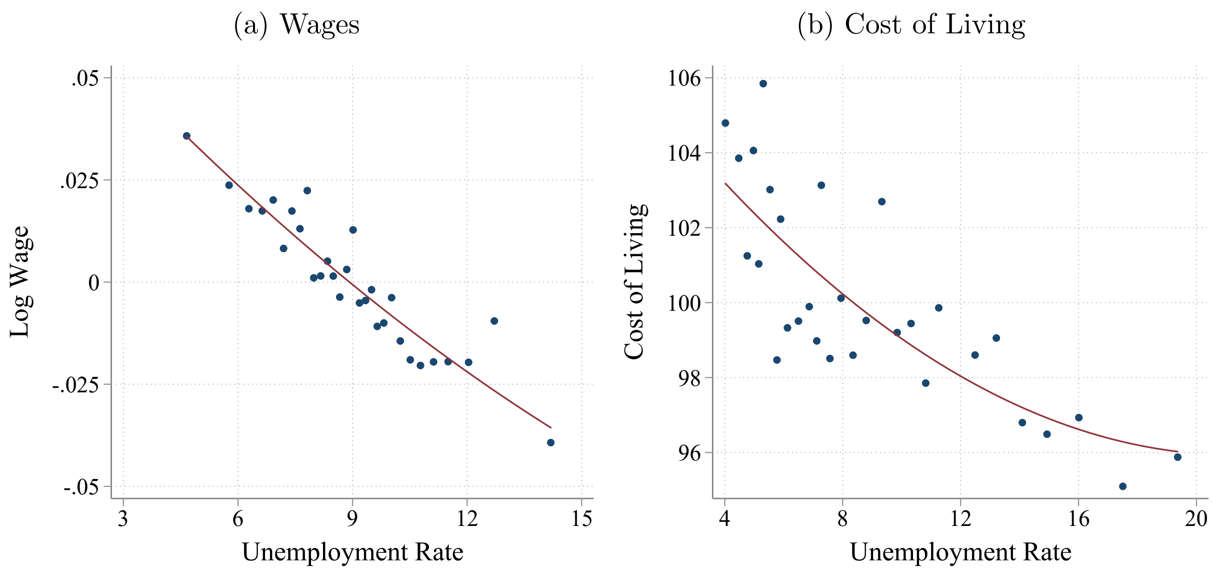
Notes: Job-to-job transition rates across local labor markets in Germany. Commuting zones are unit of analysis for local labor markets. Horizontal axis shows local unemployment rates. Blue dots show bin-scatter data and the solid red line shows linear fit to raw data.

I.1.8 Wages and Cost of Living

The left panel of Figure A-7 shows average wage differences across local labor markets. Wage data are daily wages for full-time employed workers from the IAB social security data. We rely on full-time employed workers as the data do not contain fine-grained hours worked information. We aggregate average wages for each local labor market and remove year and labor market composition effects as in the case of productivity. We find an almost linear negative relationship between local unemployment rates and (log) wages across local labor markets.

In the right panel of Figure A-7, we show evidence on local cost of living differences. We rely on data compiled by the Federal Office for Building and Regional Planning (BBSR, 2009). The data provide a county-level cost of living index for 2008. The underlying consumption basket corresponds to the consumption basket of the German Consumer Price Index (CPI). We average county-level prices at the commuting zone level and normalize the average cost of living to 1 across local labor markets. We find again a clear negative relationship between local cost of living and unemployment rates. Local cost of living vary by about 8% between the lowest and the highest unemployment labor market. Note that the support of unemployment rates differs as we residualize them in the left panel.

Figure A-7: Wage and Cost of Living across German Local Labor Markets



Notes: Wage and cost of living differences across local labor markets in Germany. The left panel shows average (log) wages across local labor markets in Germany. Wage data for full-time employed workers with year and local labor market composition effects removed. Local cost of living in Germany in 2008. Cost of living for CPI consumption basket for each local labor market in 2008 from BBSR (2009). We show in both figures bin-scatter data as blue dots and solid red lines show a linear fit to the data. The horizontal axes show local unemployment rates.

I.2 United States

I.2.1 Local Unemployment Dispersion and Persistence

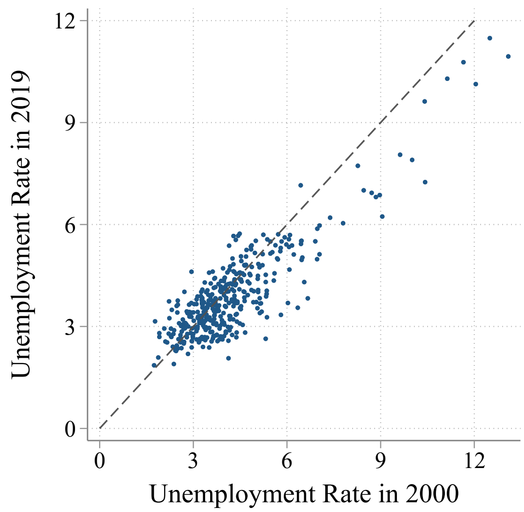
In the empirical analysis of local labor market differences for the United States in Section 2.2, we consider commuting zones as unit of observation for local labor markets. In this robustness analysis, we demonstrate that considering metropolitan statistical areas (MSAs) yields the same conclusions regarding differences in local labor market outcomes.

Figure 6 in the main text documents the persistence of local unemployment rate differences between 2000 and 2019 at the commuting zone level. Figure A-8 reports the corresponding results at the MSA level. In 2000, the (unweighted) average unemployment rate across MSAs is 4.3%, with a standard deviation of 1.9%. We observe an unemployment rate of as low as 1.7% in Ames, IA and as high as 17.5% in El Centro, CA.[51] Hence, we find as in the case of commuting zones large dispersion of local unemployment rates. We also find that unemployment rates are highly persistent at the MSA level as most data points cluster closely around the 45-degree line.

The high persistence of local unemployment rates is not sensitive to our choice of the specific

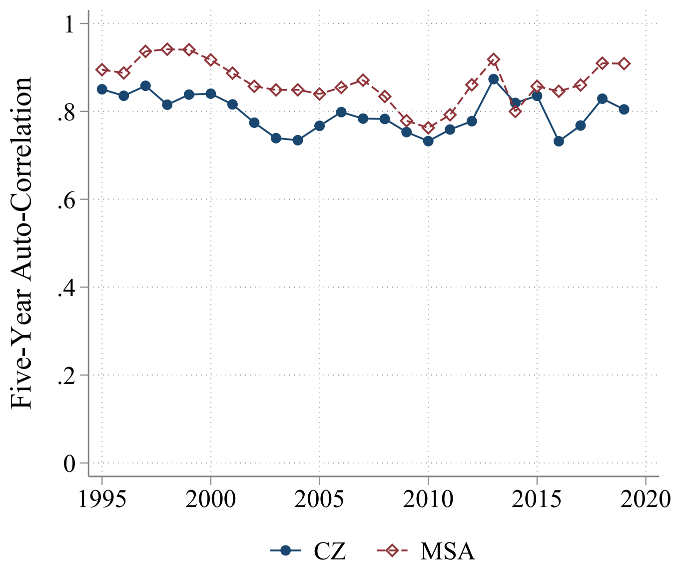
[51]These two locations are not the only extreme lows or highs. For example, the second to the sixth highest MSA-level unemployment rates are 16.4%, 13.6%, 13.1%, 12.5%, and 12.1%. The second to the sixth lowest MSA-level unemployment rates are 1.8%, 1.9%, 1.9%, 1.9%, 2.1%.

Figure A-8: Dispersion and Persistence of Unemployment across U.S. Local Labor Markets



Notes: Each dot is a metropolitan statistical area in the United States. The vertical axis represents the unemployment rate in 2019 and the horizontal axis represents the unemployment rate in 2000. The dashed gray line is the 45-degree line. The data source is BLS Local Area Unemployment Statistics program. Three MSAs with 2019 unemployment rates higher than 12% are excluded.

Figure A-9: Persistence of Local Unemployment Rates in the United States



Notes: Auto-correlation of local unemployment rates in the United States from 1990 to 2020. Each dot shows the correlation of local unemployment rates in that year with local unemployment rates five years ago. The first 5-year correlation estimate exists in 1995. Blue dots show data for commuting zones as local labor markets, red diamonds show data for MSAs as local labor markets.

two years 2000 and 2019. Figure A-9 shows the 5-year rolling correlation of unemployment rates in the United States over the time period from 1995 to 2019.[52] We compute the correlation in each year as the correlation of local unemployment rates in that year with local unemployment

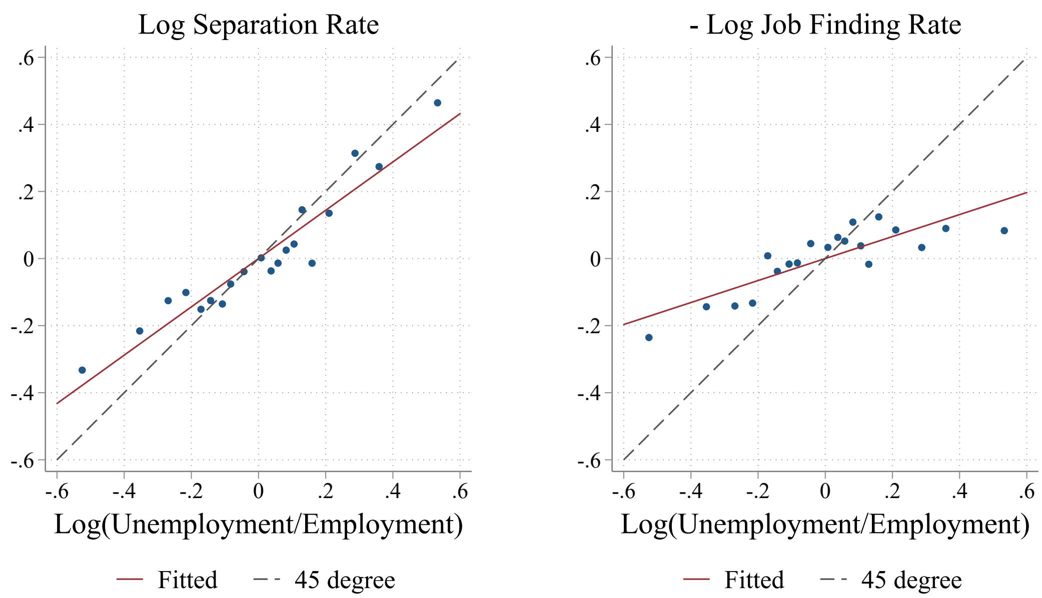
[52]Underlying data start in 1990 to construct the 5-year correlation in year 1995.

rates five years ago. The figure illustrates a consistently high correlation both for commuting zones (blue line with circles) and MSAs (red line with squares) over the past 30 years. Local unemployment rates at the MSA level are slightly more persistent.

I.2.2 Unemployment Decomposition

Figure A-10 visualizes the relative importance of separation rate and job finding rate differences across U.S. local labor markets in accounting for the spatial unemployment differences. Comparing the fitted lines for separation rates and job-finding rates with the 45-degree line, we observe separation-rate differences to align much more closely implying that differences in unemployment rates are mainly accounted for by differences in separation rates.

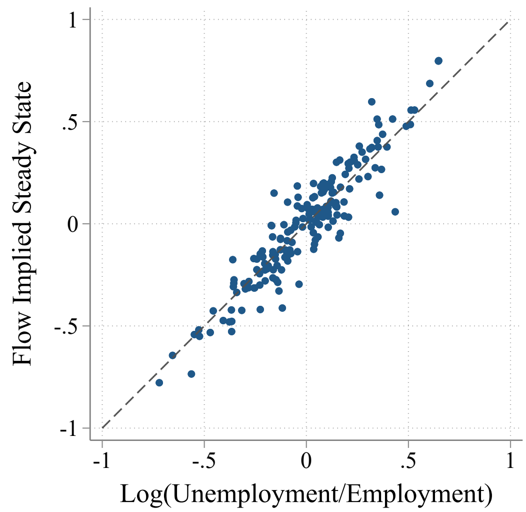
Figure A-10: Decomposition of Unemployment Differences across U.S. Local Labor Markets



Notes: Decomposition of local unemployment rate differences across metropolitan statistical areas in the United States into differences of separation and job-finding rates. The left panel plots bin-scatter data of the (demeaned) log separation rate (vertical axis) against the (demeaned) log unemployment-employment ratio (horizontal axis). The right panel plots bin-scatter data of the negative (demeaned) log job-finding rate (vertical axis) against the (demeaned) log unemployment-employment ratio (horizontal axis). In both panels, the blue dots show the raw data, the solid red line is the linear fit to the data, and the dashed gray line shows the 45-degree line.

The decomposition of the sources of local unemployment rate dispersion in Section 2.2.1 of the main text relies on a steady-state approximation of the unemployment rate from a 2-state model of unemployment dynamics. Figure A-11 shows the demeaned empirical log unemployment-employment ratio ($\log(U/E)$) to the demeaned steady state log unemployment-employment ratio implied by estimated worker-flow rates ($\log(s/f)$). We find that the data align closely along the 45-degree line indicating that the 2-state steady state approximation matches the data well. We also see no pattern that the approximation deteriorates for large positive or negative deviations. The close alignment of the observed data and the steady-state approximation accords well with the fact that the residual in the decomposition of Section 2.2.1 is small.

Figure A-11: Steady-State Approximation of Local Unemployment Rates in the United States



Notes: Empirical unemployment and steady state approximation based on worker-flow rates for the United States. The horizontal axis shows (demeaned) log unemployment-to-employment ratio against steady-state approximation based on worker flow rates ($\log(s/f)$). Blue dots show data and the dashed gray line shows the 45-degree line.

I.2.3 Three-State Decomposition

We apply the three-state model as laid out in Appendix I.1.3 also for the U.S. data. We find that in the United States, a formal three-state decomposition delivers that the separation rate accounts for 72.0%, the job-finding rate for 32.8%, nonparticipation for -5.7%, and the residual for 0.9% of the spatial dispersion of unemployment rate.

I.2.4 Construction of Labor Market Composition Controls

We construct controls for labor market compositions from the Quarterly Workforce Indicators (QWI) dataset, which is in turn tabulated from the Longitudinal Employer-Household Dynamics linked employer-employee microdata. QWI allows us to construct employment shares by age, gender, education, and industry of each local labor market.[53] For age, we use groups of workers below 25 years old, prime age (25-54), and above 55. For gender, we use the share of males and

[53] Occupations are not available in QWI.

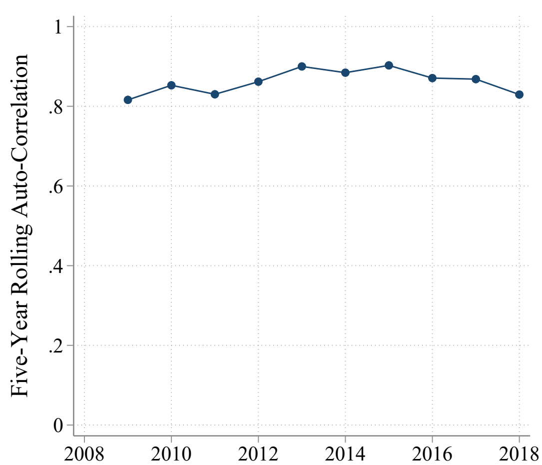
females. For education, we consider four education groups: less than high school, high-school or equivalent, some college or associate degree, bachelor and above. For industries, we consider 10 broad divisions according to the Standard Industrial Classification (SIC): Agriculture, Forestry, and Fishing; Mining; Construction; Manufacturing; Transportation, Communications, Electric, Gas, and Sanitary Services; Wholesale Trade; Retail Trade; Finance, Insurance, and Real Estate; Services; and Public Administration.

I.3 United Kingdom

I.3.1 Local Unemployment Persistence

In Section 2.3, we demonstrate that large unemployment rate differences persistent in the United Kingdom between 2004 and 2018. Figure A-12 shows 5-year rolling correlations of unemployment rates in the United Kingdom over the entire time period from 2004 to 2018. We compute the correlation in each year as the correlation of local unemployment rates in that year with local unemployment rates five years ago, so that the first data point is for 2009. The figure relies as before on local authority districts as definition of local labor markets. We find that the persistence over the entire time period to be high with values between 0.8 and 0.9.

Figure A-12: Persistence of Local Unemployment Rates in the United Kingdom



Notes: Auto-correlation of local unemployment rates in the United Kingdom from 2004 to 2018. Each dot shows the correlation of local unemployment rates in that year with local unemployment rates five years ago. The first 5-year correlation estimate exists in 2009.

I.3.2 Unemployment Decomposition

To construct local worker flow rates in the United Kingdom, we rely on job seeker allowance (JSA) data. These data only cover unemployment benefit recipients so that we have to adjust worker flows rates for those unemployed workers who do not receive job search allowance. We proceed as follows. First, we calculate the fraction of unemployed workers in each local authority district j who are JSA claimants

$$\Omega_j = \frac{\text{JSA claimants in LAD}_j}{\text{unemployed workers in LAD}_j},$$

using data on the total number of unemployed workers from Nomis. Second, we assume JSA inflows and the JSA outflows also represent a fraction Ω_j of the EU and UE flows in local labor market j. Thus, the imputed EU and UE flow levels are

$$\text{EU flows}_j = \frac{\text{JSA inflows}_j}{\Omega_j}, \quad \text{UE flows}_j = \frac{\text{JSA outflows}_j}{\Omega_j}.$$

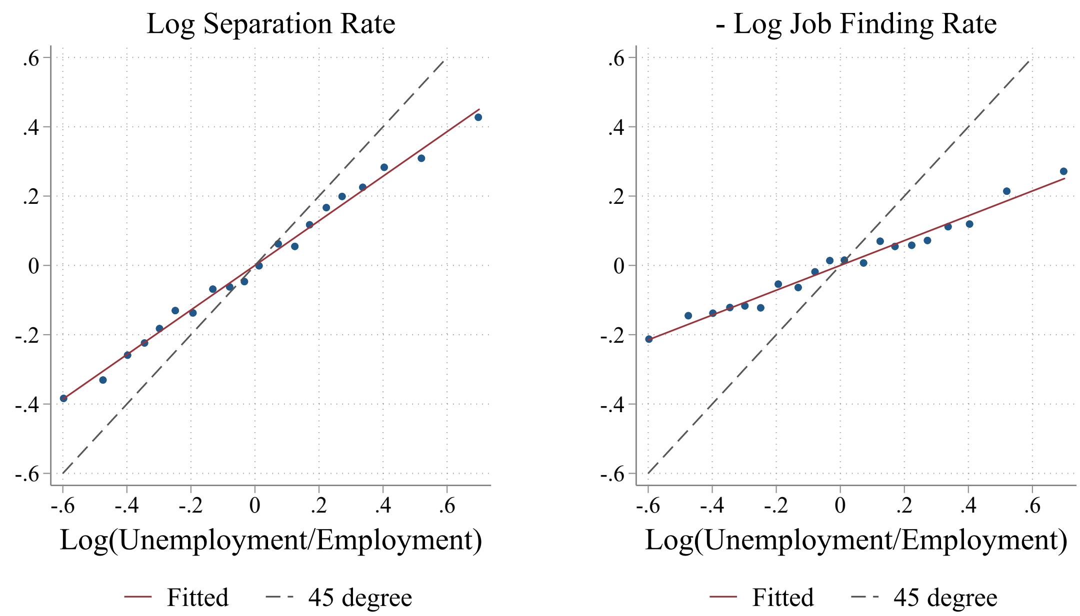
Finally, the flow rates are computed as usual, by dividing flows by stocks, i.e.,

$$\text{EU rate}_j = \frac{\text{EU flows}_j}{\text{E stock}_j}, \quad \text{UE rate}_j = \frac{\text{UE flows}_j}{\text{U stock}_j}.$$

Using these constructions, Figure A-13 plots the demeaned log separation rate (in the left panel) and the demeaned log job finding rate (in the right panel) against the demeaned log U/E ratio across U.K. local labor markets. The blue dots in the left panel align more closely along the 45 degree line than the right panel, implying that separation rate differences explain more of spatial unemployment differences than job finding differences.

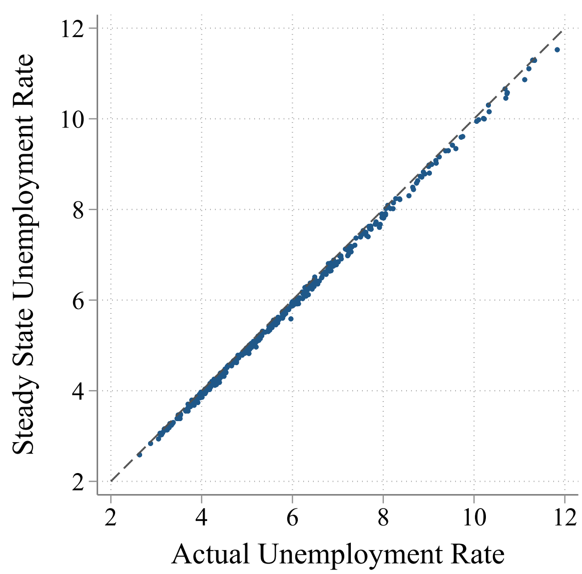
To check the quality of the constructed worker-flow rate estimates, we plot in Figure A-14 the steady state unemployment rate implied by these worker flow rates (using a two-state approximation) against the actual unemployment rate of each local authority district. We find that the constructed flow rates imply a steady state unemployment rate that corresponds extremely closely with the observed unemployment rate as all data align closely with the 45-degree line.

Figure A-13: Decomposition of Unemployment Differences across U.K. Local Labor Markets



Notes: Decomposition of local unemployment rate differences across local authority districts in the United Kingdom into differences of separation and job-finding rates. The left panel plots bin-scatter data of the (demeaned) log separation rate (vertical axis) against the (demeaned) log unemployment-employment ratio (horizontal axis). The right panel plots bin-scatter data of the negative (demeaned) log job-finding rate (vertical axis) against the (demeaned) log unemployment-employment ratio (horizontal axis). In both panels, the blue dots show the raw data, the solid red line is the linear fit to the data, and the dashed gray line shows the 45-degree line.

Figure A-14: Steady-State and Empirical Local Unemployment Rates in the United Kingdom



Notes: Empirical unemployment rates and steady-state approximation of unemployment rates based on worker-flow rates for the United Kingdom. The horizontal axis shows the local unemployment rate. The vertical axis shows the steady-state approximation of the unemployment rate based on worker flow rates ($s/(s+f)$). Blue dots show data and the dashed gray line shows the 45-degree line.

I.3.3 Construction of Labor Market Composition Controls

We obtain controls for local labor market composition from the Nomis system of the Office for National Statistics. The local labor market compositions are tabulated from the Annual Population Survey. We construct the employment share of each local authority district by gender, age, industry, and occupation. For gender, we use the percentage of all people aged 16+ who are male and female. For age, we calculate three groups: the share of among all workers 16 years and older who are 16 to 24 years, 25 to 49 years, and 50 years and older, respectively. We consider 9 broad industries based on 2007 UK Standard Industrial Classification and construct the employment shares for agriculture and fishing; energy and water; manufacturing; construction; distribution, hotels and restaurants; transport and communications; banking, finance and insurance; public administration, education and health; and other services. We also consider 9 broad occupation groups based on SOC2010 and construct employment shares of managers, directors and senior officials; professional occupations; associate professional and technical occupations; administrative and secretarial occupations; skilled trades occupations; caring, leisure and other service occupations; sales and customer service occupations; process, plant and machine operatives; and elementary occupations.

II Model Details

This section provides additional model details and results. Section II.1 derives the characterization of wages and the separation cutoff for the baseline model from Section 3. Section II.2 proves constrained efficiency of the baseline model. Section II.5 states value functions and derives wages and separation cutoffs for the model with on-the-job search from Section 4. Finally, Section II.6 provides the details for the model with aggregate fluctuations from Section 4.2.

II.1 Separation Cutoff and Wage Equation in Baseline Model

To derive the bargaining outcome for wages in Equation (8) and characterize the privately efficient separation cutoff in Equation (6), we start from the result that the value of a vacant job is zero in equilibrium, so that the joint match surplus of a match with productivity ε is $S_j(\varepsilon) = V_j^p(\varepsilon) + V_j^e(\varepsilon) - V_j^u$. Nash bargaining implies that the total match surplus is split according to the bargaining weights, so that the firm's share of surplus is $V_j^p(\varepsilon) = (1-\eta) S_j(\varepsilon)$ and the worker's share of surplus is $V_j^e(\varepsilon) - V_j^u = \eta S_j(\varepsilon)$. Combining the value functions, the surplus function can be written as

$$S_j(\varepsilon) = A_j\varepsilon - z + \beta(1-\delta)(1-\eta f(\theta_j))\mathbb{E}_{\varepsilon'}[S_j(\varepsilon')]^+ . \tag{A2}$$

The condition for efficient separations is $S_j\left(\varepsilon_j^R\right)=0$ and the probability of endogenous separation is $F(\varepsilon_j^R)$. Evaluating the surplus function (A2) at $\varepsilon=\varepsilon_j^R$ characterizes the reservation productivity threshold ε_j^R (job destruction equation):

$$0=A_j\varepsilon_j^R-z+\beta\left(1-\delta\right)\left(1-\eta f\left(\theta_j\right)\right)\mathbb{E}_{\varepsilon'}\left[S_j\left(\varepsilon'\right)\right]^+. \tag{A3}$$

The free-entry condition characterizes equilibrium job creation by pinning down equilibrium tightness θ_j (job creation equation):

$$\frac{\kappa}{\beta\left(1-\eta\right)\left(1-\delta\right)q\left(\theta_j\right)}=\mathbb{E}_{\varepsilon'}\left[S_j\left(\varepsilon'\right)\right]^+. \tag{A4}$$

Subtracting Equation (2) from Equation (3), we get the worker surplus as

$$V_j^e\left(\varepsilon\right)-V_j^u=w_j\left(\varepsilon\right)-z+\beta\left(1-\delta\right)\left(1-f\left(\theta_j\right)\right)\mathbb{E}_{\varepsilon'}\left[V_j^e\left(\varepsilon'\right)-V_j^u\right]^+.$$

Combining it with the surplus sharing rule from Nash bargaining by equating $\eta V_j^p\left(\varepsilon\right)$ with $\left(1-\eta\right)\left(V_j^e\left(\varepsilon\right)-V_j^u\right)$, we get

$$\begin{aligned}&\left(1-\eta\right)\left\{w_j\left(\varepsilon\right)-z+\beta\left(1-\delta\right)\left(1-f\left(\theta_j\right)\right)\mathbb{E}_{\varepsilon'}\left[V_j^e\left(\varepsilon'\right)-V_j^u\right]^+\right\}\\=&\eta\left\{A_j\varepsilon-w_j\left(\varepsilon\right)+\beta\left(1-\delta\right)\mathbb{E}_{\varepsilon'}\left[V_j^p\left(\varepsilon'\right)\right]^+\right\}.\end{aligned}$$

Noticing that $\left(1-\eta\right)\left(V_j^e\left(\varepsilon'\right)-V_j^u\right)=\eta V_j^p\left(\varepsilon'\right)$ holds for any ε' because of continuous Nash bargaining, we have

$$\left(1-\eta\right)\left(w_j\left(\varepsilon\right)-z\right)=\eta\left\{A_j\varepsilon-w_j\left(\varepsilon\right)+\beta\left(1-\delta\right)f\left(\theta_j\right)\mathbb{E}_{\varepsilon'}\left[V_j^p\left(\varepsilon'\right)\right]^+\right\}.$$

Substituting $\mathbb{E}_{\varepsilon'}\left[V_j^p\left(\varepsilon'\right)\right]^+=\frac{\kappa}{\beta(1-\delta)q(\theta_j)}$ from free entry, we obtain the wage equation as

$$w_j\left(\varepsilon\right)=\left(1-\eta\right)z+\eta A_j\varepsilon+\eta\kappa\theta_j.$$

II.2 Efficiency

We consider a social planner's problem where the social planner faces the same frictions as the agents in the model. The planner can reallocate unemployed workers across locations instantaneously, but can only reallocate employed workers across locations by first separating them into unemployment.[54] The planner can decide how many job openings to post in each

[54]In optimum, the planner has no incentive to reallocate employed workers across location by going through unemployment, as any matched pair has a positive surplus.

location and which matches to consummate, but is subject to search frictions. The solution to the planner's problem characterizes the (constrained) efficient allocation. We will show that the equilibrium defined in Section 3 coincides with the efficient allocation. We prove the efficiency property in two steps. First, we show that for an arbitrary allocation of unemployed workers across space, the search equilibrium within each location is efficient as long as the Hosios (1990) condition holds. Second, we show that the spatial allocation of unemployed workers arising from the Rosen-Roback equilibrium condition also coincides with the planner's optimal allocation.

II.2.1 Efficiency Within a Location

Given a spatial allocation of the work force, the social planner chooses $\left(\theta_j, \varepsilon_j^R\right)$ to maximize the average present discounted value per person in the labor force for each location j. The problem can be written recursively as

$$\Omega_j\left(u_j, y_j\right)=\max_{\theta_j, \varepsilon_j^R} u_j z+\left(1-u_j\right) y_j-\kappa u_j \theta_j+\beta \Omega_j\left(u_j^{\prime}, y_j^{\prime}\right),$$

where y_j is defined as the average output per employed worker. The law of motion for the unemployment rate is given by

$$u_j^{\prime}=u_j\left(1-\underbrace{f\left(\theta_j\right)(1-\delta)\left(1-F\left(\varepsilon_j^R\right)\right)}_{\pi_j^{ue}}\right)+\left(1-u_j\right)\left(\underbrace{1-(1-\delta)\left(1-F\left(\varepsilon_j^R\right)\right)}_{\pi_j^{eu}}\right),$$

and the average output per worker in the next period is

$$y_j^{\prime}=\frac{1}{1-F\left(\varepsilon_j^R\right)} A_j \int_{\varepsilon_j^R}^{\varepsilon_{\max}} \varepsilon d F(\varepsilon),$$

which is independent of y_j because of the i.i.d. structure of the idiosyncratic shocks.

After some algebra, the first order conditions with respect to θ_j and ε_j^R can be characterized by the following two equations:

$$A_j \varepsilon_j^R-z+\beta(1-\delta)\left(1+\theta_j f^{\prime}\left(\theta_j\right)-f\left(\theta_j\right)\right)\left(1-F\left(\varepsilon_j^R\right)\right)\left(y_j^{\prime}-A_j \varepsilon_j^R\right)=0.$$

$$\frac{\kappa}{\beta(1-\delta) f^{\prime}\left(\theta_j\right)}=\left(1-F\left(\varepsilon_j^R\right)\right)\left(y_j^{\prime}-A_j \varepsilon_j^R\right).$$

Note that $\mathbb{E}_{\varepsilon^{\prime}}\left[S_j\left(\varepsilon^{\prime}\right)\right]^{+}=\left(1-F\left(\varepsilon_j^R\right)\right)\left(y_j^{\prime}-A_j \varepsilon_j^R\right)$. These two equations coincide with the job destruction equation (A3) and job creation equation (A4) if and only if

$$1 - \eta = \frac{\theta_j f'(\theta_j)}{f(\theta_j)} = 1 - \alpha.$$

This extends the standard Hosios (1990) condition to allow for endogenous separation. See also Chapter 8.2 in Pissarides (2000) for a similar characterization in a slightly different setup.

II.2.2 Efficiency Across Locations

Now consider the efficient allocation of unemployed workers across locations. Given any allocation, the planner will then optimally choose vacancy postings and separate matches within each local labor market as described in the previous subsection. The efficiency property established above implies that the social planner's problem coincides with the search equilibrium within a location as long as the Hosios condition holds. As a result, the average welfare per labor force for location j is

$$\Omega_j = u_j V_j^u + e_j V_j^e + e_j V_j^p.$$

Define $\tilde{V}_j^u = V_j^u + \frac{1}{1-\beta} c_j$ and $\tilde{V}_j^e = V_j^e + \frac{1}{1-\beta} c_j$ as the value of unemployed and employed before deducting the present discounted cost of living. Because of constant returns to scale, $\tilde{V}_j^u$, $\tilde{V}_j^e$, and V_j^p are not affected by the size of the labor force.

Following Kline and Moretti (2013), we assume a competitive housing sector. Denote by $g_j(N)$ the total cost of producing housing in location j when the size of the labor force is N. Assume $g_j(N)$ is twice differentiable and convex. Regardless of their employment status, each worker demands one unit of housing that is rented at a competitive rate

$$c_j = g_j'(N_j),$$

where $N_j := N_j^u + N_j^e$ is the size of the labor force in location j. In the Rosen (1979)-Roback (1982) equilibrium, $\tilde{V}_j^u - \frac{1}{1-\beta} c_j$ are equalized across locations.

The social planner chooses a reallocation of unemployed workers across locations $\{N_j^u\}_{j \in \mathcal{J}}$ to solve

$$\max_{\{N_j^u\}_{j \in \mathcal{J}}} N_j^u \tilde{V}_j^u + N_j^e \tilde{V}_j^e - \frac{1}{1-\beta} g_j\left(N_j^u + N_j^e\right) + N_j^e V_j^p$$

subject to

$$\sum_{j \in \mathcal{J}} N_j^u = N^u.$$

The interior first-order condition is

$$\tilde{V}_j^u - \frac{1}{1-\beta} g_j' \left(N_j^u + N_j^e \right) = \lambda,$$

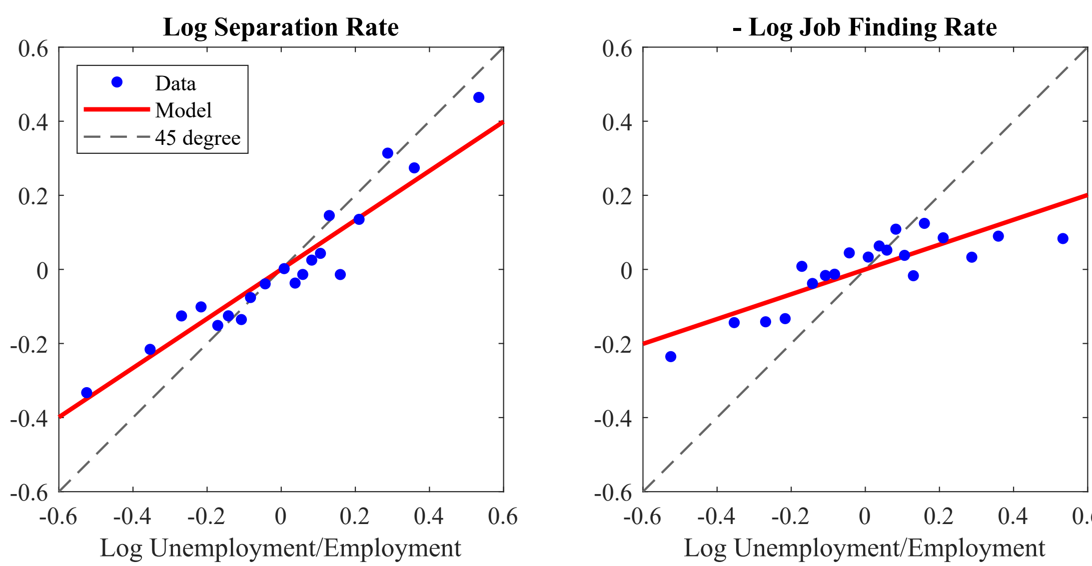
where λ is the Lagrange multiplier. Thus, the social planner equalizes $\tilde{V}_j^u - \frac{1}{1-\beta} g_j' \left(N_j^u + N_j^e \right)$ across locations. Since $c_j = g_j' (N_j)$ holds for every location j due to the competitive housing market, the Rosen-Roback equilibrium coincides with social planner's allocation of unemployed workers across locations.

Combining the above two results, we have established that the equilibrium defined in Section 3 is indeed (constrained) efficient.

II.3 Unemployment Decomposition

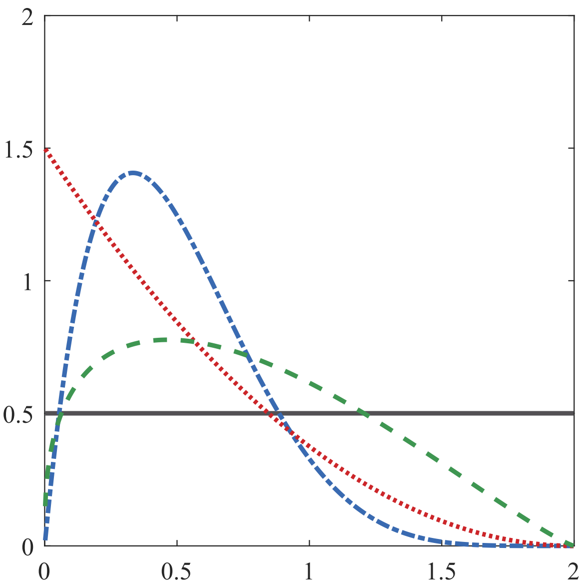
Figure A-15 shows the graphical decomposition of local unemployment rate differences in the data in comparison to the model. The figure corroborates the result from the formal decomposition in Section 3.2 that demonstrates the close fit between the model and the empirical decomposition of local unemployment rate differences.

Figure A-15: Decomposition of Unemployment Differences across Local Labor Markets



Notes: Decomposition of local unemployment rate differences in the model and data into differences of separation and job-finding rates. The left panel shows the (demeaned) log separation rate from the model (red line) and from the data (blue dots) against the (demeaned) log unemployment-employment ratio (horizontal axis). The right panel shows the negative (demeaned) log job-finding rate from the model (red line) and from the data (blue dots). The dashed gray line in each panel shows the 45 degree line. The data points are from from Figure A-10.

Figure A-16: Alternative Distributional Assumptions in the Robustness Exercise

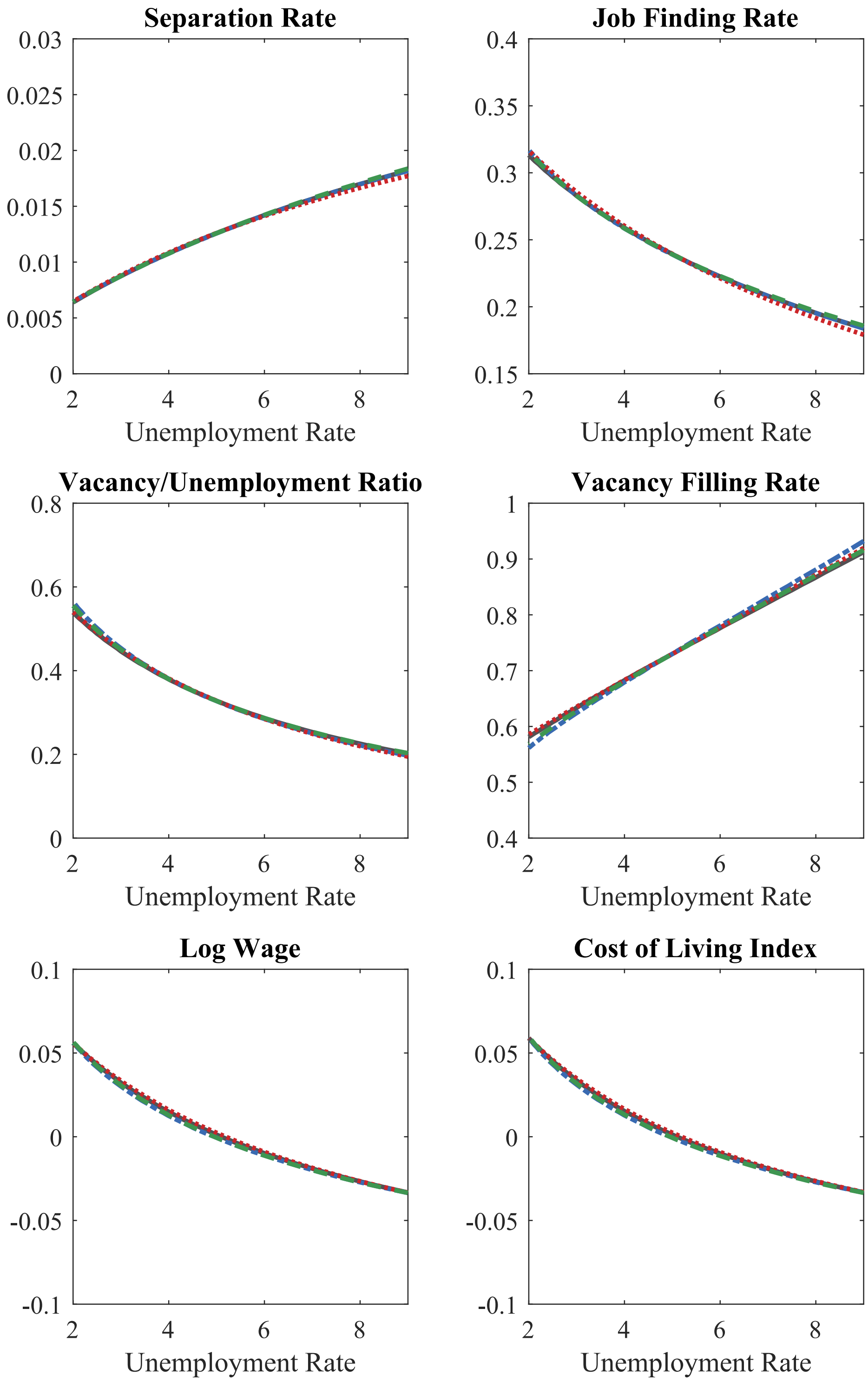


Notes: This figure plots the probability density functions of alternative distributional assumptions in the robustness exercise. We use the Beta(α, β) distribution to parameterize various shapes. The blue line is a lognormal-like distribution, parameterized by $\alpha = 2, \beta = 6$. The red line is a Pareto-like distribution, parameterized by $\alpha = 1, \beta = 3$. The green line takes Bilal (2021)'s estimated Beta distribution with $\alpha = 1.36, \beta = 2.19$. The black line is our baseline uniform distribution, corresponding to $\alpha = \beta = 1$.

II.4 Alternative Distributional Assumptions

In this section, we provide a robustness analysis with respect to the distributional assumption on idiosyncratic productivity shocks. We rely on a Beta distribution because of its flexible functional form nesting our baseline assumption of a uniform distribution. The flexible form allows us to approximate shapes of the other distributional assumptions that have been used in the literature. The original Mortensen and Pissarides (1994) paper uses a uniform distribution as we do too in our baseline specification. Den Haan, Ramey, and Watson (2000) assumes the idiosyncratic productivity shock distribution to be log-normal. Bilal (2021) imposes a Pareto assumption for firm productivity in theory while relying on a Beta distribution in the quantitative implementation. Fournier (2021) assumes that the distribution of idiosyncratic match output follows a Pareto distribution. In the robustness analysis, we vary only the shape of the distribution but keep the support of the shocks unchanged. For the upper part of the shock distribution where production takes place, what matters is only the expected value of the shock, reflected in the option value, but not the shape of the shock distribution. As part of our calibration strategy, we have matched this endogenous component of productivity. For the lower part of the shock distribution, it is natural to restrict the support to positive productivity realizations. In addition, the separation decision renders the distribution below the separation cutoff irrelevant, as those shocks are never realized. The quantitative results therefore depend only on the shape of the distribution around the separation cutoff. We show that we can allow for very different distributional assumptions for the lower part of the distribution around the cutoff value and find results to be robust. Figure A-16 plots the probability density functions of the different distributional assumptions. Under each distributional assumption, we re-calibrate the model using the same calibration strategy and show model predictions in Figure A-17. Despite very different shapes of these distributions as made clear by Figure A-16, the four curves in each panel of Figure A-17 are virtually on top of each other, suggesting that model predictions are barely changed across these distributional specifications.

Figure A-17: Model Predictions Under Alternative Distributional Assumptions



Notes: This figure plots the model predictions under alternative distributional assumptions as detailed in Figure A-16. The color coding of the curves is the same as in the previous figure.

II.5 Model with On-the-Job Search

II.5.1 Value Functions and Characterization

Adding on-the-job search to the baseline model does not directly affect unemployed searchers so that their value function is unchanged and given by Equation (2). Employed workers are now searching on-the-job and receive job offers, yet, their value function remains unaffected and is still given Equation (3) because the *ex ante* pecuniary value of each job is the same for an employed worker so that job switching and remaining with the current employer yield the same continuation value to an employed worker.

Using that free entry in equilibrium implies $V_j^v = 0$ in each local market, the value of a vacant job in local labor market j is

$$V_j^v = -\kappa + \beta\left(1-\delta\right) q\left(\theta_j\right) \varphi_j\left(u_j\right) \mathbb{E}_{\varepsilon'}\left[V_j^p\left(\varepsilon'\right)\right]^+ . \tag{A5}$$

The value function of a producing job in local labor market j with match productivity realization ε becomes

$$V_j^p\left(\varepsilon\right) = A_j\varepsilon - w_j\left(\varepsilon\right) + \beta\left(1-\delta\right)\left(1-\phi f\left(\theta_j\right)\chi_j\right) \mathbb{E}_{\varepsilon'}\left[V_j^p\left(\varepsilon'\right)\right]^+ , \tag{A6}$$

where $\phi f\left(\theta_j\right)\chi_j$ is the probability that a worker searches on-the-job, receives an outside offer, and decides to accept it.

To derive the separation cutoff and the bargained wages, we derive the surplus function following the same steps as in the baseline model and get

$$S_j\left(\varepsilon\right) = A_j\varepsilon - z + \beta\left(1-\delta\right)\left(1-\eta f\left(\theta_j\right) - \left(1-\eta\right)\phi\chi_j f\left(\theta_j\right)\right) \mathbb{E}_{\varepsilon'}\left[S_j\left(\varepsilon'\right)\right]^+ . \tag{A7}$$

Using that $S_j(\varepsilon_j^R) = 0$, we obtain the characterization of the separation cutoff ε_j^R in local labor market j as

$$0 = A_j\varepsilon_j^R - z + \beta\left(1-\delta\right)\left(1-\eta f\left(\theta_j\right) - \left(1-\eta\right)\phi\chi_j f\left(\theta_j\right)\right) \mathbb{E}_{\varepsilon'}\left[S_j\left(\varepsilon'\right)\right]^+ . \tag{A8}$$

To derive the bargaining outcome for wages, we use the surplus splitting rule and set $\eta V_j^p\left(\varepsilon\right) = \left(1-\eta\right)\left(V_j^e\left(\varepsilon\right) - V_j^u\right)$ to get

$$\begin{aligned}
&\left(1-\eta\right)\left\{w_j\left(\varepsilon\right) - z + \beta\left(1-\delta\right)\left(1-f\left(\theta_j\right)\right)\mathbb{E}_{\varepsilon'}\left[V_j^e\left(\varepsilon'\right) - V_j^u\right]^+\right\} \\
=&\eta\left\{A_j\varepsilon - w_j\left(\varepsilon\right) + \beta\left(1-\delta\right)\left(1-\phi\chi_j f\left(\theta_j\right)\right)\mathbb{E}_{\varepsilon'}\left[V_j^p\left(\varepsilon'\right)\right]^+\right\}.
\end{aligned}$$

Noticing that $(1-\eta)\left(V_j^e(\varepsilon') - V_j^u\right) = \eta V_j^p(\varepsilon')$ holds for any ε', we obtain

$$(1-\eta)(w_j(\varepsilon)-z) = \eta\left\{A_j\varepsilon - w_j(\varepsilon) + \beta(1-\delta)(1-\phi\chi_j) f(\theta_j)\mathbb{E}_{\varepsilon'}\left[V_j^p(\varepsilon')\right]^+\right\}.$$

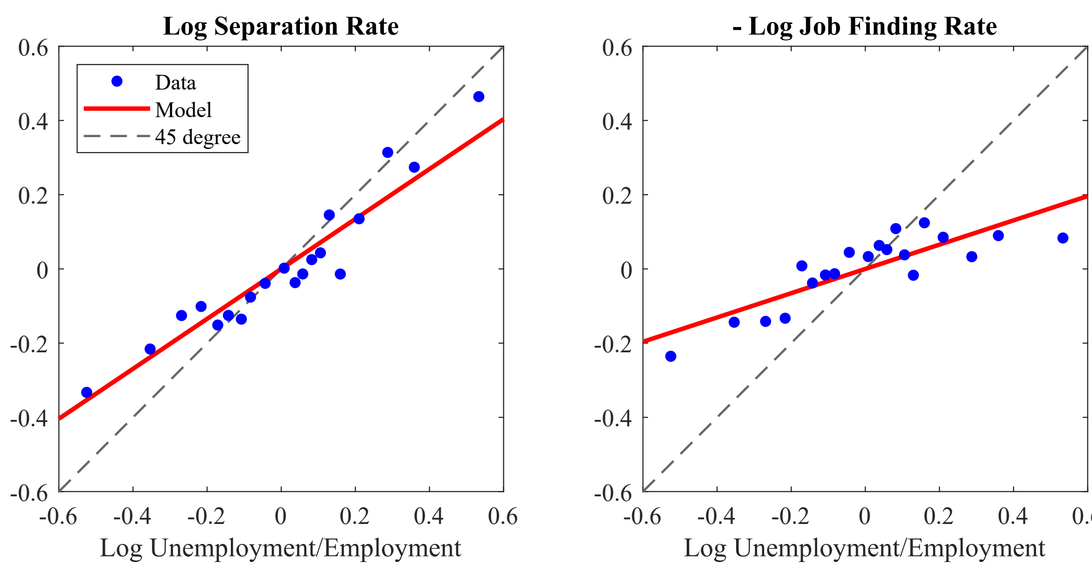
Substituting $\mathbb{E}_{\varepsilon'}\left[V_j^p(\varepsilon')\right]^+ = \frac{\kappa}{\beta(1-\delta)q(\theta_j)\varphi_j}$ from free entry, we get the wage equation as

$$w_j(\varepsilon) = (1-\eta)z + \eta A_j\varepsilon + \eta\kappa\theta_j\frac{(1-\phi\chi_j)}{\varphi_j}.$$

II.5.2 Model with On-the-Job Search, Additional Quantitative Findings

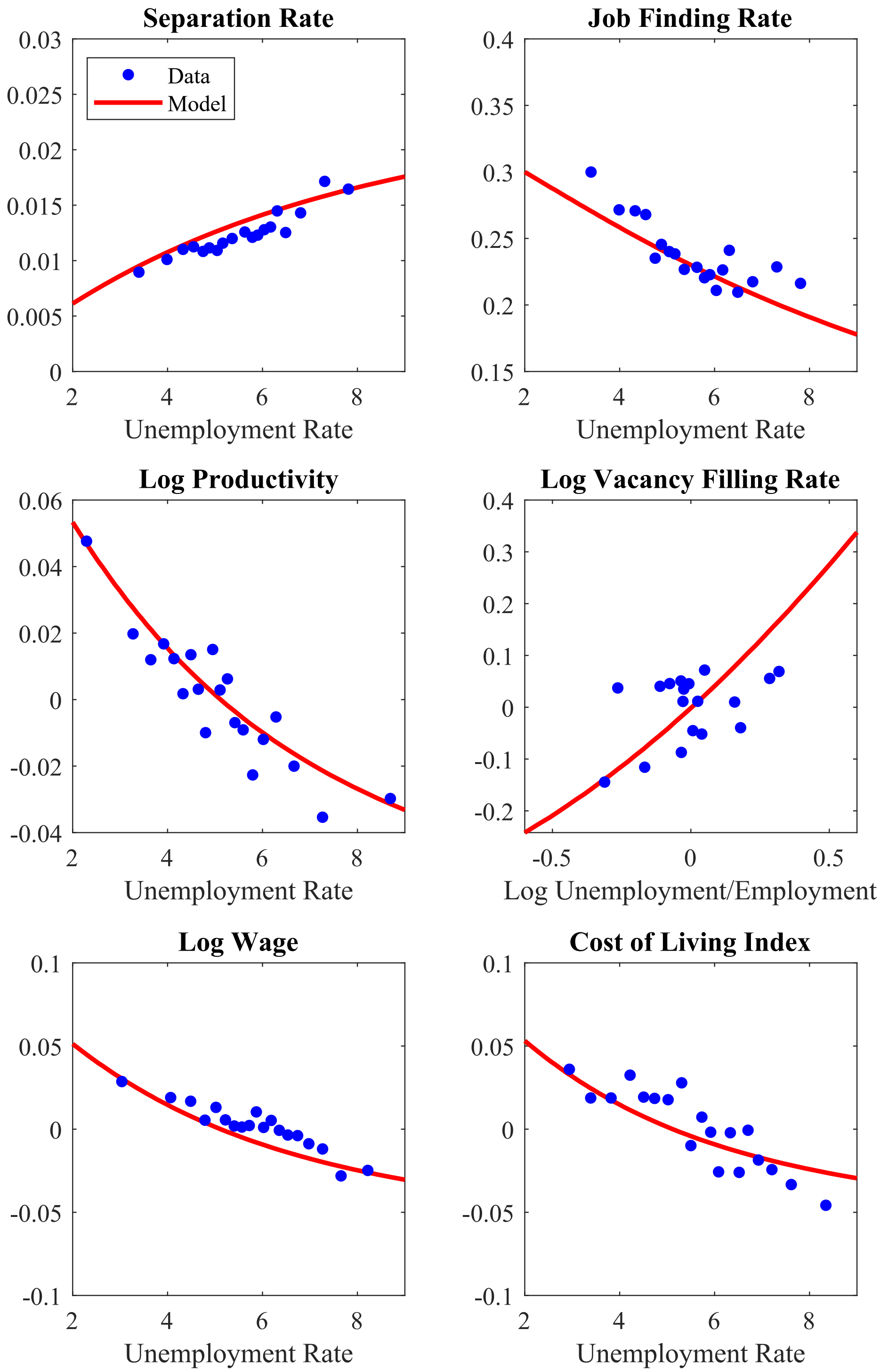
Section 4 demonstrates that the model with on-the-job search closely matches the sources of local unemployment rate differences and yields an improved fit over the baseline model with respect to vacancy posting behavior of employers. Figure A-18 highlights that the extended model also accounts very well for the cross-sectional decomposition of the sources of unemployment rate differences. Figure A-19 provides additional model predictions from the model with on-the-job search for separation rates, job-finding rates, productivity, vacancy duration, wages, and costs of living that we documented for the baseline model in Section 3. We find that the extended model with on-the-job search matches the data along all these dimensions as well as the baseline model.

Figure A-18: Decomposition of Unemployment Differences across Local Labor Markets



Notes: Decomposition of local unemployment rate differences in the model with job-to-job transitions and data into differences of separation and job-finding rates. The left panel shows the (demeaned) log separation rate from the model (red line) and from the data (blue dots) against the (demeaned) log unemployment-employment ratio (horizontal axis). The right panel shows the negative (demeaned) log job-finding rate from the model (red line) and from the data (blue dots). The dashed gray line in each panel shows the 45 degree line. The data points from Figure A-10.

Figure A-19: Model with On-the-Job Search, Additional Quantitative Findings



Notes: Model predictions and data for model with on-the-job search. Panels show from top left to bottom right separation rates, job-finding rates, (log) productivity differences, (log) vacancy filling rate differences, (log) wage differences, and differences in costs of living across local labor markets. Solid red lines show model predictions in each panel, blue dots show U.S. data as described in Section 2.2. The construction of model counterparts is described in Section 3.

II.6 Business-Cycle Model

Section 4.2 explores the business cycle version of the model with on-the-job search. We study business-cycle dynamics by introducing time-varying fundamental productivity p_t. The current unemployment rate becomes an additional state variable because the composition of the pool of searchers changes over time so that the share of contacts that result in new matches, $\varphi_j\left(u_j\right)$, changes over time. Denote the unemployment rate of the current period by u and the aggregate productivity by p and use primes to denote next period's values. The value function for the unemployed worker in local labor market j becomes

$$V_j^u\left(p,u\right) = z - c_j + \beta \mathbb{E}_{p'|p,\varepsilon'|\varepsilon}\left\{V_j^u\left(p',u'\right) + f\left(\theta_j\left(p\right)\right)\left(1-\delta\right)\left[V_j^e\left(p',u',\varepsilon'\right) - V_j^u\left(p',u'\right)\right]^+\right\}.$$

The value function for an employed worker is

$$V_j^e\left(p,u,\varepsilon\right) = w_j\left(p,\varepsilon\right) - c_j + \beta \mathbb{E}_{p'|p,\varepsilon'|\varepsilon}\left\{V_j^u\left(p',u'\right) + \left(1-\delta\right)\left[V_j^e\left(p',u',\varepsilon'\right) - V_j^u\left(p',u'\right)\right]^+\right\}.$$

The value function for a vacant job is

$$V_j^v\left(p,u\right) = -\kappa + \beta q\left(\theta_j\left(p\right)\right)\left(1-\delta\right)\varphi_j(u)\mathbb{E}_{p'|p,\varepsilon'|\varepsilon}\left[V_j^p\left(p',u',\varepsilon'\right)\right]^+.$$

Finally, the value function for a producing job is

$$V_j^p\left(p,u,\varepsilon\right) = pA_j\varepsilon - w_j\left(p,\varepsilon\right) + \beta\left(1-\delta\right)\left(1-\phi\chi_j f\left(\theta_j\left(p\right)\right)\right)\mathbb{E}_{p'|p,\varepsilon'|\varepsilon}\left[V_j^p\left(p',u',\varepsilon'\right)\right]^+.$$

The law of motion for unemployment is standard. The law of motion of p_t follows an AR(1) process as described in the main text.