# Search-and-Matching in Macro and Spatial Economics

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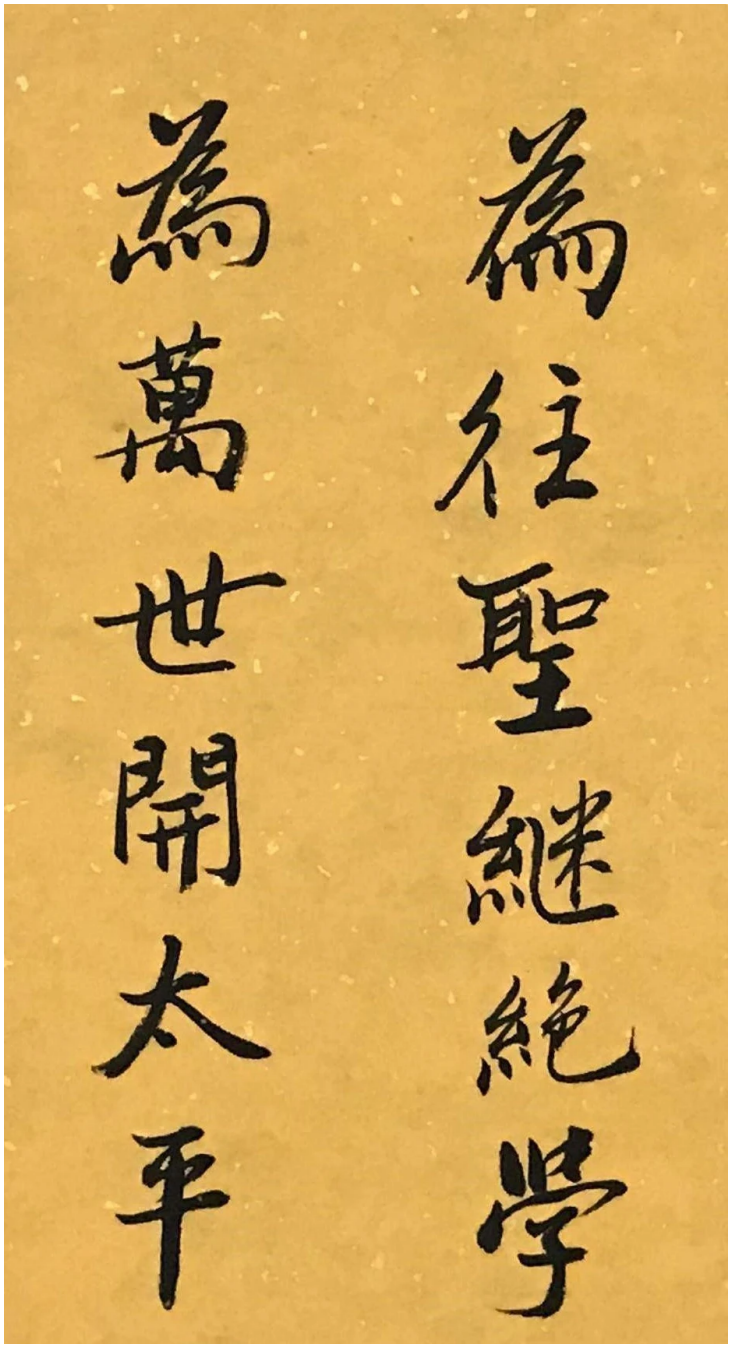

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To my family.


爲往聖繼絶學
爲萬世開太平

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Completing this PhD has been both the hardest and the most rewarding journey I have undertaken. Perhaps it began with a series of misunderstandings that pushed me toward economics, but with the benefit of full information—if I had to choose again—I would choose the same path a thousand times over.

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# Abstract

This thesis comprises three self-contained chapters, each examining markets with search-and-matching frictions in a spatial environment.

**Chapter 1: Capital.** This chapter investigates spatial disparities in capital unemployment—idle units of capital searching for a new match. Using a proprietary dataset, we document that these disparities are highly persistent and are primarily driven by spatial variation in separation rates between capital and firms. We show that a dynamic search-and-matching model can quantitatively replicate these patterns. Market frictions depress aggregate output and cause the decentralised equilibrium to diverge from the social planner's allocation. Implementing place-based policies that restore the planner's allocation increases capital supply and yields welfare gains.

**Chapter 2: Labor.** This chapter develops a quantitative model of labor markets and migration with heterogeneous workers to study how labor market conditions and migration costs shape migration flows across Europe. To preserve the rich heterogeneity in economic fundamentals across countries documented in EU Labor Force Survey micro-data, we introduce a novel calibration strategy that calibrates each country individually while remaining consistent with bilateral migration flows. The calibrated model shows that migrants face sizable labor market frictions as well as substantial migration costs. A counterfactual experiment indicates that improving labor market fundamentals for migrants enhances their labor market outcomes and increases cross-country mobility.

**Chapter 3: Housing.** This chapter argues that search-and-matching costs in rental housing markets play a role in internal migration. Motivated by emerging anecdotal evidence, I develop a model of rental market microstructure with endogenous migration. Rising search

costs lead to out-migration by absorbing available resources and reducing effective housing consumption, with the effect strongest in tight markets. I validate the model's predictions using a proprietary panel dataset. Finally, I show that demand-side policies, such as rental subsidies, are ineffective in tight markets as they exacerbate search frictions, while supply-side expansions of housing stock alleviate these frictions and enhance welfare.

# Chapter 1

# Unemployed Capital in Space

*Andrea Chiavari*[1] *Charles Cheng Zhang*[2]

## Abstract

This paper exploits a unique dataset to document novel facts on spatial differences in capital unemployment—defined as idle units searching to be traded. The data reveal that these differences are persistent and primarily driven by spatial variation in separation rates between capital and firms. We demonstrate that a dynamic spatial search-and-matching model of local capital markets can quantitatively account for these patterns. Frictions in these markets reduce aggregate output and imply that the social planner's allocation diverges from the decentralized equilibrium. Place-based policies implementing the planner allocation stimulate capital supply leading to welfare gains. [3]

**Keywords:** Local Capital Markets; Capital Unemployment; Search-and-Matching; Spatial Equilibrium; Place-Based Policies

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## 1.1 Introduction

A central theme in spatial economics is understanding the causes and consequences of the geographic distribution of economic activity. A long-standing tradition in economics assigns a central role to physical capital in shaping such activity. More recently, a growing body of empirical research using micro-level data has documented that markets for physical capital are subject to trading frictions, which result in protracted intervals between the supply of a capital unit and its eventual absorption by demand (Ramey and Shapiro, 2001; Gavazza, 2011). These frictions generate substantial capital unemployment—defined as idle capital units actively searching for utilization—at the aggregate level (Ottonello, 2021).[4] However, due to limited spatially disaggregated data on this phenomenon, relatively little is known about its contribution to local economic performance or its broader implications for welfare.

We address this gap by introducing a novel dataset that provides new insights into local capital unemployment. In doing so, we make three main contributions. First, the dataset reveals that spatial differences in capital unemployment are large, persistent, and primarily driven by spatial variation in separation rates between firms and the capital they utilize. Second, we develop a dynamic spatial model of frictional capital markets grounded in search-and-matching frictions and show that it quantitatively replicates our empirical findings. Third, we demonstrate that frictions in local capital markets have sizable negative effects on aggregate output and give rise to an inefficient decentralized equilibrium, providing a novel rationale for place-based policies.

Specifically, this study utilizes a *unique* panel dataset from Property Market Analysis (PMA) LLP, a global independent real estate research consultancy established in 1981. PMA's data is derived from a combination of secondary sources (national accounts, brokers, data providers) and in-depth primary research, which involves site visits and meetings with market participants. Spanning from 1981 to 2022, the dataset reports detailed spatial information on a widely used form of capital—structures such as offices, industrial properties, and logistics facilities—which represents more than 50 percent of the physical capital in the UK economy and covers 67 UK cities, contributing approximately 46 percent of the total UK GDP in 2021.[5]

[4] In the real estate literature, the capital unemployment rate is sometimes referred to as the vacancy rate (e.g., Han and Strange, 2015).

[5] While our dataset focuses solely on structures, substantial empirical evidence indicates that the phenomenon of capital unemployment extends beyond structures to the entire capital stock. Ottonello (2021) and the main

It encompasses various real estate categories, including offices, industrial properties, and logistics facilities, providing data for each location and year. This dataset includes information on total capital stock (in thousands of square meters), the capital unemployment rate, and take-ups, representing the space becoming occupied in the year. Thus, this dataset offers a first glimpse into the distribution of capital, both employed and unemployed, allowing for the study of how frictions in local capital markets influence the spatial distribution and utilization of this factor of production. We assess and confirm the data quality by correlating our capital measure with official sources.

This dataset allows us to establish the following novel set of stylized facts on the spatial distribution of unemployed capital:

***Fact 1:*** *Differences in local capital unemployment rates are large and persistent.*

***Fact 2:*** *Local net investment rates are at the replacement rate level and do not move to close the local capital unemployment rate gaps.*

Empirically, large and persistent differences in local capital unemployment rates cannot be readily explained by differences in labor unemployment rates, even though the latter are well known to exhibit large and persistent spatial variation. Nor can these disparities be attributed to persistent shocks from deindustrialization. Although such shocks may create mismatches between demand and supply in local capital markets, a series of robustness exercises examining the role of local industry composition and exposure to nationwide industry cycles suggest that these factors have limited explanatory power. Instead, the evidence points to long-run forces: net investment rates remain near the replacement rate and do not adjust to close these gaps, as they would if persistent shocks were the main driver.

To explore these long-run patterns, we employ a flow-based approach inspired by labor market methods (Shimer, 2012). This methodology uses reported observables from our dataset to infer unobservable transition probabilities for each location and period. Specifically, it allows to measure the *finding rate*, representing the likelihood of unemployed capital becoming employed, and the *separation rate*, representing the likelihood of employed capital becoming unemployed. Additionally, this approach leads to a spatial decomposition, akin to Fujita and Ramey (2009) and Bilal (2023), linking capital unemployment rate differences to these rates.

text provide a detailed discussion on this.

Applying this methodology to our data reveals the following additional facts about the spatial distribution of unemployed capital:

***Fact 3:*** *The average capital finding rate, defined as the ratio of transacted to unemployed capital, is 40 percent per year, coexisting with persistently high capital unemployment levels.*

***Fact 4:*** *Local capital unemployment rate gaps are mostly acconted for by differences in separation rates across locations.*

Our findings indicate that the amount of transacted capital as a percentage of total unemployed capital, i.e., the finding rate, averages 40 percent, suggesting that high capital unemployment rates coexist with substantial demand for capital. Meanwhile, separation rates average 3 percent. These high transaction rates confirm the limited explanatory power of persistent deindustrialization shocks, which would instead predict low rates, instead pointing to the presence of market frictions that slow down the matching of demand and supply. Furthermore, our findings show that variations in the separation rate account for 68 percent of the differences in capital unemployment rates across locations, while the finding rate explains 30 percent, with the remaining 2 percent attributed to measurement error.

Motivated by the coexistence of unfulfilled demand and unexhausted supply (Fact 3), which points to frictions impeding matches between the two sides of the market, we develop a dynamic spatial model of capital accumulation that incorporates search-and-matching frictions à la Pissarides (2000) in local capital markets to examine the aggregate implications of this phenomenon. In the model, geographic locations differ in productivity levels across the production and real estate sectors, as well as in amenities. Each location is inhabited by a representative family, a construct similar to Merz (1995) and Andolfatto (1996), which pools all income from labor and capital ownership. The family demands housing units, decides how much to invest in capital, and supplies its capital units in the local capital market. Participation in the local capital market requires the services of the real estate sector. On the other side of the market, heterogeneous firms with free entry, subject to idiosyncratic productivity shocks, search for capital. As in Den Haan et al. (2000), matches dissolve when a firm's productivity falls below an endogenous location-specific threshold. Finally, the model's spatial equilibrium is sustained by the free movement of workers, as in Rosen (1979b) and Roback (1982).

The model yields two elasticities to spatial productivity differences that clarify how separation and finding rates contribute to variation in capital unemployment (Fact 4). These elasticities extend the concept of the fundamental surplus from Ljungqvist and Sargent (2017) to a spatial setting with endogenous match separations. The elasticity of the finding rate to productivity is governed by the fundamental surplus, which depends on a few key parameters. This object constrains the fraction of output that can be allocated to match creation, thereby influencing the strength of the marginal impact of an additional unit of productivity on this margin. In contrast, the elasticity of the separation rate to productivity depends on the value of the marginal operating firm, as they determine which firm-capital matches are maintained, and is also shown to depend on a few key parameters. A lower marginal value increases the responsiveness of separations to productivity, as an additional productivity unit yields a high contribution to their ability to keep operating. While the model clarifies the underlying mechanisms and the key parameters governing them, it does not impose ex-ante restrictions on the relative strength of these forces, leaving their quantitative relevance to be determined in the calibration exercise.

We calibrate the model by targeting finding and separation rates in the UK local capital market with a median capital unemployment rate, as well as the capital unemployment rate, capital stock, and population in each location. We intentionally leave finding and separation rates outside the median market untargeted, allowing the model to freely determine their relative contributions to capital-unemployment gaps. A battery of validation exercises confirms the model quantitative fit on untargeted moments, including the investment rate being at the replacement rate across locations (Fact 2), among others.

We then assess the model's ability to explain the relative importance of finding and separation rates in driving spatial variations in capital unemployment rates. The model's calibration yields a high fundamental surplus and a low value for the marginal firm operating, which implies a small role for the finding rate and a dominant role for the separation rate in explaining capital unemployment rate differences. Specifically, our findings show that the model can quantitatively match all described facts, attributing 68 percent of spatial capital unemployment rate differences to the separation rate and 32 percent to the finding rate, closely aligning with the empirical data (Fact 4).

Finally, after evaluating the model's positive implications, we conduct two main aggregate

counterfactual analyses. First, we assess the aggregate costs of local capital market frictions. Second, we solve the social planner's problem to quantify the welfare gains from place-based policies. For the first exercise, we increase matching efficiency in local capital markets, which accelerates the matching process and alleviates frictions. We find that doubling matching efficiency leads to an approximately 4 percent increase in aggregate output. Although the previous exercise shows that search frictions in local capital markets are quantitatively important, it does not directly quantify the attainable gains. To assess these gains, we instead solve the planner's problem requiring the Hosios (1990) condition, which is not directly recovered by our calibration. Solving for the planner's allocation, which we show can be implemented through place-based subsidies to the stock of unemployed capital, results in sizeable, albeit hardly transformative, gains. In particular, it results in a 4 percent expansion of the total capital stock and in a 0.28 percent increase in consumption-equivalent welfare, equivalent to approximately $2.15 billion USD in the UK context. Furthermore, we find that welfare gains are almost twice larger in locations that historically experienced higher capital unemployment rates, implying a decline in spatial inequality.

*Literature review.* This paper contributes to several strands of the literature. First, this paper relates to the vast literature on frictions in physical capital markets, particularly the strand that emphasizes search frictions in capital markets (Gavazza, 2011; Wright et al., 2018, 2020; Cao and Shi, 2023; Rocheteau, 2025) and in commercial real estate markets (Koijen et al., 2025).[6] In this extent, the closets paper to our work is Ottonello (2021), who emphasizes the role of search frictions in generating capital unemployment and their implications for business cycle dynamics. We contribute to this paper—and to the broader literature—by presenting the first empirical evidence on the spatial variation in capital unemployment. Our findings indicate that these differences are substantial, persistent, and not arbitraged away through investment dynamics.

Second, this paper relates to Kleinman et al. (2023), who develops a model of dynamic capital accumulation within a spatial general equilibrium framework, focusing on a neoclassical investment block where capital is traded in a Walrasian market. We complement this work by introducing realistic trading frictions in local physical capital markets. Embedding search-

[6]Evidence of friction in residential real estate markets have been also extensively documented, e.g., Wheaton (1990), Krainer (2001), Caplin and Leahy (2011), Genesove and Han (2012), Ngai and Tenreyro (2014), Han and Strange (2015), Piazzesi et al. (2020), among others.

and-matching frictions allows the model to directly account for our novel empirical evidence on the spatial distribution of capital unemployment. In addition, our analysis also highlights that frictions in local capital markets play a quantitatively significant role in shaping local capital accumulation dynamics.

Finally, this paper relates to studies by Kline and Moretti (2013), Şahin et al. (2014), Marinescu and Rathelot (2018), Schmutz and Sidibé (2019), Kuhn et al. (2025), Bilal (2023), and Jung et al. (2023), which explore spatial variants of the Diamond (1982), Mortensen (1982), and Pissarides (1985) models embedded in spatial equilibrium frameworks like Rosen (1979b) and Roback (1982).[7] Empirically, this paper shows that several patterns documented in the context of spatial labor market flows and unemployment also hold for capital markets and capital unemployment. Theoretically, it introduces a novel mechanism within a search-and-matching framework, highlighting a key distinction from labor markets: unlike labor, physical capital is produced, and its production is influenced by capital unemployment. This mechanism has important negative implications for both local and aggregate output, generating inefficiencies calling for place-based interventions. In this respect, the paper is closely related to the growing literature on place-based policy, as recently reviewed by Fajgelbaum and Gaubert (2025), to which we contribute by offering a new rationale grounded in imperfections in local capital markets.

*Outline.* Section 1.2 introduces our dataset. Section 1.3 details our stylized facts. Section 1.4 introduces the model, while Section 1.5 provides a quantitative assessment and presents the positive implications of the model. Section 1.6 presents the main counterfactual analysis. Finally, Section 1.7 offers concluding remarks.

## 1.2 Data

This section outlines the data used for the empirical analysis.

[7] This study, along with many of the studies cited above, also belongs to the literature emphasizing spatial persistence, which is extensive in scope. This literature review does not aim to fully do justice to the many important papers that have contributed to it; for a recent review, see Allen and Donaldson (2022).

### 1.2.1 Main Data Source

Here, we introduce the main dataset, explain how we validate its quality, and discuss how its insights can be generalized to the entire capital stock.

#### 1.2.1.1 Description of the Main Data

Understanding the dynamics of capital transitioning between being employed and unemployed is crucial for assessing its utilization in an economy. While time series data highlights variations in capital unemployment rates over time (Ottonello, 2021), spatial information is limited. This scarcity is due to the absence of detailed geographical data on capital, often available only at a high level of aggregation, and the lack of data sources offering insights into the spatial distribution and flows of unemployed capital.

This study utilizes panel data from Property Market Analysis (PMA) LLP, a global independent real estate research consultancy established in 1981, serving private sector entities, including real estate companies (JLL, Knight Frank, CBRE, Savills), financial institutions (BlackRock, AIG), sovereign wealth funds (The Crown Estate, GIC, Temasek), and banks (Barclays, UBS, BNP Paribas). The dataset reports detailed spatial information on a widely used form of capital—structures—that represents more than 50 percent of the physical capital in the UK economy.[8] The quality of this data is central to PMA's core business, which is property forecasting.[9] Analysts there gather and scrutinize data from various secondary sources like national accounts, brokers, and data providers. They complement this with thorough primary research, including on-site visits and engagements with key market stakeholders.

The dataset, covering 1981 to 2022, encompasses 67 UK cities, contributing about 46 percent to the total UK GDP in 2021, and several European cities.[10] This paper primarily uses UK data from 1990 due to its extensive coverage and data quality, with European data serving as a secondary source for validation. The dataset spans several real estate categories—offices, in-

[8]Buildings and structures constitute between 48 to 68 percent of total physical capital, which is defined as buildings and structures plus equipment. These numbers are based on the author's own calculations using nationally representative ONS data.

[9]While the quality and representativeness of their information for the locations they cover are crucial for the company's objectives—a point also validated in Section 1.2.1.2—we expect that their sample of locations is tilted toward more profitable real estate markets. However, as we demonstrate in this section, the range of locations they cover is extensive and accounts for a significant share of the UK's total GDP.

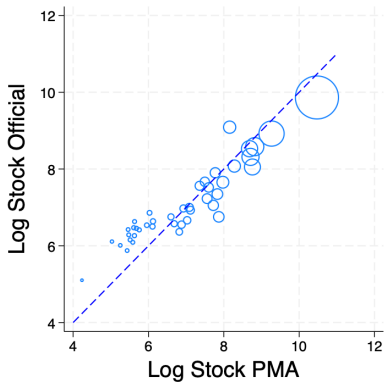
[10]Included European cities: Amsterdam, Antwerp, Barcelona, Berlin, Brussels, Budapest, Cologne, Copenhagen, Dublin, Dusseldorf, Frankfurt, Hamburg, Helsinki, Lille, Lisbon, Luxembourg, Lyon, Madrid, Marseille, Milan, Oslo, Paris, Prague, Rome, Rotterdam, Stockholm, Stuttgart, Vienna, and Warsaw.

dustrial properties, and logistics facilities—providing information for each location and year, including total capital stock (in thousands of square meters), the capital unemployment rate, and take-ups, indicating the space taken up in the year.[11]

#### 1.2.1.2 Validation of Data Quality

We gauge data quality by correlating our capital measure with official sources (Figure 1.1). The official capital stock data is obtained from the *Energy Performance of Buildings* project, initiated by the Department for Levelling Up, Housing & Communities. This project collects information, including floor area, for most commercial real estate buildings. Unfortunately, only cross-sectional variation is available, with no time variation, and thus it can be used solely for validation purposes. We aggregate the floor area by city to estimate the capital stock at the city level. A robust spatial correlation between this official source and our measure suggests the reliability of our data. Additional details on data cleaning and validation exercises are provided in Appendices A.1.1 and A.1.2.

**Figure 1.1: Official vs. PMA Capital Stock**




Note: Figure 1.1 depicts the spatial correlation between time-averaged log capital stocks from our dataset and official sources. Both measures are in thousands of square meters. Circle size represents each UK location's relative size.

[11] PMA takes regular care to check that its capital measure contains only viable structures. The capital unemployment rate follows the standard definition used for the labor unemployment rate and is measured as those viable structures on the market but not yet occupied.

#### 1.2.1.3 Relationship with Equipment and Whole Capital Stock

As highlighted by Ottonello (2021), empirical evidence suggests that the phenomenon of capital unemployment extends to capital equipment and the broader capital stock. Ramey and Shapiro (2001) document that selling equipment from closing aerospace plants often takes years, indicating significant unemployment spells. Similarly, Becker et al. (2006) find that, on average, only 64 percent of an exiting establishment's capital is acquired by other firms within a year, using US Census data. Harris and Drinkwater (2000) show that the capital stock in the UK manufacturing sector was 30 percent lower when adjusted for plant closures. These studies indicate that capital unemployment is not limited to structures alone.

### 1.2.2 Additional Data Sources

We complement the PMA data with information from the Office for National Statistics (ONS). Local output by industry is obtained from the *Regional Gross Value Added (Balanced) by Industry: All ITL Regions* dataset, which is used to calculate local labor and capital productivity, as well as measures of local exposure to persistent deindustrialization shocks. Measures of local population are obtained from *Population Profiles for Local Authorities* dataset. Local labor unemployment rates are sourced from the *Regional Labour Market: Local Indicators for ITL3 Geography* dataset. Finally, we obtain local amenities measures from the *Access to local amenities in England and Wales* dataset.

## 1.3 Empirical Analysis

This section explores the spatial patterns of local capital unemployment rates, establishing four main facts.

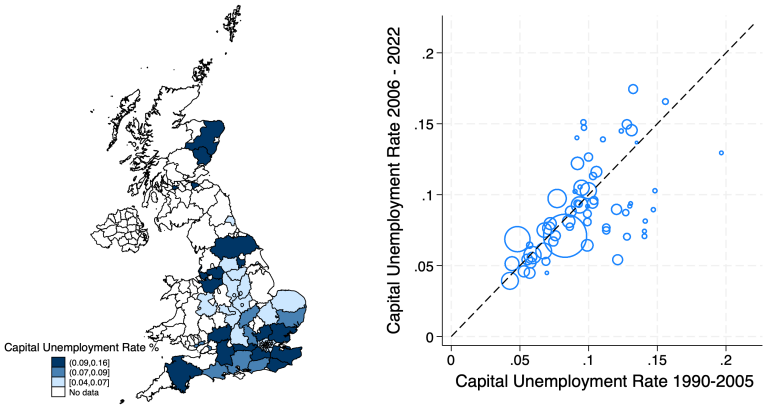
### 1.3.1 Distribution and Spatial Persistence of Capital Unemployment Rates

This section explores the spatial distribution and persistence of local capital unemployment rates in the UK, establishing two regularities.

***Fact 1:*** *Differences in local capital unemployment rates are large and persistent.*

Figure 1.2 shows this point. Figure 1.2a displays the capital unemployment rate across UK cities, where darker shades of blue represent higher rates. The data highlights substantial differences among cities, with unemployment rates of capital ranging on average from 4 to 16 percent. To assess the persistence of local capital unemployment rates, we divide the sample into two subperiods, pre and post-2006. Figure 1.2b plots the local capital unemployment rate in the second subperiod against the local capital unemployment rate in the first subperiod for every UK city. The local capital unemployment rates across UK cities exhibit notable persistence, aligning closely around the dashed black 45-degree reference line. This visual inspection is confirmed by a weighted autocorrelation coefficient across the two subperiods of 0.89.

**Figure 1.2: Spatial Distribution and Persistence of Capital Unemployment Rate**




**(a) Local Capital Unemployment Rate**

**(b) Persistence of Capital Unemployment Rate**

Note: Figure 1.2 provides an overview of the spatial distribution and persistence of the capital unemployment rate in cities across the UK. Figure 1.2a maps capital unemployment rates in UK cities based on the PMA dataset. Figure 1.2b plots capital unemployment rates in UK cities in two subperiods of the sample. The blue circles represent cities in the UK, and the size of each circle corresponds to the total capital within that city.

Appendix A.1.3 presents additional evidence that complements our findings using bin-scatter plots of capital unemployment rates, documenting the strong persistence of these patterns across different time horizons. Furthermore, Appendix A.1.3 extends this analysis to European cities, confirming the observed patterns.

Two potential explanations for Fact 1 are: (i) spatial differences in labor unemployment

rate that carry over to capital markets (Kline and Moretti, 2013; Bilal, 2023; Kuhn et al., 2025), and (ii) persistent shocks that generate mismatches between the existing local capital stock and shifting demand caused by changes in sectoral composition during the UK's ongoing deindustrialization (Kitson and Michie, 2014; Rice and Venables, 2021). In Appendix A.1.3, we show that controlling for these factors—by netting out time fixed effects, local labor unemployment gaps, and a location's exposure to economy-wide industry cycles from local capital unemployment rates—yields a picture similar to Figure 1.2.[12]

Thus, neither persistent differences in local labor unemployment rates nor persistent deindustrialization shocks appear sufficient to explain our findings. The former suggests that frictions in other local input markets, such as labor—though well documented and important for local prosperity—are unlikely to account for persistent gaps in capital unemployment rates, pointing instead to frictions in local capital markets. A plausible reason for the latter is that our dataset, including a large fraction of offices, contains properties that are highly substitutable across sectors and therefore less sensitive to shifts in sectoral demand. Having established the existence and persistence of large cross-location differences in capital-unemployment rates, we now present our second fact.

***Fact 2:*** *Local net investment rates are at the replacement rate level and do not move to close the local capital unemployment rate gaps.*

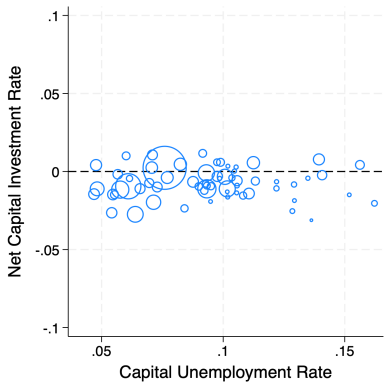
Figure 1.3 presents the average net investment rate across UK cities sorted by local capital unemployment rate. There is no pattern of net investment rates moving to close local capital unemployment rate gaps. Moreover, we observe that in our data the average net investment rate is approximately zero with more than fifty cities having a net investment zero below 1 percent. Appendix A.1.3 demonstrates that the magnitude of our net investment rate aligns with figures from aggregate national accounts.[13] Since by definition investment rate equals the net investment rate plus the depreciation rate, we conclude that most local investment is

[12]More generally, we find that local industry composition and exposure to economy-wide industry cycles are not correlated with capital-unemployment gaps, which explains why removing their contribution does not affect our results. We do find the expected positive association between labor and capital unemployment rates, although netting out this association also leaves the results unchanged.

[13]The alignment between our investment rate—calculated as percentage changes in square meters of capital stock in each location—and the measure from national accounts, which accounts for the value of capital, suggests that our findings are not driven by the inability to observe investments in building quality.

close to depreciation, i.e., at the replacement rate.

**Figure 1.3: Local Net Investment Rates**




Note: Figure 1.3 provides an overview of average local net investment rates across UK cities. The blue circles represent cities in the UK, and the size of each circle corresponds to the total capital within that city.

Taking stock, we find that the local capital unemployment rates are both large and persistent (Fact 1). Robustness exercises show that local gaps in labor unemployment rates cannot easily account for this fact. Further robustness exercises also indicate that neither of these two observations can be easily explained by persistent shocks triggered by deindustrialization forces, which could potentially create a mismatch between demand and supply in local capital markets. Specifically, accounting for the industrial composition of a location and its exposure to industry cycles does little to explain our findings. Furthermore, if these shocks were the primary drivers of local capital unemployment rate differences, we would expect significant capital flows away from affected locations toward unaffected ones. However, this is inconsistent with our finding that net investment rates in the data are close to the replacement rate and do not appear to adjust in a way that would close these gaps (Fact 2).

Taken together, this evidence suggests that the underlying drivers of these spatial differences must be rooted in long-run, steady-state-like economic forces, such as frictions. In search of these long-run forces shaping persistent differences in local capital unemployment rates, the next section examines the flows into and out of capital unemployment, establishing our additional facts.

### 1.3.2 The Spatial Ins and Outs of Unemployed Capital

This section introduces a flow-based approach to understanding unemployed capital rate differences and establishes our third and fourth facts.

#### 1.3.2.1 Flow-Based Approach to Unemployed Capital

Here, we introduce a flow-based approach, akin to the labor market approach in Shimer (2012) and Bilal (2023), to understand the spatial distribution of unemployed capital.

Time is discrete and indexed by $t$, locations by $j$. Observable variables are in bold. Specifically, $\boldsymbol{K}_{jt}$ is the total capital stock; $\boldsymbol{K}^u_{jt}$ is unemployed capital, obtained by multiplying the total stock by the unemployment rate; $\boldsymbol{K}^e_{jt}$ is employed capital, i.e., the difference between total stock and unemployed capital; and $\boldsymbol{M}_{jt}$ denotes the capital transitioning into employment.

The law of motion of total capital stock is given by:

$$\boldsymbol{K}_{jt} = (1-\delta)\boldsymbol{K}_{jt-1} + X_{jt-1}, \tag{1.1}$$

where $\delta$ is the depreciation rate and $X_{jt-1}$ is total investment. In line with BEA calculations for structures, we use a depreciation rate of 2 percent.[14] The law of motions of total employed and unemployed capital is given by:

$$\boldsymbol{K}^e_{jt} = f_{jt}[(1-\delta)\boldsymbol{K}^u_{jt-1} + X_{jt-1}] + (1-s_{jt})(1-\delta)\boldsymbol{K}^e_{jt-1}, \tag{1.2}$$

$$\boldsymbol{K}^u_{jt} = (1-f_{jt})[(1-\delta)\boldsymbol{K}^u_{jt-1} + X_{jt-1}] + s_{jt}(1-\delta)\boldsymbol{K}^e_{jt-1}; \tag{1.3}$$

where $f_{jt}$ denotes the probability of unemployed capital becoming employed, which we refer to as "finding rate ", while $s_{jt}$ is the probability of employed capital becoming unemployed, which we refer to as "separation rate". Equation (1.2) assumes that newly invested capital starts as unemployed.

The total amount of unemployed capital that is taken up in a given period is given by:

$$\boldsymbol{M}_{jt} = f_{jt}[(1-\delta)\boldsymbol{K}^u_{jt-1} + X_{jt-1}], \tag{1.4}$$

[14] Sourse: BEA Depreciation Rates.

i.e., the probability that unemployed capital becomes employed times the total stock of unemployed capital that carries over from the previous period.

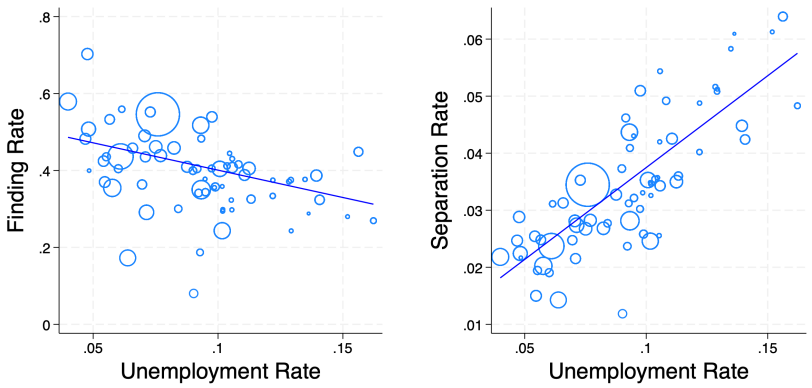
Equations (1.1), (1.2), (1.3), and (1.4) can be employed to describe total investment $X_{jt}$, the finding rate $f_{jt}$, and the separation rate $s_{jt}$ as functions of observables and parameters denoted by:

$$X_{jt} = \boldsymbol{K}_{jt+1} - (1-\delta)\boldsymbol{K}_{jt}, \tag{1.5}$$

$$f_{jt} = \boldsymbol{M}_{jt}/[(1-\delta)\boldsymbol{K}^{u}_{jt-1} + X_{jt-1}], \tag{1.6}$$

$$s_{jt} = \{\boldsymbol{M}_{jt} - [\boldsymbol{K}^{e}_{jt} - (1-\delta)\boldsymbol{K}^{e}_{jt-1}]\}/[(1-\delta)\boldsymbol{K}^{e}_{jt-1}]. \tag{1.7}$$

**Figure 1.4: Capital Market Flows Across Space**




**(a) Finding Rate** **(b) Separation Rate**

Note: Figure 1.4 shows the finding rate, separation rate, and employment margin across different UK local capital markets sorted by their capital unemployment rate. Figure 1.4a displays the finding rate and Figure 1.4b the separation rate all against the capital unemployment rate, across cities in the UK. Open blue circles represent cities in the UK, with size proportional to their total capital. Each data point represents a within-city average. The straight line in blue represents the best fit.

Figure 1.4 illustrates the relationship between the local capital unemployment rate, the finding and the separation rate. The median finding rate is 40 percent (Figure 1.4a) while the median separation rate is 3 percent (Figure 1.4b), establishing our third fact.

***Fact 3:*** *The average capital finding rate, defined as the ratio of transacted to unemployed capital, is 40 percent per year, coexisting with persistently high capital unemployment levels.*

Overall, high finding rates in local capital markets imply substantial demand for these structures, helping explain why low demand or mismatch explanations associated with persistent deindustrialization shocks did not seem to have a major role in the previous section.

Finally, we can derive the following steady-state relation for $\delta \approx 0$ using equation (1.3):

$$\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right) \approx \log(s_j) - \log(f_j), \tag{1.8}$$

where $\boldsymbol{k}_j^u$ is the capital unemployment rate and $\boldsymbol{k}_j^e$ is the employment capital rate. Equation (1.8) states that the log of the unemployment-employment capital rate ratio equals the log of the separation rate net of the log of the finding rate. Appendix A.1.4 generalizes equation (1.8) to any value of $\delta$, showing that this approximation does not affect our conclusions.

From equation (1.8), we arrive at a spatial application of the unemployment decomposition formula (e.g., Fujita and Ramey, 2009), given by:

$$\mathbb{V}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right)\right) = \mathbb{C}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), \log(s_j)\right) + \mathbb{C}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), -\log(f_j)\right) + \varepsilon_j. \tag{1.9}$$

Equation (1.9) systematically breaks down the impact of each component in equation (1.8), i.e., separation and finding rates, on the variance of the log of the unemployment-employment capital rate ratio. Additionally, it allows for an error wedge $\varepsilon_j$, which may result both from measurement error in the data or departures from the steady-state assumption imposed above.[15]

#### 1.3.2.2 Descriptive Findings

In this section, we depict the contribution of separation rates and finding rates to the local capital unemployment rate using equation (1.8).

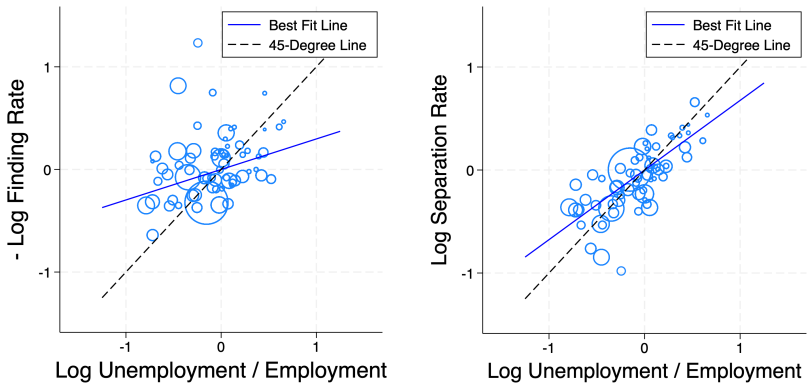
***Fact 4:*** *Local capital unemployment rate gaps are mostly accounted for by differences in separation rates across locations.*

Figure 1.5 plots minus the log of finding rates $f_j$ and the log of separation rates $s_j$ against the log of the unemployment-employment capital rate ratio $\boldsymbol{k}_j^u/\boldsymbol{k}_j^e$ across cities in the UK.

[15] In principle it could arise also form the assumption of $\delta \approx 0$. However, we generalize equation (1.8) to any value of $\delta$ in Appendix A.1.4, showing that this approximation does not matter significantly for our results.

Figure 1.5a shows that finding rates exhibit low variation across locations, with the best-fit line notably distant from the 45-degree line (dashed black line). In contrast, separation rates are the main factor driving differences in local capital unemployment rates, as indicated in Figure 1.5b. Separation rates vary substantially across locations, and their best-fit line closely aligns with the 45-degree line.

**Figure 1.5: Capital Market Flows Decomposition Across Space**




**(a) Finding Rate** **(b) Separation Rate**

Note: Figure 1.5 shows graphically the contribution of minus the log of the finding rate and the log of the separation rate to local capital unemployment rate differences across UK locations. Figure 1.5a scatterplots minus the log of the finding rate against the log of the unemployment-employment capital ratio, across cities in the UK. Figure 1.5b scatterplots the log of the separation rate against the log of the unemployment-employment capital ratio, across cities in the UK. Open blue circles represent cities in the UK, with size proportional to their total capital. Each data point represents a within-city average, with cross-sectional means removed for the plot. The 45-degree line is in dashed black.

Quantitatively, our analysis, using equation (1.9) for a precise variance decomposition, reveals that in the UK, the separation rate accounts for 68 percent of the cross-sectional variation in spatial capital unemployment rates. Finding rates contribute 30 percent of the variation. With the remaining 2 percent attributable to the error wedge. This leads us to conclude that neither measurement error nor the steady-state assumption is particularly demanding in our setting. The latter supports the conclusion on steady-state-like behavior from Section 1.3.1.

We confirm the robustness of our findings through additional exercises. Online Appendix A.1.4 demonstrates that the importance of separation rates in driving differences in local unemployment rates is not unique to the UK; it holds for European cities as well. Finally, expanding equation (1.8) to accommodate $\delta$ greater than zero enables us to consider the contribution of the extensive margin from newly invested capital. Online Appendix A.1.4 demonstrates

that this extended decomposition reaffirms the predominant role of the separation rate, revealing a limited role for the extensive margin. These conclusions hold for both the UK and the European context.

## 1.4 Model

This section presents the model of local capital markets used in the paper to study the long-run spatial distribution of capital unemployment rate gaps, unveils the economic forces driving the contribution of different capital flows to their persistence, and investigates its efficiency properties.

### 1.4.1 Primitives, Capital Markets, and Timing

#### 1.4.1.1 Primitives

Time is discrete. The economy is populate by a mass $\overline{L}$ of workers distributed among $J$ locations, indexed by $j = 1, \ldots, J$. Each location $j$ is characterized by its fundamental productivity $\mathcal{Z}_j$, amenities $\mathcal{A}_j$, and real estate productivity $\mathcal{P}_j$. In each location, there is a mass $L_j$ of workers who can freely move across locations and are organized in a infinitely lived representative family, pooling all sources of income (e.g. Merz, 1995; Andolfatto, 1996), a real estate and housing sector, and an endogenous measure of firms operating under free entry.[16] The representative family discounts the future at rate $\beta$, derives utility $\mathcal{A}_j \log(C_j)$ from local amenities $\mathcal{A}_j$ and consumption $C_j$, supplies labor $L_j$ and capital $K_j$, and invests in capital $X_j$. Capital is either employed, denoted by $K_j^e$, i.e., rented and paying a return, or unemployed, denoted by $K_j^u$. The firms, as well as the real estate and housing sectors, are owned by the representative family.

To operate its $K_j$ capital units, the representative family inelastically demands the services of the real estate sector at a per-period price $p_j^r$. The operating cost for these capital units is given by $(K_j/\mathcal{P}_j)^{1/\phi}$. This assumption is important because under the production structure described below—where the marginal product of capital is independent of the capital level—the congestion forces inherent in the real estate sector alone determine the equilibrium

[16] While the literature has at times departed from free worker mobility across locations, we think free mobility is a reasonable and not-too-costly assumption in our context, since we will ultimately use the model for long-run analysis.

distribution of capital. This is also consistent with anecdotal evidence suggesting that a significant portion of the UK real estate market is intermediated.[17] We assume that each worker inelastically demands one unit of housing. Accordingly, the housing sector supplies $L_j$ units of housing at a per-period price $p_j^h$, incurring a cost $L_j^{1/\gamma}$. As is standard in geographic models, the congestion forces embedded in the housing sector determine the equilibrium distribution of workers.

Firms are indexed by their idiosyncratic productivity, $z$, which is redrawn each period with probability $1-\rho$ from a Beta distribution with parameters $(\lambda_1, \lambda_2)$, defined over the interval $[a, b]$, with cumulative distribution function $F(z)$. Idiosyncratic productivity shocks are crucial for generating endogenous separations in the model. Following the search-and-matching literature (e.g., Pissarides, 2000) firms operate with constant returns to scale using capital and labor as inputs, so that firm size remains undetermined and we assume a one-to-one capital unit–firm match.[18] Thus, each match yields period output $y_j(z) = (\mathcal{Z}_j z)^\alpha \ell^{1-\alpha}$. Firms' output is an homogeneous good that is freely traded across locations, so its price $p_j^y$ is equalized across $j$; we normalize $p_j^y \equiv 1$ and use it as the numeraire. Producing firms incur a fixed cost $c$ associated with operating the production technology. Capital unit–firm matches are destroyed exogenously with probability $d$. Firms have free entry and can choose where to search for capital at a per-period cost $\kappa$. It is natural to assume that firms exert search effort for capital, as is often the case in real estate markets.

#### 1.4.1.2 Capital Markets and Timing

We follow Kleinman et al. (2023) and, consistent with our structure-based empirical evidence, assume that capital is geographically immobile, depreciates at rate $\delta$, and is produced from output using local savings. Consequently, the law of motion for location-specific capital in location $j$ is $K_j' = (1-\delta)K_j + X_j$.

Motivated by our evidence showing that high capital transaction rates coexist with substantial capital unemployment (Fact 3), which points to frictions impeding matches between the demand and supply sides of the market, we model the underlying market structure of

[17] Although not legally required, the vast majority of commercial real estate services are handled by third party professionals, such as agents and solicitors. According to HM Land Registry, professional assistance is overwhelmingly preferred. In the event of a transaction, 0.25 % to 1.25% of the transaction value would be charged by these third parties, as reported online by comparemymove.

[18] Search-and-matching models with firm size determined through decreasing returns include Elsby and Michaels (2013), Kaas and Kircher (2015), and Schaal (2017).

local capital markets using search-and-matching frictions, enabling sustained demand to coexist with idle capacity.[19] Our approach aligns with a broad real estate literature emphasizing the presence of search-and-matching frictions in these markets (e.g., Genesove and Han, 2012; Ngai and Tenreyro, 2014; Han and Strange, 2015; Koijen et al., 2025), and with research highlighting trading frictions and the long delays between the listing and sale of capital units (e.g., Ramey and Shapiro, 1998; Gavazza, 2011; Ottonello, 2021; Wright et al., 2018, 2020; Cao and Shi, 2023; Rocheteau, 2025).[20]

Although asking rents are visible on UK listing platforms, the effective rent tenants actually pay is different because capital leases are brokered and bilaterally negotiated off the list price. This motivates a random-search framework with ex post bargaining.[21] In particular, we assume that contacts between searching capital units and firms follow a constant-returns-to-scale Cobb-Douaglas matching function $M((1-\delta)K_j^u + X_j, E_j^k) = m((1-\delta)K_j^u + X_j)^\mu (E_j^k)^{1-\mu}$ in each local capital market, where $(1-\delta)K_j^u + X_j$ represents the total capital searching—comprising undepreciated unemployed capital plus investment—and $E_j^k$ denotes the total search effort by firms in market $j$.[22] Capital market tightness is defined as $\theta_j = E_j^k/((1-\delta)K_j^u + X_j)$. The contact rate for capital units searching in the market is $p(\theta_j) = M/((1-\delta)K_j^u + X_j) = m\theta_j^{1-\mu}$, and for searching firms it is $q(\theta_j) = M/E_j^k = m\theta_j^{-\mu}$, with the relationship $p(\theta_j) = \theta_j q(\theta_j)$.

If a capital unit–firm match dissolves the unit of capital starts the next period as unemployed. Additionally, matches are destroyed exogenously with probability $d$. Rental rates, $r_j(z)$, are determined through state-contingent generalized Nash bargaining, where the representative family have bargaining power $\eta \in (0, 1)$.

The model timing is as follows: period $t$ comprises two stages, A and B. In stage A, unemployed units of capital and firms search, then exogenous separations $d$ realize. Subsequently, firms decide whether to maintain the match once the shock $z$ is realized. In stage B, produc-

[19] Note that search frictions in other markets—such as the labor market—cannot generate these patterns so long as the capital market is Walrasian.

[20] Anecdotal evidence further supports the presence of these frictions in local commercial real estate markets (e.g., PIP; Tolj CRE; PeerStorage).

[21] Effective rents are the realized rents paid, as opposed to the posted asking rents that anchors negotiations; they net out concessionary items such as rent-free months and fit-out/tenant-improvement (TI) contributions among other things. Broker research documents cyclical swings in concessions and effective rents—see CBRE (2024); CBRE (2023)—and UK practice explicitly treats these as negotiated terms rather than fixed prices—see RICS Lease Code; Sprintlaw UK; Falcon Chambers. For recent UK commentary on incentive variability, see Savills (2023).

[22] As in the empirical section, we assume that new capital starts as unemployed.

tion occurs, followed by capital depreciation with probability $\delta$. Value functions are written in stage B.

### 1.4.2 Local Capital Market Equilibrium

#### 1.4.2.1 The Representative Family

The representative family takes market tightness as given and solves the following problem:

$$\mathcal{W}(K_j, K_j^e) = \max_{\{C_j, K_j'\}} \mathcal{A}_j \log(C_j) + \beta \mathcal{W}(K_j', K_j^{e'}), \tag{1.10}$$

$$\text{s.t.} \quad C_j = W_j L_j + \int_{z \geq z_j^c} r_j(z) dF(z) K_j^e + (1-\delta) K_j + \Pi_j - p_j^r K_j - p_j^h L_j - K_j', \tag{1.11}$$

$$K_j^{e'} = (1-s_j)(1-\delta) K_j^e + f_j (K_j' - (1-\delta) K_j^e). \tag{1.12}$$

Equations (1.10)–(1.12) present the recursive formulation of the representative family's problem. Equation (1.10) defines the family's value function, while equation (1.11) specifies the budget constraint. In this constraint, consumption, $C_j$, equals the sum of labor income, $W_j L_j$, capital income, $\int_{z \geq z_j^c} r_j(z) dF(z) K_j^e + (1-\delta) K_j$—where $z_j^c$, defined in the next section, denotes the productivity cutoff below which firms cease operations—and profits, $\Pi_j$, from firms as well as the real estate and housing sectors, net of payments to the real estate sector, $p_j^r K_j$, the housing sector, $p_j^h L_j$, and new capital, $K_j'$. Finally, equation (1.12) provides the law of motion for total employed capital. Total capital employed tomorrow, $K_j^{e'}$, is the sum of two components. First, the undepreciated employed capital that remains employed today, $(1-\delta) K_j^e$, surviving separations with probability $(1-s_j)$. Second, searching capital that successfully becomes employed, $f_j(K_j' - (1-\delta) K_j^e)$, where $K_j' - (1-\delta) K_j^e = (1-\delta) K_j^u + X_j$, with $X_j = K_j' - (1-\delta) K_j$. The next section endogenizes separations, $s_j$, and finding rates, $f_j$.

The solution to the representative family's problem—derivations of which are provided in Online Appendix A.2.1—yields the following Euler equation:

$$Q_j = \beta \left[ Q_j' \left( 1 - \delta - p_j^{r'} \right) + f_j \eta \mathbb{E} S_j \right], \tag{1.13}$$

where $Q_j \equiv \mathcal{A}_j/C_j$ defines the marginal utility of the representative family, and $\eta\mathbb{E}S_j \equiv \partial\mathcal{W}(K'_j, K_j^{e'})/\partial K_j^{e'}$ represents the fraction of the total surplus created by a match between a unit of capital and an average firm that the representative family appropriates.

Equation (1.13) has a standard interpretation. When choosing how much new capital to create, the representative family trades off forgoing one unit of consumption, valued at $Q_j$, against the expected return from that foregone consumption, discounted at rate $\beta$. This return consists of the net value of that unit tomorrow, $Q'_j(1-\delta-p_j^{r'})$, plus the investment return, $\eta\mathbb{E}S_j$, which is received with probability $f_j$.

#### 1.4.2.2 Local Capital Market Equilibrium

The value functions of an unemployed and employed unit of capital in the local capital market $j$ have the following recursive representation:

$$V_j^u = -Q_j p_j^r + (1-\delta)\beta\left\{V_j^u + p(\theta_j)(1-d)\mathbb{E}[V_j^e(z') - V_j^u]^+\right\}, \tag{1.14}$$

$$V_j^e(z) = Q_j(r_j(z) - p_j^r) + (1-\delta)\beta\left\{V_j^u + (1-d)\mathbb{E}[V_j^e(z') - V_j^u]^+\right\}; \tag{1.15}$$

where $\mathbb{E}[\cdot]^+$ denotes the expectation over the $\max\{\cdot, 0\}$ with respect to future productivity $z'$. This operator over continuation values represents the optimal separation decision.

Firms take wages, $W_j$, as given and hire labor in a spot market to maximize their static profits:

$$\pi_j(z) = \max_{\ell_j(z)} (\mathcal{Z}z)^\alpha \ell_j(z)^{1-\alpha} - W_j\ell_j(z). \tag{1.16}$$

The value of a matched firm and a firm searching for capital in the local capital market $j$ have the following recursive representations:

$$V_j^p(z) = Q_j(\pi_j(z) - c - r_j(z)) + (1-\delta)\beta(1-d)\mathbb{E}[V_j^p(z') - V_j^v]^+, \tag{1.17}$$

$$V_j^v = -Q_j\kappa + \beta q(\theta_j)(1-d)\mathbb{E}[V_j^p(z') - V_j^v]^+. \tag{1.18}$$

As discussed in Section 1.4.1, we follow the literature and assume that total surplus, denoted as $S_j(z) \equiv V_j^e(z) - V_j^u + V_j^p(z) - V_j^v$, is split between capital owners and firms according to a Nash bargaining protocol, with $\eta$ representing the capital owners' bargaining power. In this protocol, the capital owners' surplus, $V_j^e(z) - V_j^u$, equals a fraction $\eta$ of the total surplus,

while the firm surplus, $V_j^p(z) - V_j^v$, equals the $1-\eta$ remaining fraction. The rental rate for capital that achieves this split, as shown in Online Appendix A.2.2, is given by:

$$r_j(z) = \eta\left(\pi_j(z) - c + (1-\delta)\kappa\theta_j\right). \tag{1.19}$$

As firms can freely choose which local capital market $j$ to enter, the value of a firm with a capital vacancy must be zero in equilibrium, leading to the following free-entry condition:

$$Q_j\kappa = \beta q(\theta_j)(1-d)(1-\eta)\mathbb{E}[S_j(z')]^+, \tag{1.20}$$

saying that the cost of searching for capital must equalize the expected value of producing with that unit of capital. A corollary of this is that the firms are indifferent between searching for capital in different capital markets.

Combining equations (1.17), (1.19), and (1.20) with the definition of total surplus yields:

$$S_j(z) = Q_j\left(\pi_j(z) - c + (1-\delta)\frac{1-\eta p(\theta)}{1-\eta}\frac{\kappa}{q(\theta_j)}\right), \tag{1.21}$$

and since capital-firm matches are sustained as long as they yield a weekly positive surplus, the threshold level $z_j^c$ blow which capital-firm matches are dissolved is defined implicitly as:

$$0 = \pi_j(z_j^c) - c + (1-\delta)\frac{1-\eta p(\theta)}{1-\eta}\frac{\kappa}{q(\theta_j)}. \tag{1.22}$$

Thus, in the model separation rate $s_j$ and finding rate $f_j$ are as follows:

$$s_j = 1 - (1-d)\left(1 - F(z_j^c)\right), \tag{1.23}$$

$$f_j = p(\theta_j)(1-d)\left(1 - F(z_j^c)\right); \tag{1.24}$$

where $1-d$ is the exogenous match survival probability, $1-F(z_j^c)$ is the endogenous match survival probability, and $p(\theta_j)$ is the contact rate for searching capital.

#### 1.4.2.3 The Real Estate and Housing Sectors

The real estate and housing sectors solve the following profit maximization problems:

$$\text{Real estate sector:} \qquad \Pi_j^r = \max_{K_j} \; p_j^r K_j - \left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1}{\phi}}, \tag{1.25}$$

$$\text{Housing sector:} \qquad \Pi_j^h = \max_{L_j} \; p_j^h L_j - (L_j)^{\frac{1}{\gamma}}. \tag{1.26}$$

Profit maximization yields the following prices:

$$p_j^r = \frac{1}{\phi}\left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1-\phi}{\phi}} \frac{1}{\mathcal{P}_j}, \quad \text{and} \quad p_j^h = \frac{1}{\gamma} L_j^{\frac{1-\gamma}{\gamma}}; \tag{1.27}$$

which imply that the prices charged in both sectors equal their respective marginal costs.

#### 1.4.2.4 Spatial Allocation of Workers and Equilibrium

Following Rosen (1979b)-Roback (1982), we assume that workers have an outside option given by $\underline{\mathcal{W}}$. This implies that the allocation of worker across locations satisfies the following relation:

$$Q_j(W_j - p_j^h) = \underline{\mathcal{W}}, \tag{1.28}$$

where the left-hand side represents the representative family's remuneration to a worker moving to location $j$. In other words, the family pays the worker the worker's marginal value to the family itself, measured in the family's utility by the wage net of housing costs, and this must equal the worker's outside option.[23]

Therefore, using equation (1.28) and the aggregate constraint $\sum_j L_j = \overline{L}$, we can derive the following condition for the distribution of workers across locations:

$$L_j = \frac{\left[\gamma\left(W_j - \frac{W}{Q_j}\right)\right]^{\frac{\gamma}{1-\gamma}}}{\sum_j \left[\gamma\left(W_j - \frac{W}{Q_j}\right)\right]^{\frac{\gamma}{1-\gamma}}} \overline{L}. \tag{1.29}$$

Thus, in this economy, for each location $j \in \{1, \ldots, J\}$, given $\{\mathcal{Z}_j, \mathcal{A}_j, \mathcal{P}_j\}$, a *recursive competitive spatial equilibrium* is a set equilibrium outcomes $\{\theta_j, z_j^c, S_j(z), p_j^r, p_j^h, \ell_j(z), W_j; L_j,$

[23] Note that the bracketed term is akin to the worker's consumption, as in the textbook Rosen (1979b)–Roback (1982) spatial equilibrium condition. The difference here is that, because the family—not the worker—is the decision maker, consumption is evaluated in the family's marginal utility rather than in the worker's utility.

$K_j, C_j\}$ satisfying the following conditions: (i) $\theta_j, z_j^c, S_j(z)$ solve (1.20)-(1.22); (ii) $p_j^r$ and $p_j^h$ are given by (1.27); (iii) $\ell_j(z)$ solves (1.16); (iv) $W_j$ is such that the local labor market clears, i.e., $\int_{z \geq z_j^c} \ell_j(z) dz = L_j$; (v) $L_j$ solves (1.29); (vi) $K_j$ solves (1.13); and (vii) $C_j$ is given by (1.11).

### 1.4.3 Inspecting the Mechanism

Section 1.3.2 showed that differences in capital unemployment rates across locations are primarily driven by separation rates, with finding rates playing a minor role (Fact 4). Equations (1.23) and (1.24) imply the following elasticities for separation and finding rates out of fundamental productivity differences $\mathcal{Z}_j$:[24]

$$\boldsymbol{\varepsilon_{s_j,\mathcal{Z}_j}} = -\frac{1-s_j}{s_j} \varepsilon_{1-F(z_j^c),z_j^c} \boldsymbol{\varepsilon_{z_j^c,\mathcal{Z}_j}}, \tag{1.30}$$

$$\boldsymbol{\varepsilon_{f_j,\mathcal{Z}_j}} = (1-\mu)\boldsymbol{\varepsilon_{\theta_j,\mathcal{Z}_j}} + \varepsilon_{1-F(z_j^c),z_j^c} \boldsymbol{\varepsilon_{z_j^c,\mathcal{Z}_j}}; \tag{1.31}$$

where $\varepsilon_{1-F(z_j^c),z_j^c}$ denotes the elasticity of the survival probability to the separation threshold, $\varepsilon_{z_j^c,\mathcal{Z}j}$ is the elasticity of the separation threshold to fundamental productivity, and $\varepsilon_{\theta_j,\mathcal{Z}j}$ is the elasticity of market tightness to fundamental productivity. While the first two elasticities are negative, the third is positive. Equations (1.30) and (1.31) demonstrate that $\varepsilon_{z_j^c,\mathcal{Z}j}$ and $\varepsilon_{\theta_j,\mathcal{Z}_j}$ are the two key endogenous elasticities generated by the model that determine its ability to account for Fact 4.[25] The role of the separation rate dominates that of the finding rate—as in the data—if the former elasticity is large and the latter is small. In the next section, we characterize the conditions under which this is the case. Full derivations are provided in Online Appendix A.2.3.

The elasticity of the separation threshold level to location-specific productivity, $\varepsilon_{z_j^c,\mathcal{Z}_j}$, takes the following form:

$$\boldsymbol{\varepsilon_{z_j^c,\mathcal{Z}_j}} = -\underbrace{1}_{\substack{\text{Direct}\\ \text{effect}}} \underbrace{-\frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(\frac{\mu}{p(\theta_j)}-\eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j}}_{\text{Indirect effect}} + \underbrace{\frac{1-\alpha}{\alpha}\varepsilon_{W_j,\mathcal{Z}_j}}_{\text{GE effect}}. \tag{1.32}$$

The elasticity of the separation threshold level to location-specific productivity, $\varepsilon_{z_j^c,\mathcal{Z}_j}$, consists

[24] Other location-specific primitives such as amenities and real estate sector productivities influence outcomes only indirectly through equilibrium effects.

[25] $\varepsilon_{1-F(z_j^c),z_j^c}$ is fully determined by the choice of the distribution $F(\cdot)$ and is therefore not an endogenous outcome of the model.

of three components: (i) the direct effect of location-specific productivity on the separation threshold, (ii) the indirect effect of location-specific productivity on market tightness, and (iii) the general equilibrium effect.

Clearly, $\varepsilon_{z_j^c,\mathcal{Z}_j}$ is negative if general equilibrium forces do not dominate and $\mu/p(\theta_j) > \eta$.[26] Moreover, $\varepsilon_{z_j^c,\mathcal{Z}_j}$ is large when the indirect effect is strong. Assuming a small $\varepsilon_{\theta_j,\mathcal{Z}_j}$ (analyzed below), the indirect effect is strong if the term multiplying $\varepsilon_{\theta_j,\mathcal{Z}_j}$ is sufficiently large. This happens when either $\pi_j(z_j^c)$ or $\eta$ is sufficiently low, or when the effective cost of searching, $k\theta_j$, is sufficiently high. In all these cases, the marginal producing firm has a very low value, causing small differences in location-specific productivity to trigger large differences in separation thresholds.

The elasticity of market tightness to location-specific productivity, $\varepsilon_{\theta_j,Z_j}$, takes the following form:

$$\boldsymbol{\varepsilon_{\theta_j,\mathcal{Z}_j}} = \underbrace{\Upsilon_j \frac{\mathbb{E}\pi_j(z')}{\mathbb{E}\pi_j(z') - c}}_{\substack{\text{Standard} \\ \text{search-and-matching} \\ \text{amplification}}} \left[ \underbrace{1}_{\substack{\text{Direct} \\ \text{effect}}} + \underbrace{\Omega_j \varepsilon_{z_j^r,\mathcal{Z}_j}}_{\substack{\text{Endogenous} \\ \text{separation} \\ \text{effect}}} - \underbrace{\frac{1-\alpha}{\alpha} \varepsilon_{W_j,\mathcal{Z}_j}}_{\text{GE effect}} \right], \tag{1.33}$$

where $\Upsilon_j$ and $\Omega_j$ take the following form:

$$\Upsilon_j \equiv \frac{(1-\delta)\beta(1-d)(1-F(z_j^c))\eta p(\theta_j) + (1-(1-\delta)\beta(1-d)(1-F(z_j^c)))}{(1-\delta)\beta(1-d)(1-F(z_j^c))\eta p(\theta_j) + (1-(1-\delta)\beta(1-d)(1-F(z_j^c)))\mu}, \tag{1.34}$$

$$\Omega_j \equiv \varepsilon_{\mathbb{E}z',z_j^c} + \frac{\mathbb{E}\pi_j(z') - c}{\mathbb{E}\pi_j(z')} \left( 1 + \frac{\kappa(1-\eta p(\theta_j))}{q(\theta_j)(1-\eta)(\mathbb{E}\pi_j(z') - c)} \right) \varepsilon_{1-F(z_j^c),z_j^c}. \tag{1.35}$$

Equation (1.33) shows that the elasticity of market tightness to location-specific productivity is driven by (i) a direct effect, (ii) an indirect effect of location-specific productivity on the separation threshold, and (iii) a general equilibrium effect. The combined impact of these forces is proportionally scaled by the standard search-and-matching amplification mechanism, which includes a constant $\Upsilon_j$ and the well-known inverse fundamental surplus term, $\frac{\mathbb{E}\pi_j(z')}{\mathbb{E}\pi_j(z')-c}$, introduced in Ljungqvist and Sargent (2017). Effectively, equation (1.33) extends the concept of the fundamental surplus, from Hagedorn and Manovskii (2008) and Ljungqvist and

[26] Under an empirically plausible calibration $\mu/p(\theta_j) > \eta$ is satisfied as $\mu$ is estimate by Ottonello (2021) around 0.70 and $p(\theta_j)$ is on average 0.40, with $\eta \in (0,1)$.

Sargent (2017), to a spatial equilibrium setting with endogenous separations.

The direct effect is dampened both by the general equilibrium effect and by the indirect effect stemming from endogenous separations, provided that $\Omega_j$ is positive. Conversely, if $\Omega_j$ is negative, the indirect effect from endogenous separations acts as an amplifying force. While it is not possible to determine the sign of $\Omega_j$ a priori, even for well-behaved distributions of firm-level productivity, our quantitative analysis suggests that it is often positive for reasonable calibrations. As a result, the indirect channel from endogenous separations tends to have a dampening effect.

Therefore, capital market tightness—and consequently, finding rates—do not vary significantly across locations due to differences in location-specific fundamental productivity if the amplification in the search-and-matching model is relatively weak. For this to hold, both $\Upsilon_j$ and the inverse fundamental surplus, $\frac{\mathbb{E}\pi_j(z')}{\mathbb{E}\pi_j(z')-c}$, must be relatively small. $\Upsilon_j$ is bounded above by $\frac{1}{\mu}$. The inverse fundamental surplus represents the upper bound on the fraction of output that the invisible hand can allocate to match creation. Clearly, whether this value is high or low depends on $c$. Thus, we can conclude that the spatial variation in capital market tightness—and consequently, the finding rate—is primarily governed by two parameters: $\mu$ and $c$.

In conclusion, equations (1.32) and (1.33) demonstrate that the model can accommodate different degrees of variation in separation threshold and capital market tightness across locations out of fundamental productivity differences. As a result, the relative importance of separation and finding rates in driving local capital unemployment disparities remains a quantitative question, dependent on calibration. The above analysis highlights key parameters that must be carefully disciplined in the quantitative analysis to determine which margin prevails.

### 1.4.4 Efficiency

This section examines the efficiency properties of the model. The planner's problem in this framework has the following recursive formulation:

$$\mathcal{W}^{SP}(K_j, K_j^e, z_j^c) = \max_{\{K_j', E_j^k, z_j^{c'}, \ell_j(z), L_j\}} \mathcal{A}_j \log(C_j) + \beta \mathcal{W}^{SP}(K_j', K_j^{e'}, z_j^{c'}), \tag{1.36}$$

subject to the following constraints:

$$C_j = \left[\frac{1}{1-F(z_j^c)}\int_{z\geq z_j^c}\left[(\mathcal{Z}_j z)^\alpha \ell_j(z)^{1-\alpha} - c\right] f(z)dz\right] K_j^e + (1-\delta)K_j - \left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1}{\phi}} - (L_j)^{\frac{1}{\gamma}} - \kappa E_j^k - K_j', \tag{1.37}$$

$$K_j^{e'} = (1-d)(1-F(z_j^{c'}))(1-\delta)K_j^e + p(\theta_j)(1-d)(1-F(z_j^{c'}))(K_j' - (1-\delta)K_j^e), \tag{1.38}$$

$$\theta_j = \frac{E_j^k}{K_j' - (1-\delta)K_j^e}, \tag{1.39}$$

$$L_j = \int_{z\geq z_j^c} \ell_j(z) f(z) dz K_j^e, \tag{1.40}$$

$$\sum_j L_j = \overline{L}. \tag{1.41}$$

At the production stage, i.e., after search and matching have occurred, the planner selects next-period capital $K_j'$, search effort, $E_j^k$, the next-period separation threshold $z_j^{c'}$, firm-level labor demand, $\ell_j(z)$, and total labor, $L_j$ in order to maximize total consumption, subject to the aggregate budget constraint (1.37), the law of motion for capital employment (1.38), the definition of capital market tightness (1.39), the location-specific labor market clearing condition (1.40), and the aggregate population constraint (1.41).

Online Appendix A.2.4 provides detailed derivations of the social planner's problem. The decentralized equilibrium is efficient if and only if

$$\mu = \eta, \tag{1.42}$$

which corresponds to the standard efficiency condition of DMP models established by Hosios (1990). This result is intuitive, as the only friction in the model arises from search frictions in the local capital market, while all other decisions are made in a frictionless manner.

To understand this condition, it is useful to realize that at the core of the local capital market structure are capital owners and firms making investment decisions: the former in capital investment and the latter in costly search effort. In this setting, two inefficiencies arise in this investment decisions. First, because of ex post bargaining, each side recoups only its own share of the return on these investments; this creates a classic hold-up (appropriability)

problem that acts as an effective tax that makes both capital investment and search effort inefficiently low. The severity tilts with the relative bargaining strengths of each side: when $\eta$ is low, underinvestment is stronger on the capital owners' side, when $\eta$ is high, it is stronger on the firms' side.

Second, capital owners' and firms' decisions generate congestion externalities that affect the other participants on both sides of the market. Because agents do not internalize the congestion they impose, these decisions create negative externalities that induce overinvestment. In particular, for capital owners the externality takes the form $-(1-\mu)p(\theta_j)$, and for firms $-\mu q(\theta_j)$. Thus, when $\mu$ is high, the overinvestment motive is weak for capital owners and strong for firms; when $\mu$ is low, the reverse holds.

The overall effect is determined by the balance of these opposing inefficiencies. When the Hosios (1990) condition holds, the hold-up problem depressing capital owners' and firms' investments exactly offsets the excessive search incentive caused by the congestion externality, leading to an efficient equilibrium. However, if $\mu > \eta$, the hold-up problem dominates for capital owners and the congestion externality dominates for firms: capital investment is too low, firm entry is too high, resulting in little unemployed capital and higher effective search costs. Conversely, if $\mu < \eta$, the congestion externality dominates for capital owners and the hold-up problem dominates for firms: capital is overinvested, firm entry is insufficient, and, as a result, there is higher capital unemployment and thus idle capacity.

While whether the Hosios (1990) condition holds or not is ultimately a quantitative question, it is straightforward to show that its allocation can be decentralized through the following place-based subsidy to capital owners with unemployed capital, with the full derivation in Appendix A.2.5:[27]

$$\tau_j = \frac{\mu - \eta}{1 - \eta} \left( \mathbb{E}\pi_j(z) - c + (1-\delta)\kappa\theta_j \right) \tag{1.43}$$

Equation (1.43) inherits the properties of the social planner within-location allocation described before. When $\mu = \eta$, i.e., when the Hosios (1990) condition holds, the optimal subsidy is zero in all locations. When $\mu < \eta$, the optimal subsidy is negative, meaning it is optimal to tax capital owners. Conversely, when $\mu > \eta$, the optimal subsidy is positive.

[27] Note that this place-based subsidy to capital owners with unemployed capital is equivalent to a place-based tax on firms or capital owners with employed capital.

## 1.5 Quantification and Positive Implications

This section presents the calibration strategy of the model and validates it on several untargeted moments. Then, it assesses the ability of the model to replicate the contribution of different flows to capital unemployment rate differences across locations as established in Section 1.3.2.

### 1.5.1 Calibration

The calibration strategy involves two steps: first, fixing parameters estimated outside the model; second, choosing the remaining parameters to match the identifying moment of the data.

*Fixed parameters.* Each model period is one year, so $\beta$ is set at 0.96. We set the depreciation rate to 2 percent, as in the empirical analysis. The capital share $\alpha$ is set to 0.35, a number in line with the literature. The matching function elasticity $\mu$ is set to 0.70, which is the lower bound estimate from the micro-data in Ottonello (2021).[28] This must be interpreted as a conservative choice, as a high value of this elasticity will increase the role of the separation rate in explaining spatial capital unemployment gaps, as explained in Section 1.4.3. We set the exogenous separation rate $d$ to 0.01, which is close to the minimum separation rate measured in our data and to the level in Ottonello (2021). We follow Pissarides (2000) and, more recently, Kuhn et al. (2025), assuming that $\lambda_1$ and $\lambda_2$ are both equal to 1, implying a uniform probability distribution.[29] We set the upper bound of the match-specific shock, $b$, to 2 and the lower bound, $a$, to 1, which results in an unconditional average of 1 and a variance of firm-level output of 0.58—approximately ten times larger than that of aggregate output—a finding consistent with Bloom et al. (2018). Then, the probability of match-specific shocks $1 - \rho$ is set to 0.10, implying a persistence of 0.90, which is close to Foster et al. (2008) and well within the range reported by the literature, ranging from 0.97 in Lee and Mukoyama (2015) to 0.5 in Ábrahám et al. (2006) and Castro et al. (2015). We set $\phi$ to 0.5, reflecting a high degree of decreasing

[28] See Appendix C.4, Table C.9, page 26. This value is close to the 0.75 reported by Badarinza et al. (2024) and falls within the 0.45–0.75 range reported and Ngai et al. (2025) for residential real estate markets—by contrast, Ottonello (2021) and this paper focus on non-residential real estate. This value is also similar to magnitudes used in the macro-labor literature, including the empirical estimates in Petrongolo and Pissarides (2001) and the parameterization in Shimer (2005).

[29] We adopt this functional form for the distribution of $z$ to remain consistent with the literature. However, Kuhn et al. (2025) demonstrate that this assumption is quantitatively inconsequential for this class of models.

returns, as is typical in service sectors. We set $\gamma$ to 0.12, which implies a housing supply elasticity of 0.14 as estimated for UK by Drayton et al. (2025) and is close to suggesting that only 12 percent of reproducible inputs contribute to housing supply—broadly in line with the estimates reported in Davis and Heathcote (2007). We normalize the exogenous productivity of the median capital-unemployment rate location, $\mathcal{Z}_{med}$, so that average unconditional profits form equation (1.16) in that location equal 1.[30] Finally, we normalize total population in the economy $\overline{L}$ and the workers outside option $\underline{\mathcal{W}}$ to 1.

**Table 1.1: Parameters**

| Parameter | Description | Value | | | |
|---|---|---|---|---|---|
| **Fixed** | | | | | |
| $\beta$ | Discount factor | 0.96 | | | |
| $\delta$ | Depreciation rate | 0.02 | | | |
| $\alpha$ | Capital share in production | 0.35 | | | |
| $\mu$ | Matching function elasticity | 0.70 | | | |
| $d$ | Exogenous separation rate | 0.01 | | | |
| $\lambda_1, \lambda_2$ | Beta distribution parameters | 1 | | | |
| $b$ | Match-specific shock upper bound | 2 | | | |
| $a$ | Match-specific shock lower bound | 0 | | | |
| $1-\rho$ | Probability of match-specific shocks | 0.10 | | | |
| $\phi$ | Real estate sector returns to scale | 0.50 | | | |
| $\gamma$ | Housing sector returns to scale | 0.20 | | | |
| $\mathcal{Z}_{med}$ | Median productivity | 0.93 | | | |
| $\overline{L}$ | Total population | 1 | | | |
| $\underline{W}$ | Workers' outside option | 1 | | | |
| **Fitted** | | | **Moment** | **Data** | **Model** |
| $m$ | Matching efficiency | 0.112 | Finding rate | 0.40 | 0.40 |
| $\kappa$ | Capital vacancy posting cost | 0.002 | Separation rate | 0.03 | 0.03 |
| $c$ | Fixed operating cost | 0.867 | Fixed cost share of total costs | 0.30 | 0.30 |
| $\eta$ | Capitalists bargaining power | 0.455 | Med. capital unemployment rate | 0.09 | 0.09 |
| $\{\mathcal{Z}_j\}_{j=1}^J \setminus \{\mathcal{Z}_{med}\}$ | Fundamental productivity levels | Figure A.8a | Capital unemployment rates | Figure 1.6a | |
| $\{\mathcal{A}_j\}_{j=1}^J$ | Amenities | Figure A.8b | Population | Figure 1.6b | |
| $\{\mathcal{P}_j\}_{j=1}^J$ | Real estate sector productivity | Figure A.8c | Capital stock | Figure 1.6c | |

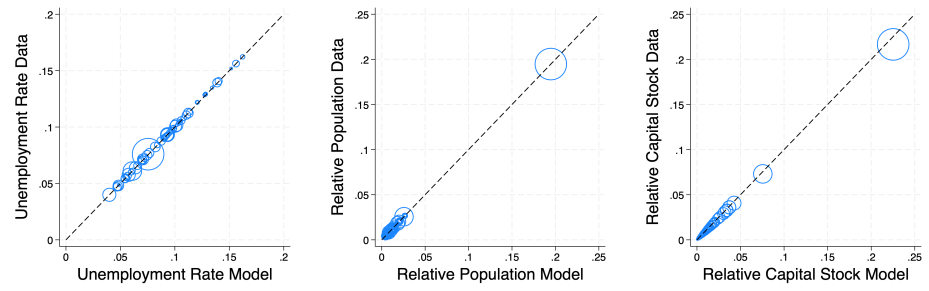
*Fitted parameters.* Thus, $3J+3$ parameters remain to be calibrated: the matching efficiency $m$; the capital vacancy posting cost $\kappa$; the fixed operating cost $c$; the capital owners bargaining power $\eta$; the location-specific fundamental productivity levels, $\{\mathcal{Z}_j\}_{j=1}^J \setminus \{\mathcal{Z}_{med}\}$; the location-specific amenities, $\{\mathcal{A}_j\}_{j=1}^J$; and the location-specific real estate sector productivity, $\{\mathcal{P}_j\}_{j=1}^J$.

We inform model parameter $\eta$ using the median observed capital unemployment rates which is 9 percent. The bargaining power of capitalists, $\eta$, is an important parameter in the model governing the efficiency of the equilibrium—thus, its extensively validations in Sections 1.5.2.1 and 1.6.2—and is inversely related to capital vacancy creation in all locations,

[30] This normalization significantly speeds up computation while being equivalent to the more standard approach of directly normalizing median productivity to one.

thus affecting the median unemployment rate. The calibration of $m$ is informed by the median location finding rate of 40 percent. The capital vacancy posting cost is informed by a separation rate of 3 percent as it pins down the expected value of producing for a firm, thus affecting the level of matches that can be sustained in equilibrium and, as a consequence, the separation threshold level. Another important parameter is the fixed operating cost $c$, which determines the size of the fundamental surplus and thus the relative importance of the finding versus separation rate in driving capital unemployment rate gaps. We calibrate $c$ to target a 30 percent average fixed cost share of total costs, close to the estimates reported by De Loecker et al. (2020). We calibrate the location-specific fundamental productivity levels, $\{\mathcal{Z}_j\}_{j=1}^{J} \setminus \{\mathcal{Z}_{med}\}$, using the unemployment rate in each location, except for the median one. The location-specific amenities, $\{\mathcal{A}_j\}_{j=1}^{J}$, are calibrated to match the relative population size in each location. Finally, the location-specific real estate sector productivity, $\{\mathcal{P}_j\}_{j=1}^{J}$, is calibrated to match the relative capital in each location.

**Figure 1.6: Capital Unemployment Rate, Population, and Capital Stock**




**(a) Capital Unemployment Rate** **(b) Population** **(c) Capital Stock**

Note: Figure 1.6 compares capital unemployment rates, population and total capital between the model and UK data. In Figures 1.6a–1.6c, blue circles represent model values plotted against data, with a dashed black 45-degree line for reference. Specifically, Figure 1.6a shows unemployment rates, Figure 1.6b shows relative population, and Figure 1.6c relative capital stock. Circle size reflects location size.

*Calibration outcome.* The parameters are jointly estimated using a search algorithm in the parameter space that minimizes the distance between the empirical and simulated moments. The parameters implied by the calibration strategy of the model and the fit of the model on several identifying moments are presented in Table 1.1. Unfortunately, as local capital markets have been relatively understudied due to the lack of available data, there is no widely accepted empirical estimate for most of the parameters. However, we note that a capitalist bargaining

power $\eta$ of 0.455 and a fixed cost $c$ of 0.850 generate an average profit share of 1 percent, well within the 0-10 percent range found by Barkai (2020) and De Loecker et al. (2020) for the period from 1980 to the present days. The same parameters in the model yield an average rental rate of 14 percent, aligning with measures of the return on capital reported by Gormsen and Huber (2024), although for the US. Further validations on $\eta$ are postponed to Section 1.6.2, where we delve into the normative implications of the model. While $\eta$ plays a minor role in the model's positive implications, it is crucial for its normative implications. Next, we proceed to explore and validate the model's positive performance on several untargeted moments.

### 1.5.2 Quantitative Performance of the Model

This section validates the quantitative performance of the model on many untargeted moments and assesses its ability to match the quantitative importance of the separation rate in driving spatial capital unemployment gaps, as documented in Section 1.3.2.

#### 1.5.2.1 Model Validation

Here we assess the quantitative performance of the model on many untargeted moments.

*Decomposition of spatial output per capita differences.* To assess the model's quantitative performance in explaining observed differences in output per capita—via differences in the capital stock, the capital-unemployment rate, and other determinants—we perform the following decomposition based on a standard Cobb-Douglas production function as used in the model:

$$\mathbb{V}\left(\log\left(\frac{Y_{jt}}{L_{jt}}\right)\right) = \underbrace{\mathbb{C}\left(\log\left(\frac{Y_{jt}}{L_{jt}}\right), \alpha \log\left(Z_{jt}\right)\right)}_{\text{Productivity contribution}} + \underbrace{\underbrace{\mathbb{C}\left(\log\left(\frac{Y_{jt}}{L_{jt}}\right), \alpha \log(1-k_{jt}^{u})\right)}_{\text{Unemployment rate contribution}} + \underbrace{\mathbb{C}\left(\log\left(\frac{Y_{jt}}{L_{jt}}\right), \alpha \log\left(\frac{K_{jt}}{L_{jt}}\right)\right)}_{\text{Total capital contribution}}}_{\text{Employed capital contribution}}. \tag{1.44}$$

Effectively, this implies that the spatial variation in output per capita can be decomposed into contributions from productivity differences and employed capital differences. The latter can be further broken down into unemployment rate differences and total capital differences.

Since each element in equation (1.44) represents the ratio of the covariance between output per capita and the component of interest to the variance of output per capita, we estimate these shares using OLS. To account for productivity differences across locations, we incorporate location- and time-fixed effects. Finally, we assume a capital share of 0.35, as in the model calibration.

**Table 1.2: Variance Decomposition of Local Output per Capita: Model vs. Data**

| | Output p.c. explained | |
|---|---|---|
| | **Data** | **Model** |
| *Employed capital (%)* | 25 | 35 |
| *Unemployment rate (%)* | 5 | 1 |
| *Total capital (%)* | 20 | 34 |
| *Productivity (%)* | 75 | 65 |

Table 1.2 presents the fraction of variation in local output per capita explained by differences in capital unemployment rates, total capital, and other factors across locations, both in the data and in the model. All numbers are reported in percent.

Table 1.2 reports the fraction of variation in the model and the data of local output per capita explained by differences across locations in capital unemployment rates, total capital, and productivity. Without calibrating any shares, we find that the model matches satisfactorily the empirical findings. It attributes a dominant share of the variation to productivity while also assigning a quantitatively significant role to differences in employed capital. Among the capital-related components, total capital differences play a major role, whereas the contribution of variations in capital unemployment rates is quantitatively smaller.

*Investment rates across space.* The model also replicates the investment patterns observed in the empirical analysis. Online Appendix A.3.2 presents a comparison of the net investment rate between the model and the data. In the model, despite the presence of permanent productivity differences across locations, investment equals depreciation in the steady state, implying a zero net investment rate—consistent with the data.

*Correlation of capital unemployment rates with untargeted observables.* Appendix A.3.3, Table A.3, reports model- and data-level correlations between capital-unemployment rates and GDP per capita, GDP per unit of capital, rental rates, and household income. Although none of these moments were targeted in the calibration, the model matches them satisfactorily.

*Amenities.* Unobserved local amenities allow the model to match the distribution of labor across locations. A natural check of the nonparametric amenity estimates $\mathcal{A}_j$ is to correlate

them with local characteristics that should affect the value of working or residing in a particular location. We correlate the estimated amenities with an amenity score provided by PMA,[31] as well as with ONS data on the location's amenity provisions. The latter includes the number of general practitioners, dentists, sports facilities, and supermarkets per 10,000 people. Online Appendix A.3.4 shows that amenity is positively associated with PMA amenity score and ONS amenity provision measures. These results support the view that estimated amenities capture salient features of the attractiveness of operating capital in a particular location.

#### 1.5.2.2 Spatial Capital Unemployment Gaps Decomposition

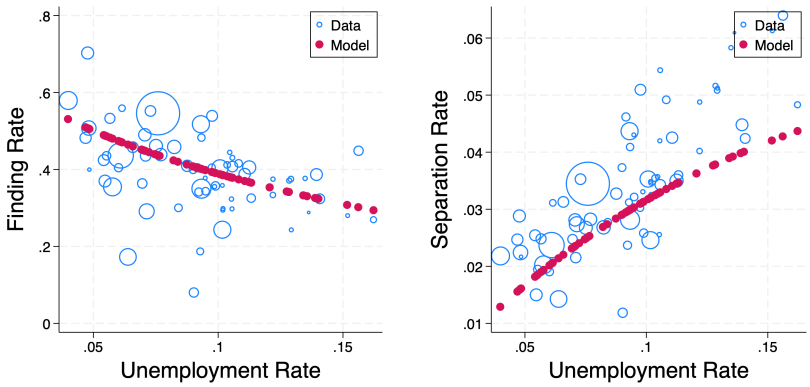
Having demonstrated the estimated model's ability to capture both targeted and non-targeted moments—such as GDP, net investment rates, rental rates, and amenities—we now turn to the main positive results. Specifically, we assess the model's ability to quantitatively explain the key features of local capital markets documented in Section 1.3.2.

Figure 1.7 displays the finding (Figure 1.7a) and separation rates (Figure 1.7b) across UK locations in the data (blue) and the model (red). The left panel illustrates a decrease in finding rates as we move from locations with low capital unemployment rates to those with high capital unemployment rates. The right panel shows an increase in separation rates with the capital unemployment rate. It is important to note that in our calibration we target only the finding and separation rates at the median capital unemployment rate location, targeting neither the role of finding rate and separation rates in determining capital unemployment rate differences across locations nor differences in capital vacancy posting or market tightness. Thus, despite not being targeted, the model aligns closely with the data, both qualitatively and quantitatively. When comparing spatial variations, we notice that finding rates exhibit considerably less variability than separation rates. Specifically, the separation rate in the capital market with the highest capital unemployment rate is more than three times as high as in the capital market with the lowest capital unemployment rate. In contrast, the finding rate is only 44 percent lower in the location with the highest capital unemployment rate compared to the location with the lowest capital unemployment rate.

A close alignment with the observed patterns of finding and separation rates across space

[31] PMA's amenity scores are based on the presence of key anchor stores, national and regional fashion, non-fashion, and food & beverage multiples within each retail location. The scores reflect both the size and quality of key anchor stores, variety stores, and fashion multiples. A high score indicates stronger retail provision.

**Figure 1.7: Finding and Separation Rate across Local Capital Markets: Model vs. Data**



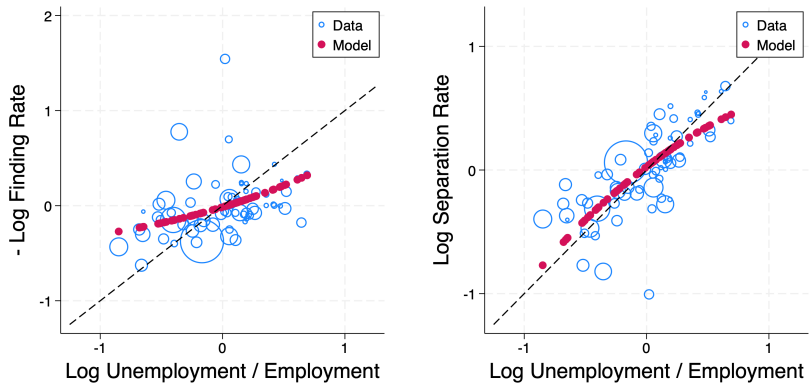

**(a) Finding Rate** **(b) Separation Rate**

Note: Figure 1.7 shows finding rates and separation rates from the model (red) and the data (blue) across UK locations. Figure 1.7a shows finding rates. Figure 1.7b shows separation rates. The size of the circles is proportional to the size of the location.

suggests that the model effectively replicates the relative significance of these two flow rates in driving spatial capital unemployment gaps. This can be seen in Figure 1.8, which presents the decomposition of the local capital unemployment rate differences between its different capital-flows, i.e., finding rate (Figure 1.8a) and separation rate (Figure 1.8b), from the model (red) and the data (blue) from Figure 1.5. The formal decomposition reveals a tight match between the model and data. In the model, separation rates account for 68 percent of the cross-sectional variation in capital unemployment rates, compared to 68 percent in the data, while finding rates contribute to 32 percent of the cross-sectional variation in capital unemployment rates in the model, close to the 30 percent observed in the data. These calculations have been done as in Section 1.3.2 assuming $\delta$ close to zero. Online Appendix A.3.5 presents the calculations for the general case, highlighting the contribution of the extensive margin and showing that the same takeaways hold.

To understand the success of the model in explaining the small contribution of the finding rate and the large contribution of the separation rate to local capital unemployment rate differences, it is helpful to refer to Section 1.4.3. First, the model generates a low elasticity of market tightness to productivity and thus of finding rate. This is because the calibration implies both a positive $\Omega$, meaning that the indirect effect from endogenous separations acts as a dampening force, and a sufficiently large fundamental surplus, which weakens the am-

**Figure 1.8: Decomposition of Spatial Capital Unemployment Gaps: Model vs. Data**




**(a) Finding Rate** **(b) Separation Rate**

Note: Figure 1.8 illustrates the contribution of minus the log of the finding rate and the log of the separation rate to local capital unemployment rate differences in the model (blue) and data (red), across UK locations. In Figure 1.8a, minus the log of the finding rate is plotted against the log of the unemployment-employment capital ratio, along with the dashed black 45-degree line. Figure 1.8b displays the log of the separation rate against the log of the unemployment-employment capital ratio, also with the dashed black 45-degree line. The size of the circles is proportional to the size of the location.

plification of productivity differences, as the retrieved fixed cost $c$ is sufficiently smaller than $\mathbb{E}\pi(z')$. Second, the model yields a high elasticity of the separation threshold level to productivity and hence of the separation rate. As shown in equation (1.32), this occurs when the term multiplying the elasticity of market tightness to productivity is sufficiently high, i.e., when the marginal producing firm has a low value, as recovered by our calibration.

## 1.6 Aggregate Implications and Counterfactual Analysis

Here, we conduct our two main counterfactual analyses. First, we examine the aggregate loss caused by search frictions in local capital markets. Second, we evaluate the potential for policy interventions to mitigate these aggregate losses by solving the social planner's problem.

### 1.6.1 Aggregate Losses from Search Frictions in Local Capital Markets

In this section, we examine the aggregate drag on the economy caused by the presence of search frictions in local capital markets. To this end, we conduct aggregate counterfactual

analyses under varying degrees of search frictions in these markets and assess their aggregate implications.

**Table 1.3: Macroeconomic Implication of Easing Search Frictions**

| | | Change | |
|---|---|---|---|
| | **Baseline** | **1.5×$m$** | **2×$m$** |
| *Avg. capital unemployment rate* | 9.25 | -1.95 p.p. | -3.50 p.p. |
| *Avg. finding rate* | 40.85 | +19.72 p.p. | +39.37 p.p. |
| *Avg. separation rate* | 2.89 | +1.02 p.p. | +1.55 p.p. |
| *Avg. rental rate* | 14.21 | -0.24 p.p. | -0.43 p.p. |
| *Total output* | 1.918 | +2.38 % | +3.83 % |
| *Total consumption* | 1.898 | +2.41 % | +3.88 % |

Table 1.3 presents the macroeconomic implication of easing search frictions, obtained by increasing $m$ by a factor of 1.5 and 2. The average changes are reported in percentage points (p.p.), and the total changes are reported in percent.

Table 1.3 presents the results of the counterfactual analysis, where we increase matching efficiency $m$, thereby reducing the severity of search frictions, by factors of 1.5 and 2. Higher matching efficiency facilitates the matching process between capital units and firms, leading to an increase in the finding rate and a reduction in capital unemployment rates. At the same time, firms experience a higher probability of matching with capital units. However, free entry and increased labor demand generate rises in market tightness and wages, which, in turn, increase the effective searching cost and lower firms' static profits. These counterbalancing general equilibrium forces have two important effects. First, the increase in effective cost of search and lower profitability raise the separation threshold at which firms can operate, leading to higher separation rates. Second, the decline in static profits puts downward pressure on rental rates, while the higher effective cost of searching exerts upward pressure, as firms compensate capital owners for avoiding the costly search process. Quantitatively, we find that the former effect dominates, resulting in an overall decline in rental rates.

Overall, we find that higher matching efficiency substantially increases both aggregate output and consumption. In particular, a rise in matching efficiency that reduces capital unemployment rates by approximately 40 percent leads to an almost 4 percent increase in aggregate output and consumption. This suggests that search frictions in local capital markets not only shape the distribution of output per capita across locations but also impose a significant drag on the overall economy. However, since these frictions are technological in nature, the large drag documented in Table 1.3 does not necessarily translate in large welfare gains from

policy interventions. To assess the potential welfare improvements from policy, we study this issue in detail in the next section by solving the social planner's problem.

### 1.6.2 Social Planner Solution and Place-Based Policies

This section explores the normative implications of the theory. First, it validates the calibrated bargaining power of the capitalists, then explores quantitatively the implications of place-based policies, and finally puts these policy implications into perspective by discussing the model's limitations.

*Capitalists' bargaining power validation.* The calibrated model reveals that capitalists' bargaining power is lower than the matching function elasticity, implying, as explained in Section 1.4.4, that the decentralized equilibrium is inefficient, with excessive firm entry. Here, we further validate the calibrated parameters, demonstrating that the capitalists' bargaining power implied by the calibration aligns with the data.

To do so, we exploit equation (1.19) to derive the unit-free rental rate elasticity of the capital unemployment rate in a given location, which is given by:

$$\varepsilon_{r_j,k_j^u} = -\eta \frac{\kappa\theta_j}{\mathbb{E}r_j(z)}, \tag{1.45}$$

which shows that the capital unemployment rate is unambiguously negatively associated with the rental rate, with the strength of this relationship mediated by $\eta$, the bargaining power of capitalists. Therefore, we can estimate this elasticity in the data and compare it to the model to validate our calibration of capitalists' bargaining power.

Table 1.4 presents this comparison. Columns (1)–(3) regress the log rental rate on the log capital unemployment rate, where the rental rate is measured as the present value of future prices. Column (1) reports a simple OLS regression. However, our empirical setting is subject to both measurement error and omitted-variable bias. While measurement error clearly biases our estimates downward, the direction of bias from omitted variables is uncertain. To address these concerns, column (2) employs a TSLS estimator using log labor productivity as an instrument for the log capital unemployment rate, while column (3) uses past unemployment as an instrument. Finally, column (4) reports the theoretical elasticity (1.45) derived from the model.

We find a statistically significant negative rental rate elasticity of the capital unemploy-

**Table 1.4: Rental Rate Elasticity of Capital Unemployment Rate: Model vs. Data**

| *Dependent Variable* | **Rental Rate** | | | |
|---|---|---|---|---|
| | Data (OLS) | Data (TSLS) | Data (TSLS) | Model |
| | (1) | (2) | (3) | (4) |
| Capital unemployment rate | -0.11** | -0.54** | -0.29*** | -0.46 |
| | (0.05) | (0.23) | (0.07) | |
| *Fixed Effects* | | | | |
| City | ✓ | ✓ | ✓ | |
| Time | ✓ | ✓ | ✓ | |
| *Controls* | | | | |
| City-specific Time Trend | ✓ | ✓ | ✓ | |
| *Instrument* | | | | |
| Labor productivity | | ✓ | | |
| Past unemployment rate | | | ✓ | |
| Observations | 743 | 642 | 453 | |

Note. Both the rental rate and the capital unemployment rate are in logs. City-specific time trends are quadratic. Column (1) performs a simple OLS, while columns (2) and (3) perform a TSLS where the capital unemployment rate is instrumented either with labor productivity or with past capital unemployment rate. Column (3) reports the theoretical elasticity in the model. +,*, **, and *** denote 15, 10, 5, and 1% statistical significance respectively.

ment rate in the data, consistent with the model's prediction. Moreover, after correcting for measurement error and omitted-variable bias, the estimated magnitudes closely align between the model and the data. Specifically, the data yield a negative elasticity between -0.29 and -0.54, compared to -0.46 in the model. Overall, this supports our calibration, confirming that capitalists' bargaining power is significantly lower than the matching function elasticity.

*Social planner allocation and quantification of place-based policies.* This section provides a quantitative exploration of the implications of place-based policies that implement the social planner allocation described in Section 1.4.4.

**Table 1.5: Macroeconomic Implication of Social Planner Allocation**

| | **Baseline** | **Social Planner** | **Change** |
|---|---|---|---|
| *Avg. capital unemployment rate* | 9.25 | 13.39 | +4.14 p.p. |
| *Avg. finding rate* | 40.85 | 30.16 | -10.69 p.p. |
| *Avg. separation rate* | 2.89 | 3.20 | +0.31 p.p. |
| *Avg. rental rate* | 14.21 | 15.59 | +1.38 p.p. |
| *Total capital* | 1.000 | 1.042 | 4.20 % |
| *Total output* | 1.918 | 1.924 | 0.30 % |
| *Total consumption* | 1.898 | 1.903 | 0.26 % |
| *Consumption equivalent welfare* | | | 0.28 % |

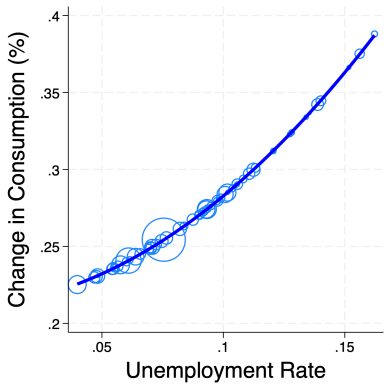
Table 1.5 presents the macroeconomic implications of achieving the social planner allocation, i.e., introducing place-based policies. Average changes are reported in percentage points (p.p.), and total changes are reported in percent.

Table 1.5 presents the results. When $\mu > \eta$, as recovered by our calibration, the hold-up

problem dominates for capital owners and the congestion externalities dominate for firms, resulting in suboptimal capital investment, excessive firm entry, too little capital unemployment, and a high effective search cost for firms. Therefore, the optimal allocation subsidizes unemployed capital, which, through Nash bargaining, is equivalent to taxing firms and subsidizing capital owners, because capital owners have a higher outside option in the planner's allocation.

As a result, in the social planner allocation, rental rates are higher, reducing firms' profits, which in turn leads to higher separation rates and lower finding rates. Consequently, the capital unemployment rate increases in the social planner equilibrium. The higher rental rate also strengthens the incentive for the representative household to invest, leading to a 4.20 percent higher total capital stock in equilibrium. Additionally, the planner's intervention alleviates congestion externalities, lowering the effective cost of searching. These combined effects result in an increase in total output and consumption, translating into an aggregate welfare gain of 0.28 percent, equivalent to approximately $2.15 billion US dollars, assuming total nominal personal consumption expenditure of £590.57 billion British pounds, as reported by FRED, and an exchange rate of 1.3.

**Figure 1.9: Local Welfare Gains in the Social Planner Allocation**




Note: Figure 1.9 illustrates the change in consumption following the implementation of the social planner's allocation. Each circle represents a city, with its size proportional to the capital stock. The thick blue line represents the quadratic best-fit curve.

Next, we examine the distribution of welfare gains across locations and their implications for inequality. Figure 1.9 illustrates these gains, which range from 0.22 to 0.39 percent, with larger increases in locations that historically experienced higher capital unemployment rates.

This suggests a pro-equality effect, as these areas benefit more from the policy intervention.

This pattern emerges because the social planner, by increasing the return on capital, strengthens investment incentives. However, investment is more accessible in high capital-unemployment locations, as these areas start with lower capital stock and lie on the flatter portion of the real estate sector cost curve. As a result, labor demand rises, triggering general equilibrium effects that push wages higher. Rising wages, in turn, discourage capital match creation, reducing the capital employment rate. However, the initial effect—greater investment in capital—dominates quantitatively. While the capital employment rate declines, it does not fall enough to offset the increase in total capital, ultimately leading to higher employed capital in these locations. Appendix A.3.6 provides further insights by illustrating the evolution of capital employment rates, total capital, total employed capital, and wages. Ultimately, the increase in employed capital boosts production in these locations, explaining the larger rise in consumption and, consequently, in welfare.

*Interpretation of the results and model discussion.* Our normative analysis is primarily exploratory, serving as a proof of concept for the model. While it reveals substantial, albeit hardly transformative, effects of place-based taxation, it remains subject to potential caveats, which we discuss below.

First, the model's rationale for implementing place-based policies is excessive firm entry. However, it abstracts from forces such as agglomeration externalities and love for variety, which could have the opposite effect, potentially dampening the impact discussed. Second, the model does not account for frictional employment considerations, which may interact with the normative analysis presented. For example, Manning and Petrongolo (2017) and Kuhn et al. (2025) show that if local labor markets are highly localized or efficient, the effects of place-based policies may be small or even undesirable. Conversely, Kline and Moretti (2013) and Bilal (2023) demonstrate that in the presence of hiring costs or significant congestion externalities from firm sorting across locations, place-based policies can have strong leveling-up effects. Fajgelbaum and Gaubert (2020) arrive at a similar conclusion without relying on frictional labor markets.

While the interaction between the mechanisms highlighted in this paper and those in the literature is not ex-ante obvious, it seems that the first strand emphasizes the case for no intervention due to minimal to no inefficiencies, suggesting minimal interaction with our

framework. In contrast, the second strand highlights inefficiencies that justify reallocation toward more deprived locations, potentially reinforcing and amplifying the mechanisms we described, which also calls for the lifting up of the same locations. However, incorporating all these forces alongside the mechanism outlined in this paper is beyond our scope.

Concluding, while we acknowledge that our normative analysis is largely exploratory, we believe that the mechanism we introduced provides a novel perspective on the desirability of place-based policies, contributing to the broader literature trying to understand the motives and scope for such policies.

## 1.7 Conclusion

This paper introduces a novel dataset to provide the first empirical insights into the spatial distribution of capital unemployment, defined as idle units actively searching to be traded. We document substantial and persistent differences in capital unemployment across locations, which are not arbitraged away by investment dynamics. To investigate the drivers of this spatial variation, we propose a decomposition framework that sheds light on capital flows into and out of unemployment. Our analysis underscores the dominant role of inflows into unemployment, which we refer to as separation rates.

We then propose a novel spatial dynamic model of capital accumulation featuring non-Walrasian local capital markets, grounded in search-and-matching frictions. The model quantitatively accounts for the empirical regularities associated with spatial differences in capital unemployment documented in our empirical analysis. Overall, it demonstrates that local capital market frictions have sizable negative implications for aggregate output and that the decentralized equilibrium is not necessarily efficient, thereby providing a new rationale for place-based policies with potentially sizeable welfare gains.

This work gives rise to a set of natural questions. First, it would be interesting to integrate local capital market frictions with labor market frictions to study how their interaction affects local prosperity and the effectiveness of policy interventions. Second, local capital market frictions serve as a natural source of persistence, as they act as adjustment costs that slow capital accumulation and reallocation. This naturally motivates the study of how localized shocks—such as the China shock—can have long-lasting local effects. These are exciting avenues for future research, which we leave to subsequent work.

# Chapter 2

# Labor Markets and Migration

*Stephen Ayerst* [1] *Charles Cheng Zhang* [2]

## Abstract

We develop a quantitative model of labor markets and migration with heterogeneous workers to study how labor market conditions and migration costs shape migration flows across Europe. To preserve the rich heterogeneity in economic fundamentals across countries documented in EU Labor Force Survey micro-data, we introduce a novel calibration strategy that calibrates each country individually while remaining consistent with bilateral migration flows. The calibrated model shows that migrants face sizable labor market frictions as well as substantial migration costs. A counterfactual experiment indicates that improving labor market fundamentals for migrants enhances their labor market outcomes and increases cross-country mobility. [3]

**Keywords: Migration, Search-and-Matching, Economic Integration**

**JEL Codes: F15, F22, J61, J64**

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## 2.1 Introduction

Recent EU policy discussions have emphasized the need for further integration of member states' labor markets (Draghi, 2024; Letta, 2024). Greater integration expands households' access to economic opportunities and provides firms with a broader pool of skills. Integration can also reduce spatial misallocation and raise European productivity (International Monetary Fund, 2025). Yet large migration barriers continue to prevent the EU from fully leveraging the benefits of a common labor market. Head and Mayer (2021) estimate that migration barriers are an order of magnitude larger in the EU than in the US, severely restricting cross-country mobility. Given that work-related motives are a leading driver of migration in Europe, understanding to what extent labor market conditions constitute migration barriers is essential for assessing the prospects for deeper European integration.[4]

In this paper, we develop a quantitative model to study how labor market and migration frictions shape the distribution and flow of workers across Europe. We proceed in three steps. First, we develop a multi-country labor market model with heterogeneous workers, in which workers transition between unemployment and employment and migrate across countries. Second, we use micro-level data from the European Union Labor Force Survey (EU-LFS) to document that migrant workers systematically face worse labor market outcomes than domestic workers, even after controlling for worker characteristics. Third, we calibrate the model and conduct quantitative analysis. Since cross-country transitions are driven by differences in labor market fundamentals, we introduce a novel calibration strategy that allows us to capture heterogeneity in country-level labor market primitives. Using the calibrated model, we show that the labor market frictions faced by migrant workers are sizeable and that systematic migration costs are also significant. A counterfactual experiment further indicates that improving labor market conditions for migrants would improve their labor market outcomes and enhance cross-border mobility.

We begin by developing a multi-country labor market model in which households transition between unemployment and employment through a standard search-and-matching framework (e.g., Pissarides, 2000). Search frictions generate unemployment risk and slow job transitions. Once matched, workers and firms draw a match-specific productivity that

[4] See Ayerst et al. (2025) for the details.

evolves stochastically over time. Unprofitable matches can be endogenously destroyed leading to endogenous separation between workers and firms and amplifying labor market outcomes. Worker value in a location depends on their expected wages as well as the probability that they find work and how long they expect to maintain their job once employed. Workers differ in their migrant status, allowing the model to reproduce systematic differences in labor market outcomes between domestic and migrant workers. Labor market differences between domestic and migrant workers deter migration when migrant workers face worse outcomes than domestic workers.

We introduce cross-country migration following a large literature examining cross-sector and cross-country worker flows (see Artuç et al., 2010; Caliendo et al., 2019; Chodorow-Reich and Wieland, 2020; Caliendo et al., 2021; Dix-Carneiro et al., 2023). Workers face a common systematic cost of moving between countries and idiosyncratic, time-varying preferences over locations. When choosing whether to migrate, workers compare their expected value of being a worker in that location with location-specific preferences and bilateral migration costs. In equilibrium, bilateral migration shares are determined by the relative value of being a worker in location–which captures labor market fundamentals such as wages, job-finding probabilities, and separation rates–and the cost of migrating between country pairs.

The model highlights that labor market conditions are a central determinant of migration flows. To study these conditions empirically, we use EU-LFS micro-data for 23 countries between 2010 and 2019 to compare labor market outcomes for domestic and migrant workers. We document three stylized facts. First, migrant workers face substantially higher unemployment risk and earn lower wages than otherwise comparable domestic workers. Second, migrants experience higher job separation rates and lower job finding rates. Third, the probability of workers exiting employment decreases with job tenure for both domestic and migrant workers.

We calibrate the model using the EU-LFS micro-data to examine the underlying labor market fundamentals that give rise to these barriers. In practice, labor market characteristics vary across countries and worker types, generating a large number of parameters and raising concerns about the curse of dimensionality. To address this problem, we introduce a novel two-stage calibration procedure. In the first stage, we calibrate parameters specific to each country individually. To accomplish this, we show in the model that all relevant equilibrium

information of other countries is captured by a single variable capturing the expected option value of migration to workers. We treat this option value of migration as an exogenous parameter in the first stage of our calibration that we target to the emigration rate. Along with the estimated model parameters, the first stage of the calibration produces a value of the outside option and the value of being a domestic or migrant worker in each country. In the second stage, we set the bilateral migration costs to exactly rationalize the country-specific worker values and outside option of migration established in the first stage. This approach enables us to capture parameter variations across countries and determine country-pair specific migration costs that match the observed bilateral migration flows in the data.

The calibrated model matches the data moments well and sheds light on the underlying labor market and migration frictions faced by migrants and domestic workers. First, migrants face substantial labor market challenges compared to domestic workers: migrants are less likely to work because they have higher home production values, and among those who do work, they have lower productivity. The productivity gap is smaller in richer economies, but migrants in these countries face higher exogenous separation risk, which weakens their incentive to migrate to these countries despite more favorable conditions. Second, we find that systematic bilateral migration costs are significant, especially for moves from the least prosperous to the most prosperous countries.

Lastly, we use the model to conduct a counterfactual experiment in which we equalize two key labor market parameters—exogenous separation risk and productivity—between domestic and foreign workers and compute the resulting labor market outcomes. We find that, although the magnitude of the effects varies across countries, reducing these labor market barriers improves migrant labor market outcomes and incentivizes greater cross-country mobility. Taken together, these results indicate that labor market conditions are a meaningful component of migration barriers.

**Contributions and related literature.** This paper makes two main contributions. First, it provides a quantitative account of how frictional labor market conditions shape cross-country migration while allowing labor market fundamentals to vary across countries and between domestic and migrant workers. A large empirical literature identifies wages and unemployment rates as important determinants of migration decisions (Clark et al., 2007; Pedersen et al., 2008; Mayda, 2010; Beine et al., 2011). These variables, however, are equilibrium outcomes and

therefore do not reveal which underlying parameters should be targeted by policy. Structural relocation models, such as Artuç et al. (2010) and Caliendo et al. (2019), provide a framework in which migration responds to location-specific economic fundamentals. However, because their labor markets are frictionless, they cannot be used to study how flows into and out of employment shape migration decisions.

The paper is therefore most closely related to quantitative migration models with frictional labor markets, including Pilossoph (2012), Chodorow-Reich and Wieland (2020), Heise and Porzio (2022), and Dix-Carneiro et al. (2023). Allowing labor market primitives to vary across both locations and worker types, however, creates a high-dimensional calibration problem. Existing studies typically preserve tractability by limiting the number of regions or household types. We address this problem through a two-stage calibration procedure, allowing the model to capture rich heterogeneity without jointly calibrating the whole migration system. Importantly, preserving this rich heterogeneity allows the model to evaluate a broader range of policy counterfactuals across a much larger set of countries and worker types than existing approaches.

Second, the paper provides a unified framework for quantifying migration barriers. Rather than using exact-hat algebra to eliminate the levels of bilateral migration costs, the second stage of the calibration recovers the full matrix of these costs. This allows the framework to quantify the systematic bilateral barriers that remain after accounting for labor market conditions. These barriers are not directly observed and may reflect policy restrictions, geographic and cultural distance, language, and migrant networks (Clemens, 2011; Ortega and Peri, 2013; Kerr et al., 2016; Clemens et al., 2019; Porcher et al., 2024). Recovering their levels allows us both to measure their magnitude across country pairs and to assess their quantitative importance in shaping migration flows.

**Outline.** Section 2.2 introduces the model. Section 2.3 highlights the data and stylized facts. Section 2.4 discusses the quantification and experiment. Section 2.5 concludes.

## 2.2 Model

To understand the barriers to labor market integration, we develop a spatial model of frictional labor markets (as in, Kline and Moretti, 2013) with heterogeneous workers. Workers differ in

their type, which we take to be either domestic or migrant workers, and, if employed, the quality of their match. Workers make migration decisions by weighing relative economic factors and idiosyncratic preferences (following Artuç et al., 2010).

### 2.2.1 Economic Setting

Time is discrete and indexed by $t \in 0, 1, 2, ....$ The economy consists of countries $c = \{1, 2, ..., C\}$ that are populated by households and an endogenous mass of firms.

**Households.** Households are risk neutral and infinitely lived. Households differ in terms of their type $a \in \mathcal{A}$ and current country $c$. In our quantitative analysis we set this to be whether the household is a domestic or migrant worker ($a \in \{Dom, For\}$), although our theoretical results would hold if type $a$ captured more granular household characteristics (e.g., age, education, or sex). Each period, households choose whether to remain in their current country $c$ or to relocate to a different country $c'$. Households receive an i.i.d. shock $\varepsilon_{at}^{c'}$ to the value of living in each location, drawn from a Type-I Extreme Value distribution and scaled by $\nu$. The idiosyncratic value captures within-country differences between households in the cost of relocating, such as, for example, familial obligations or country-specific preferences. In addition, households face a common fixed cost $\tau_a^{c,c'}$ of relocating between a pair of countries $c$ and $c'$, where the migration cost of staying in a country is normalized to $\tau_a^{c,c} = 0$. This common cost reflects structural factors—such as migration policy barriers, cultural and linguistic distance, or diaspora networks—that raise or lower the difficulty of relocating.

**Firms and production.** When a new firm–worker match is formed, the match draws a productivity $z_{at}^c$ from a type-specific distribution $\tilde{G}_a^c(z)$. After the initial draw, match-specific productivity is updated each period according to a first-order Markov process denoted by $G_a^c(z'|z)$. Active matches can be destroyed at any time when they no longer generate surplus., generating endogenous separations. Matches are also destroyed exogenously with probability $\delta_{at}^c$. Each active match produces output according to a production function $y_{at}^c(z)$ that is increasing in the match-specific productivity $z$. A household that is not matched to a firm produces home production $b_{at}^c$, where we allow this value to depend on household characteristics (e.g., because of differences in migration status) and country differences (e.g., because of unemployment benefits).

### 2.2.2 Labor Markets and Timing

Households do not have access to financial markets and consume their income each period. Firms are owned by country-specific mutual funds that consume profits and invests in new vacancies.

Labor markets are organized into submarkets $(a, c)$ in which firms and unemployed workers randomly contact. The number of vacancies in a submarket is denoted by $\mathcal{V}_{at}^c$ and the number of unemployed workers is given by $U_{at}^c$. The probability that a worker and firm contact is given by a constant return-to-scale matching function $M_a^c(U_{at}^c, \mathcal{V}_{at}^c)$. The labor market tightness in a submarket is defined by $\theta_{at}^c = \mathcal{V}_{at}^c / U_{at}^c$. The contact rate for unemployed workers searching in a submarket is $p(\theta_{at}^c) = M_a^c(U_{at}^c, \mathcal{V}_{at}^c)/U_{at}^c$, and for searching firms it is $q(\theta_{at}^c) = p(\theta_{at}^c)/\theta_{at}^c$.

Once a worker and firm are matched, they engage in Nash bargaining to determine the wage paid to the worker. As in Pilossoph (2012) and Chodorow-Reich and Wieland (2020), we assume that workers do not leave their current job for unemployment, either in the domestic or a foreign market. This implies that the match is maintained until it is either endogenously or exogenously destroyed.

**Timing.** Each period $t$ consists of three stages:

1. **Relocation phase.** The period begins with unemployed workers choosing to remain in their current labor market or relocate. Unemployed workers draw idiosyncratic preferences $\varepsilon_{at}^{c'}$ over all possible countries $c'$. Workers who relocate pay the migration cost and enter unemployment in the destination market.

2. **Search phase.** Firms observe the number of unemployed workers in each submarket $(a, c)$ and post vacancies $\mathcal{V}_{at}^c$. Unemployed workers search within their current submarket and are contacted by a firm with probability $p(\theta_{at}^c)$. Exogenous separations $\delta_{at}^c$ then occur among contacted worker-firm pairs. Subsequently, a productivity shock realizes, and the firm and worker jointly decide whether to maintain the match.

3. **Production phase.** Matched firm-worker pairs produce output $y_{at}^c(z)$ according to the production technology described above.

### 2.2.3 Equilibrium

We now describe the equilibrium of the model. The state of the economy in any period $t$ is described by the initial distribution of worker types $a$ and match qualities $z$ across employment and unemployment in each country, denoted by $E^c_{at}(z)$ and $U^c_{at}$. Given the flexibility of the model solution, we focus on a general solution that does not put structure on stationary parameters or convergence, but make further restrictions in the quantitative analysis.

#### 2.2.3.1 Worker Problem

We describe the workers problem at the time of production. Let $v^{U,c}_{at}(\boldsymbol{\varepsilon})$ be the value of unemployment of a type $a$ worker currently in country $c$ at time $t$ with a vector of preference $\boldsymbol{\varepsilon} = \{\varepsilon^c_{at}\}$. The unemployed worker's value is given by

$$v^{U,c}_{at}(\boldsymbol{\varepsilon}) = b^c_{at} + \beta \max\left\{ V^{S,c}_{at} + \nu\varepsilon^c_{at}, \max_{c' \neq c}\{V^{S,c'}_{For,t} - \tau^{c,c'}_a + \nu\varepsilon^{c'}_{at}\} \right\}, \tag{2.1}$$

where the households type is $a' = For$ if they migrate and $V^{S,c'}_{at}$ is the value of searching in a country $c'$. Let $V^{U,c}_{at} \equiv \mathbb{E}v^{U,c}_{at}(\boldsymbol{\varepsilon})$ be the expected value of unemployment. Following that the idiosyncratic location preference shock $\varepsilon$ is i.i.d and follows a Type-I Extreme Value distribution with zero mean, we obtain

$$V^{U,c}_{at} = b^c_{at} + \beta\Phi^c_{at}, \tag{2.2}$$

where (see B.1.1 for details)

$$\Phi^c_{at} = \nu \log\left[ \exp\left(V^{S,c}_{at}\right)^{1/\nu} + \sum_{c' \neq c} \left( \exp\left(V^{S,c'}_{For,t} - \tau^{c,c'}_a\right)\right)^{1/\nu} \right]. \tag{2.3}$$

The value of searching in a country $c$ can be expressed as

$$V^{S,c}_{at} = V^{U,c}_{at} + p(\theta^c_{at})(1-\delta^c_{at})\mathbb{E}_z\left[\max\{V^{W,c}_{at}(z) - V^{U,c}_{at}, 0\}\right]. \tag{2.4}$$

The value of searching is equal to the value of being unemployed plus the probability of successfully being matched multiplied by the expected option value of finding employment.

Lastly, the value of employment is given by

$$V_{at}^{W,c}(z) = w_{at}^{c}(z) + \beta \left[ V_{at}^{U,c} + (1-\delta)\mathbb{E}_{z'|z} \max\{V_{at}^{W,c}(z') - V_{at}^{U,c}, 0\} \right], \tag{2.5}$$

where $\mathbb{E}_{z'|z}$ denotes the expected productivity $z'$ conditional on the current productivity $z$.

#### 2.2.3.2 Firm Problem

Firms can be either vacant or matched with a worker. The value of a vacant firm that pays the job posting cost $\kappa_{at}^{c}$ and enters the market satisfies

$$V_{at}^{V,c} = \max_{a,c} -\kappa_{at}^{c} + q(\theta_{at}^{c})\mathbb{E}_{z} \max\{V_{at}^{J,c}(z), 0\}. \tag{2.6}$$

In equilibrium, the free-entry condition implies that $V_{at}^{V,c} \leq 0$ with equality in any market where there is a positive entry of firms. Hence, labor market tightness satisfies

$$q(\theta_{at}^{c}) = \frac{\kappa_{at}^{c}}{\mathbb{E}_{z} \max\{V_{at}^{J,c}(z), 0\}}. \tag{2.7}$$

The value of a matched firm at the production stage is given by

$$V_{at}^{J,c}(z) = y_{at}^{c}(z) - w_{at}^{c}(z) + \beta(1-\delta_{at}^{c})\mathbb{E}_{z'|z}[\max\{V_{at}^{J,c}(z'), 0\}], \tag{2.8}$$

and hence, the operation cutoff productivity $\overline{z}_{at}^{c}$ is

$$0 = y(\overline{z}_{at}^{c}) - w_{at}(\overline{z}_{at}^{c}) + \beta(1-\delta_{at}^{c})\mathbb{E}_{z'|\overline{z}_{at}^{c}}[\max\{V_{at}^{J,c}(z'), 0\}]. \tag{2.9}$$

#### 2.2.3.3 Wage Setting

The wage rate in each submarket is determined through Nash bargaining as

$$\max_{w} (V_{at}^{J,c}(z))^{1-\eta} (V_{at}^{W,c}(z) - V_{at}^{U,c})^{\eta}.$$

Therefore, as shown in B.1.2, wage satisfies

$$w_{at}^{c}(z) = (1-\eta)(1-\beta)\left[b_{at}^{c} + \beta\Phi_{at}^{c}\right] + \eta y_{at}^{c}(z). \tag{2.10}$$

#### 2.2.3.4 Law of Motion

Let $F^c_{at}(z)$ denote the distribution of match quality $z$ across active matches for type $a$ workers in country $c$. We first define job finding $\overline{p}(\theta^c_{at})$ and separation $\overline{\delta}^c_{at}$ rates in the presence of exogenous and endogenous separations. Specifically,

$$\overline{p}(\theta^c_{at}) = p(\theta^c_{at})(1-\delta^c_{at})(1-\tilde{G}^c_a(\overline{z}^c_{at})), \tag{2.11}$$

$$\overline{\delta}^c_{at} = \delta^c_{at} + (1-\delta^c_{at})\int_z G(\overline{z}^c_{at}|z)F^c_{at}(dz). \tag{2.12}$$

We denote by $\mu^{c',c}_{at}$ the share of type $a$ workers that relocate from market $c'$ to market $c$. Let $E^c_{at}(z)$ be the mass of employees with match-specific productivity $z$ or less in period $t$. Then

$$\begin{aligned} E^c_{at+1}(z) = &\int_{\tilde{z}} E^c_{at}(\tilde{z})(1-\delta^c_{at})G^c_{at}(z|\tilde{z}) \\ &+ \overline{p}^c_{at}(\theta^c_{at})\left[(U^c_{at} + \overline{\delta}^c_{at}\overline{E}^c_{at}) + 1_{a=For}\sum_{a',c'\neq c}\mu^{c',c}_{a't}(U^{c'}_{a't} + \overline{\delta}^{c'}_{a't}\overline{E}^{c'}_{a't})\right]\tilde{G}^c_a(z)\end{aligned}, \tag{2.13}$$

where $\overline{E}^c_{at} = \int_z E^c_{at}dz$. The first term in equation (2.13) represents the mass of employed workers that survive into the next period and transition to a productivity level $z$ according to the productivity transition $G^c_{at}(z \mid \tilde{z})$. The expression $1_{a=For}$ takes value one if type $a$ is $For$, and hence, the second term captures the inflow of new matches: unemployed workers from all origins $c'$ who choose to search in market $c$ with probability $\mu^{c',c}_{at}$ find a job with probability $\overline{p}^c_{at}(\theta^c_{at})$, and newly formed matches draw an initial productivity from the entry distribution $\tilde{G}_a(z)$. The distribution of active match types $z$ is defined as $F^c_{at}(z) = E^c_{at}(z)/\int_z E^c_{at}(z)$

Moreover, the law of motion of the mass of unemployed workers satisfies

$$U^c_{at+1} = (1-\overline{p}(\theta^c_{at}))\left[\mu^{c,c}_{at}(U^c_{at} + \overline{\delta}^c_{at}E^c_{at}) + 1_{a=For}\sum_{a',c'\neq c}\mu^{c',c}_{a't}(U^{c'}_{a't} + \overline{\delta}^{c'}_{a't}E^{c'}_{a't})\right], \tag{2.14}$$

where the expression inside the square bracket represents the pool of searchers in $c$. A fraction $1-\overline{p}^c_{at}(\theta^c_{at})$ of these searchers fail to form a match and remain unemployed in country $c$ at $t+1$.

Finally, the share of unemployed workers in each country $c$ that choose to search for work

in country $c'$ is given by

$$\mu_{at}^{c,c'} = \frac{\exp(V_{\tilde{a}t}^{S,c'} - \tau_a^{c,c'})^{1/\nu}}{\exp(V_{at}^{S,c})^{1/\nu} + \sum_{\tilde{c} \neq c} \exp(V_{For,t}^{S,\tilde{c}} - \tau_a^{c,\tilde{c}})^{1/\nu}}, \tag{2.15}$$

where $\tilde{a}$ takes value $Dom$ if $c' = c$ and value $For$ if $c' \neq c$. Migration corresponds to the value of relocating to $c'$ relative to all other potential destinations. The derivation of (2.15) can be found in Section B.1.3.

#### 2.2.3.5 Equilibrium Definition

An equilibrium consists of the values

$$\{w_{at}^c(z), \overline{z}_{at}^c, \theta_{at}^c, V_{at}^{U,c}, V_{at}^{W,c}(z), V_{at}^{S,c}, V_{at}^{J,c}(z), U_{at}^c, E_{at}^c(z), F_{at}^c(z)\}$$

for all submarkets $(a, c)$, bilateral pairs $(c, c')$, and periods $t$ such that:

1. unemployed worker relocation choice satisfies the expression of $\mu_{at}^{c,c'}$;
2. wages $w_{at}^c$ in each submarket are determined through Nash bargaining;
3. values $V_{at}^{U,c}$, $V_{at}^{S,c}$, and $V_{at}^{W,c}(z)$ solve the worker problems;
4. firms enter if optimal, satisfying the free-entry condition by setting $\theta_{at}^c$;
5. values $V_{at}^{J,c}(z)$ satisfies the firm problem;
6. total surplus equals to zero under the operation cut-off productivity $\overline{z}_{at}^c$
7. the mass of unemployed $U_{at}^c$ and employed $E_{at}^c(z)$ workers and distribution $F_{at}^c(z)$ evolves according to the law of motions.

### 2.2.4 Model Estimation

We conclude the model section by discussing the relationship between the model parameters and data. The model allows for flexibility in parameters between household types $a$ and countries $c$, creating a large number of parameters that could be difficult to solve for in practice, due to the curse of dimensionality.

To overcome this obstacle, we exploit a key feature of the model that allows us to estimate a large number of parameters for each country. We show that all relevant equilibrium information of other countries is captured by a single variable $\overline{V}_{at}^{c}$, which represents the expected option value of migration to workers. As shown in Appendix B.1.4, the outflow of migrants, $\underline{\mu}_{at}^{c}$, is therefore given by

$$\underline{\mu}_{at}^{c} = \frac{\exp\left(\overline{V}_{at}^{c}\right)^{1/\nu}}{\exp\left(V_{at}^{S,c}\right)^{1/\nu} + \exp\left(\overline{V}_{at}^{c}\right)^{1/\nu}}, \tag{2.16}$$

and the expected continuation value of unemployment can be written as

$$\Phi_{at}^{c} = \nu \log\left[\exp\left(V_{at}^{S,c}\right)^{1/\nu} + \exp\left(\overline{V}_{at}^{c}\right)^{1/\nu}\right].$$

It follows from the equilibrium described in Section 2.2.3 that all equilibrium variables can be solved conditional on the values of $\overline{V}_{at}^{c}$ and $\underline{\mu}_{at}^{c}$, excluding the levels of employment and unemployment which would also require the in-migration rates. In this respect, the continuation value $\Phi_{at}^{c}$ can be treated as a calibration parameter and the emigration rate $\underline{\mu}_{at}^{c}$ as data, allowing the model parameters to be solved country by country, significantly reducing the computational complexity. Further, the value functions $V_{at}^{S,c}$ consistent with the outside option $\overline{V}_{at}^{c}$ must also be consistent with the outside option for the multi-country model.[5] This implies that the consistent bilateral migration costs can be backed out from migration data and estimated outside option $\bar{V}_{at}^{c}$ values. We show later how this applies in our calibration.

This estimation strategy allows us to capture rich cross-country heterogeneity while remaining fully consistent with observed migration patterns. We next turn to the data that inform this calibration.

## 2.3 Data

Our model describes the relationship between migration decisions and labor markets. We use micro-data from the European Union Labor Force Survey (EU-LFS) data to characterize

[5]The exact hat algebra commonly used in trade literature (Dekle et al. (2008); Artuç et al. (2010)) to eliminate trade costs cannot be straightforwardly applied within our framework. This is due to labor market frictions introducing wedges that prevent the model from fully canceling out trade costs.

labor markets for 23 European countries. We start by describing the data and construction of key variables. While the EU-LFS data is ideal for our setting because it provides detailed micro-data on many European economies, a major shortcoming of the data is that it does not provide panel information. In the latter part of this section we describe how we construct informative data moments capturing differences in labor market outcomes between domestic and migrant workers.

### 2.3.1 Data Sources and Variables

We rely on micro-data from the European Union Labor Force Survey (EU-LFS), a large harmonized household survey collected by Eurostat from national statistical agencies across EU member states. The EU-LFS provides detailed information on individuals' characteristics and labor market outcomes. Although the survey includes both cross-sectional and longitudinal components, only the repeated cross-sectional micro-data are available for scientific use, as household identifiers are randomised across releases. Overall, our sample covers the period from 2010 to 2019 and includes 23 EU member states and EFTA countries.[6]

Following the standard method, we import the raw micro-data into Stata using the `Setup\_EULFS\_xxxx\_y.do` and `Labels\_EULFS\_1983--2022.do` files, where xxxx are years from 2010 to 2019. These files are made available by the GESIS – Leibniz Institute for the Social Sciences. We restrict the imported dataset to the following set of variables:

- ***country*** - Country of residence.
- ***countryb*** - Country of birth.
- ***refyear*** - Year of the survey.
- ***refmonth*** - Month of the survey.
- ***age*** - Age of the interviewed person.
- ***ilostat*** - ILO work status.
- ***hatlev1d*** - Highest level of education (ISCED-11, 3 levels).

[6]The countries included are Austria, Belgium, Bulgaria, Switzerland, Cyprus, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Italy, Lithuania, Luxembourg, Latvia, Poland, Portugal, Romania, Sweden, and Slovenia. We exclude Ireland, Malta, the Netherlands, Norway, Slovakia, the Czech Republic, and Iceland due to missing or inconsistent information in the variables required for our analysis.

- ***nace2_1d*** - Economic activity, main job, (NACE Rev 2, 1 digit)
- ***isco08_1d*** - Occupation, main job,(ISCO-08, 1 digit).
- ***startime*** - Time since person started to work (in months).
- ***yearpr*** - Year in which person last worked.
- ***monthpr*** - Month in which person last worked.

We identify whether a worker is domestic or foreign born using the variable *countryb*, and we determine their labor market status—employed, unemployed, or inactive—from *ilostat*. In addition, we construct several supplementary variables that are not directly available in the raw data that we describe below.

#### 2.3.1.1 Construction of Incomes

Information on individual income is not available in the EU-LFS micro-data for scientific use. To approximate income differences, we therefore construct a proxy that combines information from Eurostat's aggregate data and the EU-LFS micro-data. Specifically, we obtain average annual earnings by economic activity and occupation at the country level from Eurostat's Structure of Earnings Survey (SES). These earnings are linked to workers in the EU-LFS based on their economic activity and occupation classifications.

We then compute the average income of domestic and migrant workers using survey-based employment shares as weights for each country:

$$Inc_{a,t} = \sum_{s,o} \mathcal{W}^{so}_{a,t} \times Inc^{so}_{a,t}, \tag{2.17}$$

where $a$, $s$ and $o$ denote the worker type (domestic or migrant), sector (such as services) and occupation (such as managers). $\mathcal{W}^{so}_{a,t}$ is the share of domestic or migrant workers employed in sector–occupation cell $(s, o)$ in a country at time $t$, and $Inc^{so}_{a,t}$ is the SES-reported average earnings for that same cell. This procedure yields a consistent proxy for the average income of domestic and migrant workers, based on how each group is distributed across sector–occupation cells.

#### 2.3.1.2 Construction of Job Separation and Finding Rates

With only the repeated cross-sectional micro-data available, individuals cannot be tracked over time to observe their transitions between ILO labor force statuses. However, using the model structure we construct alternative data moments that captures the same information. The change in the share of workers with employment duration $d$ is closely related separation rate in the model. For each country, we infer job separation rates from the cross-sectional distribution of employment by duration using the following specification:

$$\log N_t^{E,d,x} = \alpha + \beta_1 d_t + \beta_2 (d_t \times Mig_t) + \lambda_t + \theta_x + \varepsilon_t, \tag{2.18}$$

where $x$ indexes groups defined by observable characteristics (sex, age, and educational attainment). $N_t^{E,d,x}$ denotes the (normalized) number of employed workers with employment tenure $d$ in group $x$ at time $t$. The EU-LFS reports employment tenure in exact months for durations below two years, while longer tenures are recorded in aggregated intervals (e.g., 36 months for tenure between two and three years, 48 months for tenure between three and four years, and so on). To ensure a consistent definition of tenure across the entire distribution, we discretize employment duration at the annual frequency. Accordingly, employment tenures of less than 12 months are assigned $d_t = 1$ year, tenures between 12 and 24 months are assigned $d_t = 2$ years, and longer durations follow the aggregated tenure intervals reported by Eurostat. The variable $Mig_t$ takes value one for migrant workers and zero otherwise. $\lambda_t$ captures time fixed effects and $\theta_x$ captures group fixed effects.

For an additional year of employment, the fraction of domestic workers who remain employed is given by $\exp(\beta_1)$, while the corresponding fraction for migrant workers is $\exp(\beta_1 + \beta_2)$. Interpreting these quantities as one-year employment survival probabilities, the implied separation rates are therefore $1 - \exp(\beta_1)$ for domestic workers and $1 - \exp(\beta_1 + \beta_2)$ for migrant workers.

Similarly, the job finding rate is closely related to the change in the share of workers with unemployment duration $d$. We infer job finding rate from the following equation,

$$\log N_t^{U,d,x} = \alpha + \beta_1 d_t + \beta_2 (d_t \times Mig_t) + \lambda_t + \theta_x + \varepsilon_t, \tag{2.19}$$

where $d_t$ now captures the tenure of unemployment. The EU-LFS reports unemployment

tenure in exact months. However, monthly measures tend to be noisier across survey rounds. To reduce this noise, we aggregate unemployment durations to a biannual frequency. Specifically, unemployment spells shorter than 6 months are assigned $d_t = 6$ months, spells between 6 and 12 months are assigned $d_t = 12$ months, and longer durations are grouped analogously. Our results are robust to alternative, more granular definitions of $d_t$, such as monthly or quarterly bins, with estimated job finding rates remaining largely unchanged. Finally, we exclude unemployment durations longer than two years, as these individuals may exhibit systematically different job search behavior.

Given that $d_t$ is measured in biannual units, $\exp(\beta_1)$ and $\exp(\beta_1+\beta_2)$ correspond to biannual unemployment survival probabilities for domestic and migrant workers, respectively. Hence, implied annual job finding rates are therefore $1-\exp(\beta_1)^2$ for domestic workers and $1-\exp(\beta_1+\beta_2)^2$ for migrant workers.

On average, the above methodology produces separation and job finding rates that appear reasonable in the context of the aggregate Eurostat data. The separation rates tend to be quite a bit higher than in annual separation rates in Eurostat. We expect that some of this is mechanical as we focus on shorter duration matches—where we expect separations to be more likely—and on shorter time horizons where worker transitions back to employment would cause values constructed using (2.18) to be larger than annual numbers in Eurostat. We find job finding rates to be similar magnitude as Eurostat, on average, although individual countries vary.

#### 2.3.1.3 Other Data Sources

We complement the analysis with aggregate data to fill in missing information unavailable in the EU-LFS micro-data.

**Bilateral Migration Flows.** Information regarding the precise country where migrants come from are missing in the EU-LFS micro-data. Therefore, we take the data from the Eurostat migration and migrant population statistics database, which provides the number of migrants living in an origin country that migrate to a destination country. This maps closely to the model concept of migration. For Germany, bilateral migration data for immigration and emigration is taken from the SSO as the Eurostat data does not cover Germany over the relevant period.

Data coverage tends to be relatively poor for Cyprus, Greece, Hungary, Luxembourg, Latvia, Poland, Portugal and Spain. Missing data is constructed using a gravity relationship that regresses log relative migration on the log wage gap, log distance, other factors that may impact migration (e.g., common language, common border, whether both countries are EU members) and origin, destination, and year fixed effects when these variables are available, and set to a small value when these variables are unavailable.

**Labor Market Tightness.** Job vacancies are not reported in the EU-LFS. We therefore rely on aggregate country-level data from Eurostat. Specifically, we obtain the aggregate unemployment rate and the job vacancy rate, and construct overall labor market tightness as the ratio of the vacancy rate to the unemployment rate for each country.

**Additional Data.** We complement our dataset with additional aggregate data on Purchasing Power Parity (PPP)-Adjusted output per worker from Penn World Tables v10.0.

### 2.3.2 Stylized Facts

Before moving to the model calibration, we provide an overview of the differences between domestic and migrant workers in our constructed dataset. We organize these differences into three stylized facts discussed below. These stylized facts help to provide a check on the reasonableness of the constructed data and also help to anticipate the results that we find in the following quantitative analysis.

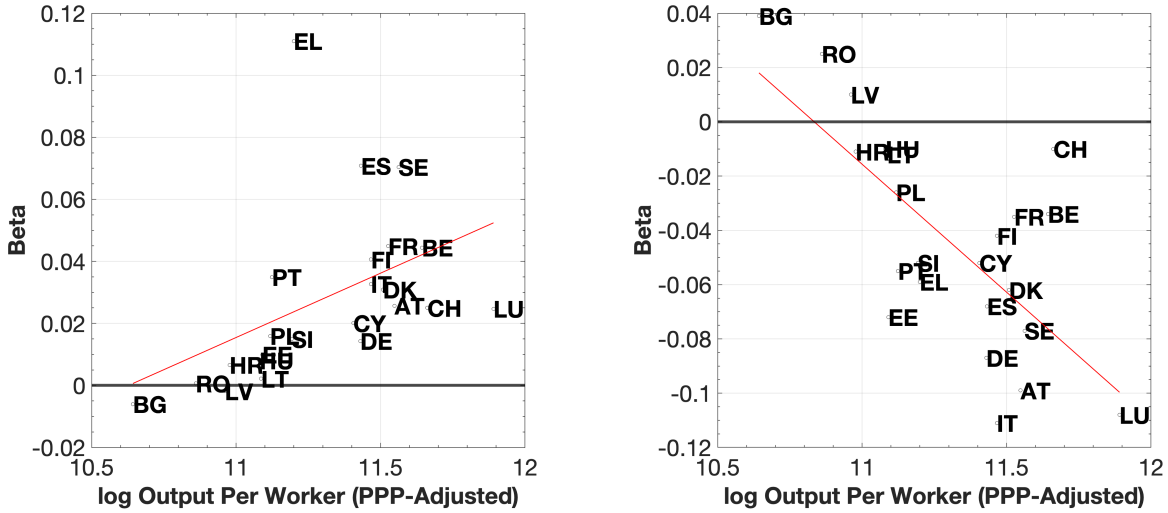
***Fact 1:*** *Migrant workers earn lower wages and are more likely be unemployed than domestic workers.*

We compare labor market outcomes between domestic and migrant workers, focusing on unemployment risk and wages. For each country, we estimate the following regression:

$$Y_{at} = \alpha + \beta_1 Mig_{at} + X_{at} + \varepsilon_{at}, \tag{2.20}$$

where $Y_{at}$ denotes unemployment status or log wage rate, $Mig_{at}$ is a migrant-status indicator, and $X_{at}$ includes controls (sex, age, education). Across countries, the mean estimated coefficient $\beta_1$ equals $0.028$ for unemployment risk and $-0.044$ for wages, and both are statis-

**Figure 2.1: Coefficients of Migrant Worker's Labor Market Outcomes**




**(a) Unemployment Risk** **(b) Wage**

Note: Figures 2.1a and 2.1b plot the estimated coefficients $\beta_1$ from (2.20) against PPP-adjusted log output per worker for unemployment risk and wages, respectively. The red line denotes the line of best fit, and the thick black horizontal line indicates zero on the y-axis.

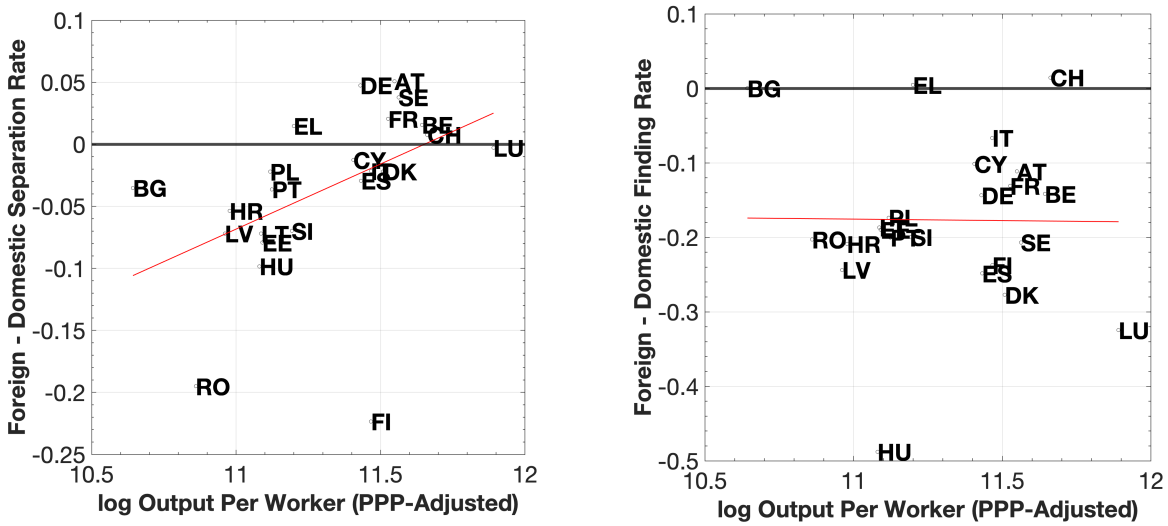
tically significant. Figure 2.1a shows that migrant workers face higher unemployment than otherwise comparable domestic workers, and that this gap increases with a country's level of prosperity. Figure 2.1b shows that migrants also earn lower wages on average, and the gap is also bigger for prosperous countries.

***Fact 2:*** *Migrant workers experience higher job separation rates than domestic workers in more prosperous locations and have lower job finding rates everywhere.*

We estimate equations (2.18) and (2.19) using OLS separately for each country. For each country, we compute the difference between migrant and domestic workers and relate these to log output per worker. These cross-country patterns are shown in Figure 2.2.

Figure 2.2a plots the job separation rate of migrant workers minus that of domestic workers against PPP-adjusted log output per worker. Migrant workers have higher job separation rates than domestic workers in more prosperous countries. In less prosperous countries, migrant workers exhibit lower separation rates than domestic workers. Figure 2.2b shows the corresponding differences in job finding rates. Except for Switzerland and Greece, migrant workers have lower job finding rates than domestic workers across the countries.

**Figure 2.2: Separation and Finding Rate Differences**




**(a) Separation Rate Differences**

**(b) Job Finding Rate Differences**

Note: Figure 2.2a plots the job separation rate of migrant workers minus that of domestic workers against PPP-adjusted log output per worker. Figure 2.2b shows the corresponding differences in job finding rates. Red lines indicate lines of the best fit. Thick black lines indicate values equal to zero. Job separation and finding rates are inferred by estimating (2.18) and (2.19).

***Fact 3:*** *The probability of exiting employment decreases with job tenure.*

To study how job tenure affects job separation, we extend equation (2.18) by interacting employment duration with tenure bands. Specifically, we estimate:

$$\log N_t^{E,d,x} = \alpha + \beta_1(d_t \times dband_t) + \beta_2(d_t \times dband_t \times Mig_t) + \lambda_t + \theta_x + \varepsilon_t, \tag{2.21}$$

where $d$ is the job tenure in years and $dband_t$ denotes an indicator for the worker's job tenure band (e.g., less than 5 years, 6–10 years, 11–15 years). Since $\exp(\beta_1)$ and $\exp(\beta_1+\beta_2)$ represent the annual job survival probabilities for domestic and foreign workers, respectively, within each tenure band, the corresponding implied annual job separation rates are given by $1 - \exp(\beta_1)$ for domestic workers and $1 - \exp(\beta_1 + \beta_2)$ for migrant workers. We compare the inferred job separation rates for workers with job tenure below 5 years to those with tenure above 10 years. On average, job separation rates are 4.01 percentage points lower for domestic workers and 2.82 percentage points lower for migrant workers in longer-tenure jobs.

In the model calibration, we use the lower likelihood of job separation in longer duration

jobs to discipline the relative strength of exogenous and endogenous job separations. This reflects that as job tenure increases the match-specific productivity distribution improves, leading to fewer endogenous separations.

Overall, the data provide the empirical moments used to discipline the model parameters. They also indicate that labor market conditions vary across countries and worker types. We use these empirical facts and constructed data moments to estimate the model parameters and conduct quantitative analysis in the next section.

## 2.4 Quantitative Analysis

The previous section highlights stark differences in labor market outcomes between domestic and migrant workers. These empirical patterns suggest substantial heterogeneity in labor market primitives across countries and worker types, implying a large number of distinct parameters in the model. Prior studies often address this complexity by limiting the number of submarkets within their models (e.g., Chodorow-Reich and Wieland, 2020; Dix-Carneiro et al., 2023). In contrast, we introduce a novel calibration method that enables us to calibrate each country individually, effectively overcoming the curse of dimensionality. We then discuss the quantitative results from the calibrated model.

### 2.4.1 Calibration Strategy

We consider the calibration of the model to average data values from 2010 to 2019. We hold parameters fixed and take these values as capturing averages over this period. We base the model moments on the equilibrium described in Section 2.2.3. For fixed parameters, the equilibrium flows do not depend on future period distributions. Given this, we can characterize the equilibrium without taking a stance on whether the economy is in a steady state.

#### 2.4.1.1 Overview

We calibrate the economy to two worker types representing domestic ($a = Dom$) and migrant ($a = For$) workers and 23 countries. Since our focus is on broad migration patterns and migration is relatively infrequent, we assume that workers always become foreign once they migrate. We parameterize the evolution of the match specific productivity using an

AR(1) process given by $\log z_a^{c'} = \rho_z \log z_a^c + \varepsilon_z$ where $\varepsilon_z$ follows a log normal distribution with standard deviation $\sigma_z^2$. The initial draw of $z$ follows a log normal distribution with the same standard deviation as the stationary AR(1) process and with zero mean. The production technology is given by $y_a^c(z) = \overline{Z}_a^c z_a^c - \chi_a^c$, where $\overline{Z}_a^c$ is the productivity scaler and $\chi_a^c$ is the fixed cost. We assume that the matching function takes the Cobb-Douglas form as $M_a^c(U_a^c, V_a^c) = m_a^c \left(U_a^c\right)^{\alpha} \left(V_a^c\right)^{1-\alpha}$, where $m^c$ is the submarket-specific matching efficiency. Therefore, the contact rate for an unemployed worker is $p(\theta_a^c) = m^c \left(\theta_a^c\right)^{1-\alpha}$, and that for a vacant firm is $q(\theta_a^c) = m^c \left(\theta_a^c\right)^{-\alpha}$. Thus, the model has parameters $\{\nu, \alpha, \eta, \beta, \rho_z, \sigma_z\}$ and $\{\delta_a^c, b_a^c, \kappa_a^c, m_a^c, \chi_a^c, \overline{Z}_a^c, \tau_a^{c,c'}\}$ for each type and country $(a, c)$.

**Fixed parameters.** We set a number of parameters to external values and targets. The discount factor $\beta$ is set to be 0.96 to reflect the annual frequency of the data. We also set $\alpha = \eta = 0.5$, assuming that firms and workers have the same bargaining power and the Hosios (1990)'s condition holds. This also sets the matching function elasticity with respect to unemployment is within the range of 0.5-0.7 reported in Petrongolo and Pissarides (2001). We take the scale of the taste parameter, which determines the elasticity of migrants to labor market conditions, to $\nu = 2$, matching the value reported in Caliendo et al. (2019). The persistence of the productivity process $\rho_z$ is set to 0.9 and the standard deviation of the productivity shock $\sigma_z$ is set to 0.4, although we note that $\overline{Z}_a^c$ will also impact the overall dispersion of the match-specific shocks.

**Fitted parameters.** We assume that vacancy costs $\kappa^c$, matching efficiency $m^c$, and the fixed production cost $\chi^c$ are common to both domestic and migrant workers in the country. This leaves us to calibrate parameters $\{\delta_a^c, b_a^c, \kappa^c, m^c, \chi^c, \overline{Z}_a^c\}$ for each submarket and the bilateral migration costs $\{\tau_a^{c,c'}\}$ for each country pair. We further restrict migration costs $\tau^{c,c'}$ to be the same for both domestic and migrant workers as our data does not allow us to construct migration by worker type.[7] In total, we calibrate $(3 \times 2 \times c + 3 \times c + c^2)$ parameters.

[7]Domestic and migrant workers will still migrate at different rates as the value of the domestic economy differs for domestic and foreign workers.

#### 2.4.1.2 Calibration Details

We follow the estimation method in Section 2.2.3. We split the joint calibration in two stages where we first calibrate the submarket-specific parameters $\{\delta_a^c, b_a^c, \kappa^c, m^c, \chi^c, \overline{Z}_a^c\}$ and then calibrate the bilateral migration costs $\{\tau^{c,c'}\}$.

**First Stage.** We introduce an auxiliary parameter, $\overline{V}^c$, capturing the value to workers of migrating. This value is the same for both domestic and migrant workers as both types become migrant workers if they relocate. This results in 10 parameters that we jointly calibrate to match data moments.

We target wage levels $w_a^c$ and job finding rates $\overline{p}(\theta_a^c)$ for domestic and migrant workers. We target separation rates for workers with less than 5 years of tenure, $\overline{\delta}_a^c \mid_{<5year}$ and more than 5 years (and less than 10 years) of tenure, $\overline{\delta}_a^c \mid_{>5year}$, for domestic and migrant workers. Within-type differences in the separation rates help to identify the relative strength of exogenous and endogenous separation. Intuitively, endogeneous selection leads to the match distribution improving over time, lowering the separation probability for longer duration matches. We match the average labor market tightness $\theta^c$ across all workers as we do not observe type-specific vacancies in the data. Finally, we target the average out-migration rate. Defining $sh_a^c$ as the share of type $a$ workers in country $c$, we construct the model moments as follows:

$$
\begin{aligned}
w_a^c(z) &= (1-\eta)(1-\beta)\left[b_a^c + \beta\Phi_a^c\right] + \eta y_a^c(z), \\
\overline{p}(\theta_a^c) &= m^c\left(\theta_a^c\right)^{1-\alpha}(1-\delta_a^c)(1-G(\overline{z}_a^c)), \\
\overline{\delta}_a^c \mid_{<5years} &= \delta_a^c + (1-\delta_a^c)\int_z G(\overline{z}_a^c|z)F_a^c(dz) \mid_{<5years}, \\
\overline{\delta}_a^c \mid_{>5years} &= \delta_a^c + (1-\delta_a^c)\int_z G(\overline{z}_a^c|z)F_a^c(dz) \mid_{>5years}, \\
\theta^c &= \sum_a sh_a^c \left(\frac{1}{m^c}\frac{\kappa}{\mathbb{E}_z \max\{V_{at}^{J,c}(z), 0\}}\right)^{-1/\alpha}, \\
\underline{\mu}^c &= \sum_a sh_a^c \frac{\exp\left(\overline{V}^c\right)^{1/\nu}}{\exp\left(V_a^{S,c}\right)^{1/\nu} + \exp\left(\overline{V}^c\right)^{1/\nu}}.
\end{aligned}
$$

None of the targeted moments depend on out-of-country parameters other than through the option value $\overline{V}^c$. The computational benefits of this method is that it allows us to calibrate country parameters piecewise, rather than all parameters simultaneously.

**Second stage.** After obtaining $\overline{V}_a^c$ for each country, we recover bilateral migration costs as:

$$\tau^{c,c'} = \nu \left[ \log \frac{\exp(V_{For}^{S,c'})^{1/\nu}}{\sum_a \tilde{s}_a^c \exp(V_a^{S,c})^{1/\nu}} - \log \frac{\mu^{c,c'}}{\mu^{c,c}} \right], \tag{2.22}$$

where

$$\tilde{s}_a^c = \frac{sh_a^c \frac{1}{\exp(V_a^{S,c})^{1/\nu} + \bar{V}_a^c}}{\sum_{a'} sh_{a'}^c \frac{1}{\exp(V_{a'}^{S,c})^{1/\nu} + \bar{V}_a^c}}. \tag{2.23}$$

Here, $\tilde{s}_a^c$ is an adjusted population share that captures the effective contribution of each worker type to the overall attractiveness of searching in country $c$, and $\mu^{c,c'}$ denotes the bilateral migration flow from $c$ to $c'$. This procedure yields a full matrix of bilateral migration costs consistent with each country's calibrated fundamentals, the empirical migrant shares, and the observed bilateral migration flows.

Table 2.1 summarizes the exogenous as well as calibrated parameters.

**Table 2.1: Parameters**

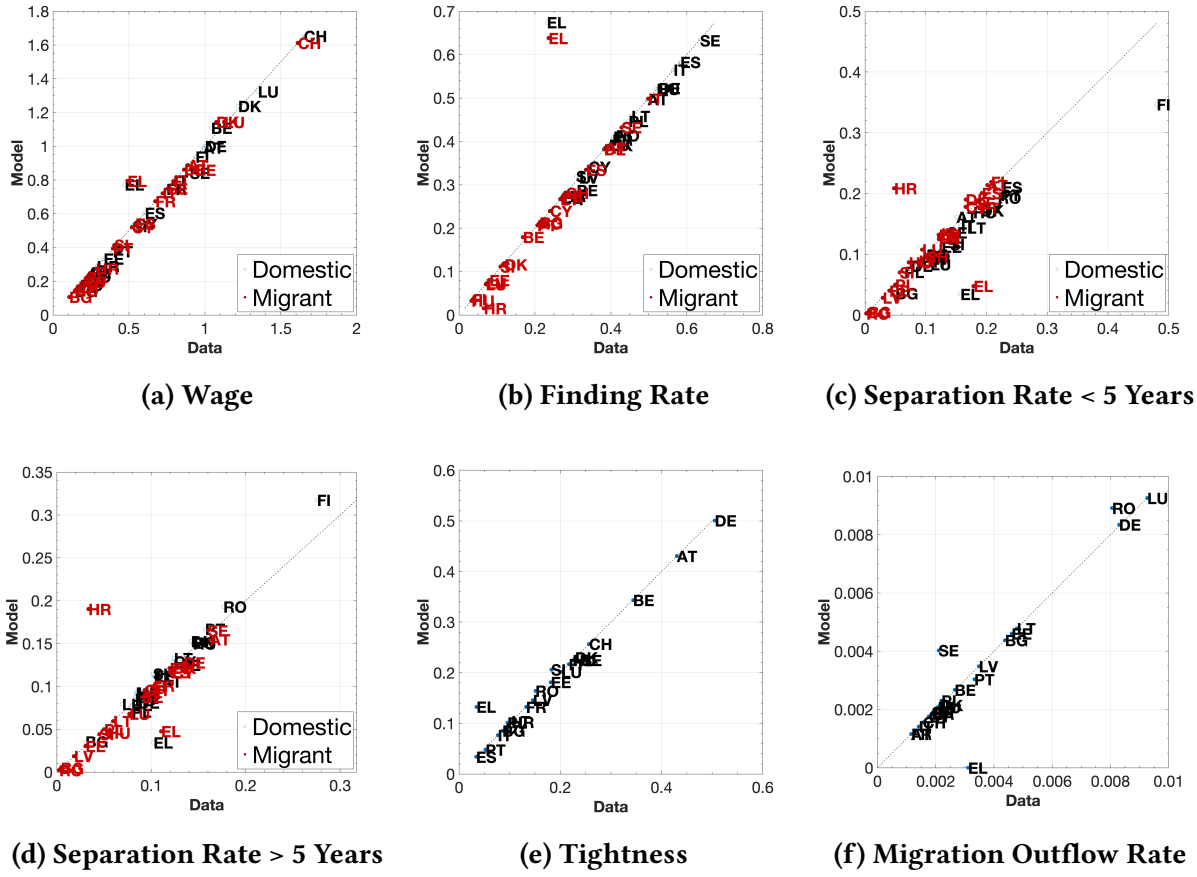
| Parameter | Description | Value | | |
|---|---|---|---|---|
| **Fixed** | | | | |
| $\beta$ | Discount factor | 0.96 | | |
| $\alpha$ | Matching function elasticity | 0.50 | | |
| $\mu$ | Worker bargaining power | 0.50 | | |
| $\nu$ | Location preference parameter scaler | 2.00 | | |
| $\gamma$ | Production function elasticity | 0.50 | | |
| $\rho_z$ | Persistence of the productivity process | 0.90 | | |
| $\sigma_z$ | Standard deviation of the productivity shock | 0.40 | | |
| **Fitted** | | | **Moment** | **Data vs Model** |
| *First stage* | | | | |
| $\kappa^c$ | Vacancy posting cost | Figure B.1a | Wage rate $w_a^c$ | Figure 2.3a |
| $m^c$ | Matching efficiency | Figure B.1b | Job finding rate $\overline{p}(\theta_a^c)$ | Figure 2.3b |
| $\chi^c$ | Fixed production cost | Figure B.1c | Job separation rate < 5y $\overline{\delta}_a^c \mid_{<5years}$ | Figure 2.3c |
| $\delta_a^c$ | Exogenous job separation rate | Figure 2.4a | Job separation rate > 5y $\overline{\delta}_a^c \mid_{>5years}$ | Figure 2.3d |
| $b_a^c$ | Home production value | Figure 2.4b | Tightness $\theta^c$ | Figure 2.3e |
| $\overline{Z}_a^c$ | Productivity scaler | Figure 2.4c | Migration outflow rate $\underline{\mu}^c$ | Figure 2.3f |
| *Second stage* | | | | |
| $\tau^{c,c'}$ | Pairwise migration cost | Figure 2.6a | Pairwise migration rate $\mu^{c,c'}$ | Figure B.2 |

## 2.4.2 Model Performance

We evaluate the model's performance by comparing model-generated moments to their empirical counterparts. Figure 2.3 plots each targeted model moment on the vertical axis against its corresponding data moment on the horizontal axis. Figures 2.3a to 2.3d show the fit be-

tween model and data for domestic workers (black) and migrant workers (red) for wages, job finding rates, and the two separation rates. Figures 2.3e to 2.3f report the country-level averages of labor market tightness and migration rates in the model and compare them to the data. In all figures, the dashed black line denotes the 45-degree line. Overall, the model moments closely align with the data moments across outcomes and worker types.

**Figure 2.3: Targeted Moments in the Model and Data**




**(a) Wage** **(b) Finding Rate** **(c) Separation Rate < 5 Years**

**(d) Separation Rate > 5 Years** **(e) Tightness** **(f) Migration Outflow Rate**

Note: Figure 2.3a compares wage moments in the model (y-axis) and the data (x-axis). Figure 2.3b reports the fit for job finding rates. Figures 2.3c and 2.3d show the separation rates for workers with less than 5 years and more than 5 years of tenure, respectively. Figure 2.3e compares country-level labor market tightness, and Figure 2.3f compares migration rates. For 2.3a to 2.3d, domestic workers are shown in black and migrant workers in red. The dashed black line denotes the 45-degree line.

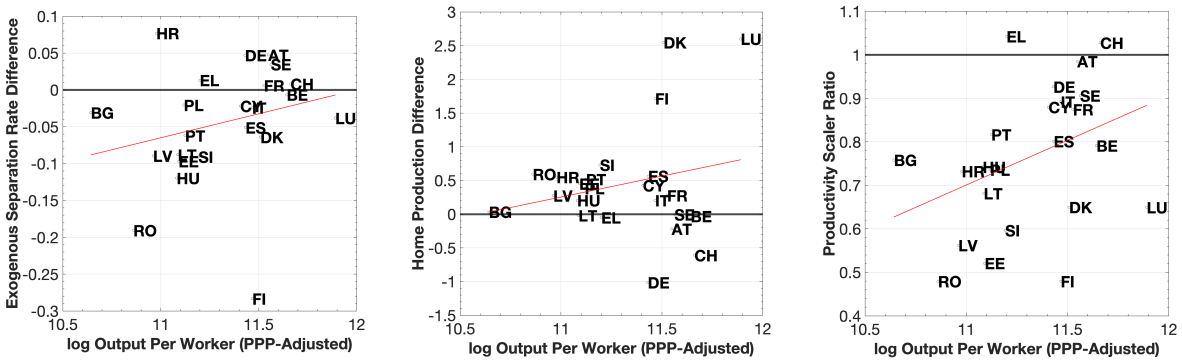
### 2.4.3 Estimated Parameters

We compare labor market fundamentals across countries and worker types. We also illustrate migration costs for all origin-destination pairs.

#### 2.4.3.1 Labor Market Fundamentals

Figure 2.4 plots the differences in calibrated parameters between domestic and foreign workers against output per worker. Figure 2.4a shows the exogenous separation rate $\delta_a^c$. The y-axis shows how much migrants' exogenous separation rate differs from that of domestic workers, while the x-axis reports the PPP-adjusted log of output per worker. We find that migrants face higher exogenous separation rates in more prosperous locations.

**Figure 2.4: Labor Market Fundamental Differences**




**(a) Exogenous Separation Rate** **(b) Home Production** **(c) Productivity**

Note: Figure 2.4a plots the difference in exogenous separation rates between migrant and domestic workers against log output per worker (PPP-adjusted). Figure 2.4b plots the difference in home production values between migrant and domestic workers. Figure 2.4c compares the ratio of foreign to domestic productivity scalers $\overline{Z}_a^c$. The red lines are lines of thge best fit. In Figure 2.4a - 2.4b, thick black horizontal lines indicates the values of y-axis equal to zero. In Figure 2.4c it indicates that the value of y-axis equals to one.

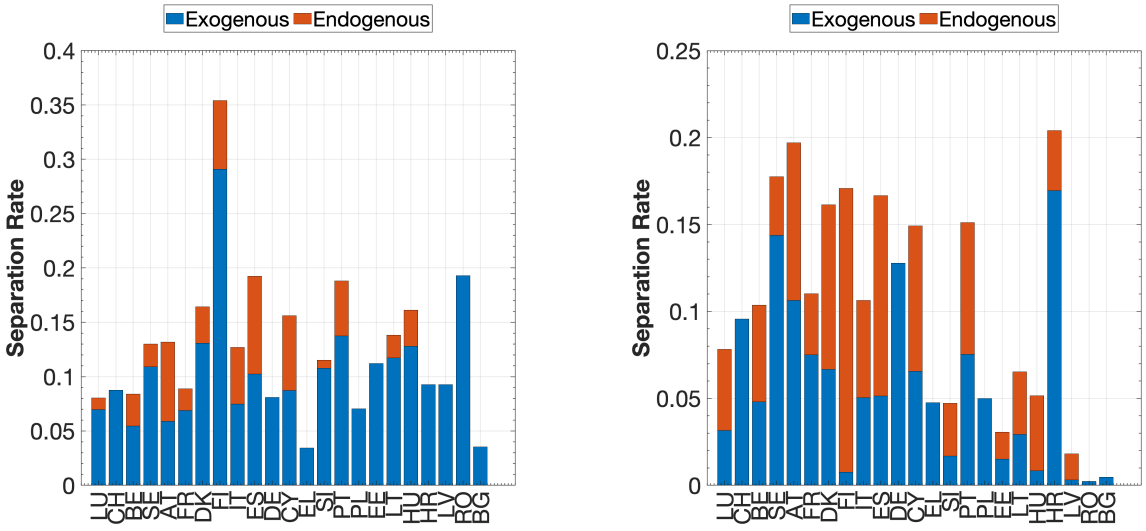
Figure 2.4b shows that in most countries the calibrated home production value $b_a^c$ is higher for foreign workers than for domestic workers. This pattern is consistent with migrants placing relatively greater value on non-market time or facing constraints that raise the opportunity cost of working. Moreover, the gap in home production values widens with a country's level of prosperity, which is consistent with more generous labor market institutions toward migrants in richer economies.

Figure 2.4c compares the ratio of the foreign productivity scaler $\overline{Z}_a^c$ to the domestic one. In general, migrant workers exhibit lower productivity than domestic workers. The productivity gap narrows as countries become more prosperous, suggesting the presence of positive selection in migrant destination choices.[8]

[8] A large body of conventional literature shows that migration towards richer economies is more likely to

Lower productivity among migrant workers also implies higher endogenous separation rates, since low-productivity matches are more likely to become unprofitable. Figure 2.5 illustrates the relative contributions of exogenous and endogenous separations for migrants and domestic workers. On average, endogenous separations account for 41.1% of total separations among migrants, compared with only 16.6% among domestic workers.

**Figure 2.5: Exogenous and Endogenous Separations**




**(a) Domestic Workers** **(b) Foreign Workers**

Note: Figure 2.5 illustrates the relative importance of exogenous and endogenous separations for domestic and foreign workers. The contribution of exogenous separation is in blue, whereas the contribution of endogenous separation is in red.

Migrant workers tend to have higher home production values, lower productivity, and higher endogenous separation rates. These labor market primitives jointly contribute to weaker labor market outcomes for migrants, including higher unemployment rates and lower wages.

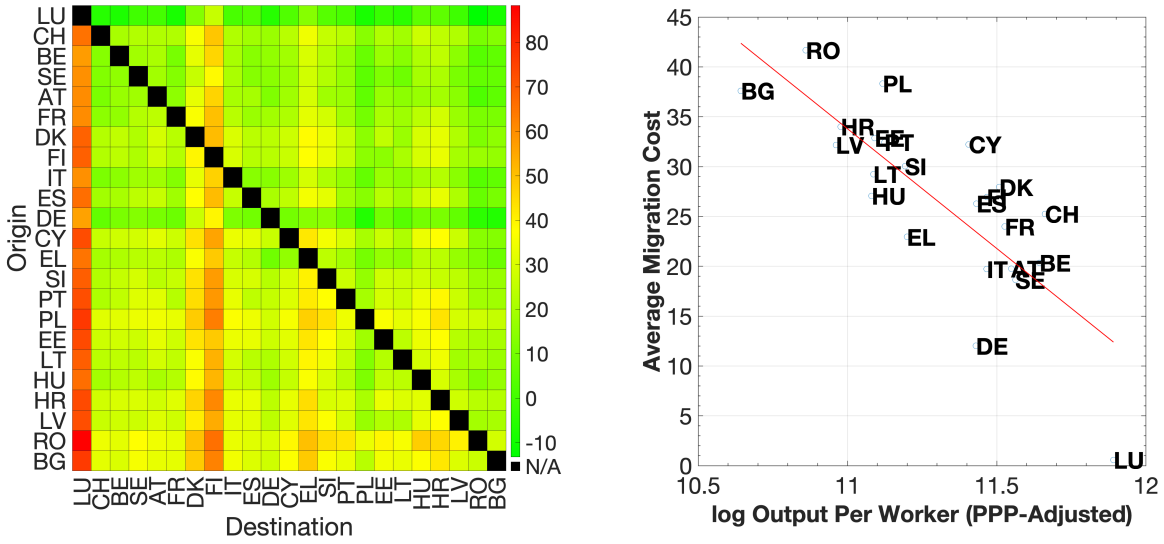
### 2.4.3.2 Migration Costs

Figure 2.6 summarizes the calibrated migration costs $\tau^{c'c}$. Figure 2.6a uses a heatmap to display pairwise migration costs for all origin (rows) and destination (columns) country pairs. Origins

be driven by economic factors. For example, Grogger and Hanson (2011) show that migration towards richer economies is often motivated by economic reasons such as higher wages, and is usually undertaken by more able migrants. In contrast, less able migrants place relatively more weight on non-wage destination characteristics.

and destinations are ordered by PPP-adjusted output per worker from highest to lowest, so cells above the diagonal correspond to moves from richer to poorer countries, while cells below the diagonal correspond to moves from poorer to richer countries. Green cells indicate low migration costs and red cells indicate high migration costs. From the heatmap in Figure

**Figure 2.6: Migration Costs**




**(a) Pairwise Migration Costs**

**(b) Average Out-Migration Costs**

Note: Figure 2.6a plots pairwise migration costs for all origin (row) and destination (column) countries. Countries are ordered by output per worker (PPP-adjusted) from highest to lowest. Green cells indicate low migration costs and red cells indicate high migration costs. Figure 2.6b plots average migration costs against log output per worker, and the red line is the line of best fit.

2.6a, migration costs are generally higher for moves from lower income to higher income countries. The least prosperous countries face the highest migration costs, as indicated by the darker red and yellow cells in the bottom-left corner of the matrix. Figure 2.6b, which plots average migration costs against log output per worker, confirms this pattern.

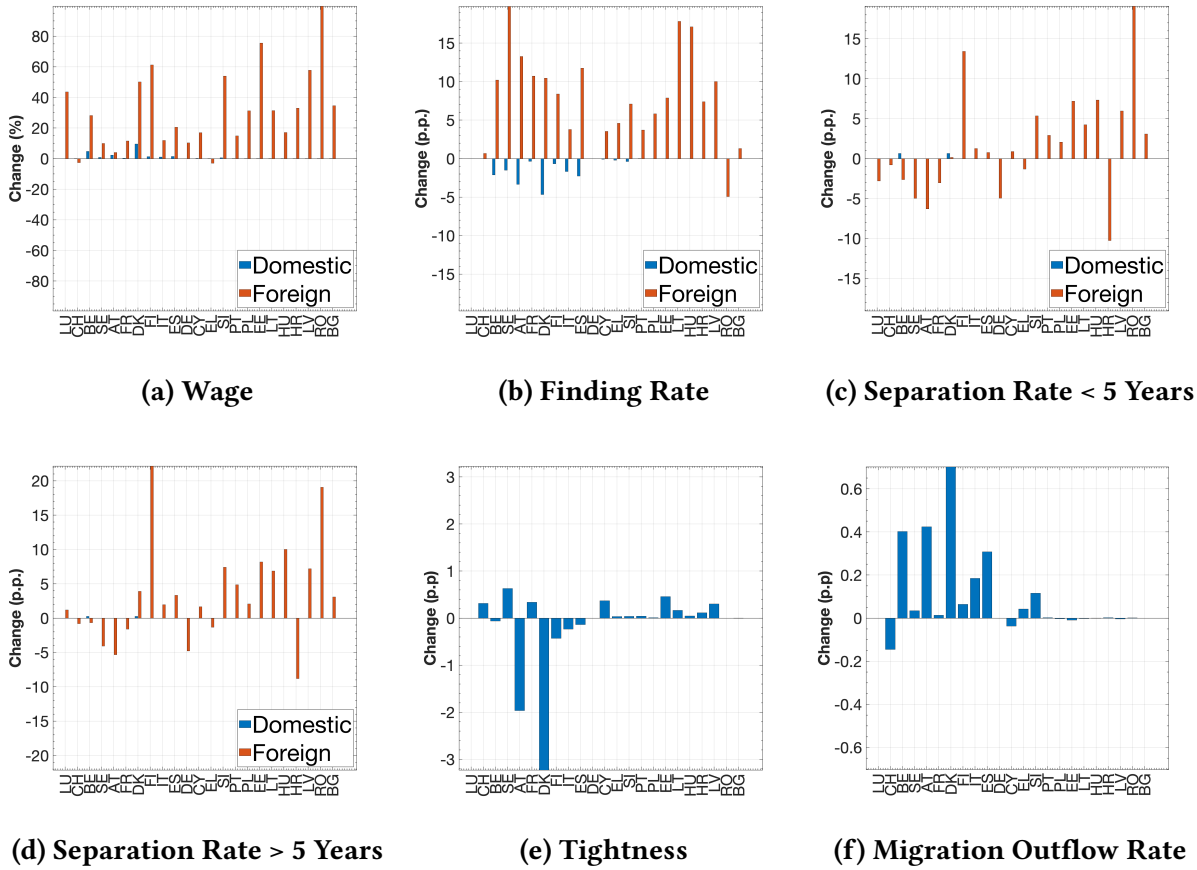
We find that migration frictions are disproportionately higher for workers living in the poorest countries. This helps explain why, despite the substantial potential economic gains, many workers in these countries refrain from migrating.

### 2.4.4 Counterfactual Experiment

In Section 2.4.3, we showed that labor market conditions are worse for migrant workers than for their domestic counterparts. We now conduct a counterfactual experiment to quantify

how eliminating these differences affects labor market and migration outcomes. Specifically, we equalize two key labor market fundamentals between domestic and migrant workers: the exogenous separation rate and the productivity shifter, $(\delta^c_{\text{For}}, \bar{Z}^c_{\text{For}}) = (\delta^c_{\text{Dom}}, \bar{Z}^c_{\text{Dom}})$. We then compare the resulting equilibrium with the baseline.

**Figure 2.7: Difference in Labor Market and Migration Outcomes**




**(a) Wage** **(b) Finding Rate** **(c) Separation Rate < 5 Years**

**(d) Separation Rate > 5 Years** **(e) Tightness** **(f) Migration Outflow Rate**

Note: Figure 2.7 compares the counterfactual equilibrium, which equalizes productivity and exogenous separation rates between domestic and migrant workers, to the baseline. Figures 2.7a-2.7d report the changes in wages, job finding rates, and separation rates for domestic (blue) and foreign (red) workers, while Figures 2.7e and 2.7f show the resulting effects on labor market tightness and migration. Countries on the x-axis are ordered from the highest to the lowest level of output per worker (PPP-adjusted).

Figures 2.7a-2.7d report the changes in wages, job finding rates, and separation rates for domestic (blue) and foreign (red) workers, while Figures 2.7e and 2.7f show the resulting effects on labor market tightness and out-migration. Countries on the x-axis are ordered from the highest to the lowest level of output per worker.

Figures 2.7a and 2.7b show that equalizing productivity substantially increases wages and job finding rates for migrant workers. Higher productivity raises the total surplus of

a match, which increases migrants' share and lowers endogenous separation, leading to more and longer-lasting matches. In several countries, job finding rates for domestic workers fall. This occurs because migrants' improved labor market conditions raise the value outside option for domestic workers, which raises their wage demand and reduces firms' incentives to post vacancies directed at domestic workers. As a result, domestic job finding declines.

Figures 2.7c and 2.7d show that separation rates for migrant workers are more likely to decline in richer countries. In the baseline, migrants in these economies face higher exogenous separation than domestic workers; equalizing $\delta^c_{For}$ downward therefore reduces their overall separation rate. By contrast, in several poorer countries, migrants experience lower exogenous separation than domestic workers. In these economies, equalizing separation probabilities raises $\delta^c_{For}$, and the productivity gain is insufficient to offset the higher exogenous separations. As a result, migrants' overall separation rate increases.

Figure 2.7e shows that the impact on labor market tightness varies across countries. Two opposing forces are at work. First, higher migrant productivity and lower separation raise firms' expected surplus and increase vacancy posting. Second, both domestic and foreign workers benefit from a stronger outside option, which raises wage demands and discourages vacancy creation. Whether tightness increases or decreases depends on which force dominates in each country.

Finally, Figure 2.7f shows that out-migration increases most strongly in richer countries, while the response is more modest in poorer countries. Two forces account for this pattern. First, productivity gaps between migrant and domestic workers are larger in poorer countries; equalizing these gaps therefore generates relatively larger improvements in labor market conditions in poorer destinations, increasing their attractiveness and dampening out-migration. Second, migration costs are asymmetric: they are relatively low for moves from richer to poorer economies and higher in the opposite direction. As a result, workers in richer countries can more easily respond to improved labor market conditions abroad, whereas the response of workers in poorer countries is partly offset by higher migration costs. Taken together, these mechanisms imply that improving labor market conditions leads to larger reallocation of workers, highlighting that labor market constitutes a meaningful component of overall migration barriers. At the same time, these improvements also promote a more equal and integrated allocation of labor across countries.

## 2.5 Conclusion

This paper develops a quantitative model to study how labor market and migration frictions shape cross-country migration flows in Europe. The model shows that both labor market conditions and migration costs influence workers' migration decisions. To preserve the rich differences in labor market fundamentals across countries and worker types as seen in the EU-LFS data, we develop a novel two-stage calibration strategy that captures substantial heterogeneity in labor market fundamentals while disciplining bilateral migration costs to match observed flows.

The calibrated model reveals that migrant workers face substantial labor market disadvantages, particularly higher separation risk, lower productivity, and higher home production values. Systematic migration costs are also large, especially for moves from poorer to more prosperous countries. A counterfactual that equalizes key labor market parameters between domestic and foreign workers further demonstrates that improving migrant labor market fundamentals significantly enhances migrant labor market outcomes and increases cross-border mobility.

Overall, our results indicate that labor market plays a meaningful role in limiting cross-country mobility within Europe. Policies that reduce labor market barriers—especially those that narrow productivity gaps or lower separation risk for migrant workers—may therefore be crucial for realizing the full benefits of a more integrated European labor market.

# Chapter 3

# Searching Costs in the Rental Housing Market and Internal Migration

*Charles Cheng Zhang* [1]

## Abstract

This paper argues that search-and-matching costs in rental housing markets play a role in internal migration among major European cities. Motivated by emerging anecdotal evidence, I develop a model of rental market microstructure with endogenous migration. Rising search costs lead to out-migration by absorbing resources and reducing effective housing consumption, with the effect strongest in tight markets. In looser markets, improved match efficiency offsets the impact of higher search costs. I validate the model's predictions using a proprietary dataset covering 34 major European cities from 2009 to 2021. Finally, I show that demand-side policies, such as rental subsidies, are ineffective in tight markets as they exacerbate search frictions, while supply-side expansions of housing stock alleviate these frictions and enhance welfare. [2]

**Keywords:** Rental Housing; Search Costs; Internal Migration; Urban Economics

**JEL Codes:** R21, R23, R31, J61

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## 3.1 Introduction

Spatial economics, dating back to the classic Rosen (1979a) and Roback (1982) framework, emphasises the joint role of labour and housing markets in shaping internal migration decisions. Recent evidence shows that internal migration from large European cities typically involves short-distance moves, allowing individuals to remain within the same labour market and therefore experience little change in expected income.[3] As a result, housing-related considerations naturally become a key driver of mobility. Indeed, 41.6% of internal moves are explicitly motivated by housing reasons in 2023.

The recent surge in out-migration from major European cities[4] has occurred against the backdrop of an increasingly severe housing crisis. This raises a central question: *how do housing market conditions shape internal migration decisions?* While the conventional literature emphasises housing affordability, this paper advances a different mechanism. Because housing markets operate with significant search frictions, I suggest that search costs in these markets—encompassing both the financial and non-financial burdens of securing accommodation—play a role in out-migration from large European urban centres.

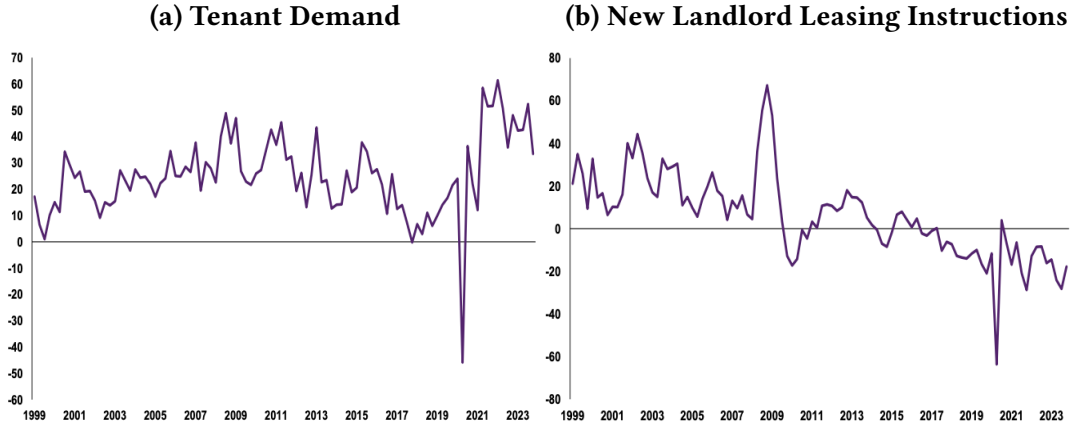
This hypothesis is motivated by the following patterns. First, rental markets in large cities display persistent excess demand. Figure 3.1 uses Royal Institution of Chartered Surveyors (RICS) survey data to show that, after COVID-19, large UK cities experienced a divergence between tenant demand and new landlord leasing instructions, creating tight market conditions. Similar trends were also observed in other major European cities. Second, prices may not adjust sufficiently to clear this pressure. In several European rental markets, rent adjustment is constrained by regulation or tenancy rules. For example, Ireland's Rent Pressure Zones capped annual rent increases at the lower of inflation or 2%, while Germany's *Mietpreisbremse* limits new rents in designated tight markets to 10% above local comparative rents. These institutional constraints imply that excess demand may also appear through non-price rationing, such as queues, repeated viewings and longer search times. Third, direct measures of rental search pressure suggest that this non-price margin is quantitatively large.

[3]Between 2014 and 2017, 42% of those leaving England's twenty largest cities relocated less than 25 km away. Similar patterns are observed in Scotland, where moves of fewer than 5 miles account for more than half of all internal migration (see Consensus 2011). During the COVID-19 pandemic, the rise of remote work further reinforced this trend, with many households moving from major cities to nearby suburbs.

[4]For the past decade, domestic emigration has consistently exceeded immigration in major European cities such as London (Greater London Authority, 2023) and Vienna (City of Vienna, 2023).

Rightmove reports that the average advertised rental property in Great Britain received 25 enquiries in Q3 2023, compared with 8 in 2019. Taken together, these facts suggest that tight rental markets affect households not only through higher rents, but also through the difficulty of securing rental housing. When these costs become sufficiently large, households may adjust by relocating away from tight urban markets. Patterns in commuter-belt rental activity are consistent with this mechanism. Search volumes in Lower Saxony's commuting zones rose by 30% (REFIRE, 2024); in the UK, rental demand growth has been strongest in suburban areas near London (SpareRoom, 2025). These patterns motivate a framework in which rental housing search costs shape internal migration decisions. The rest of the paper formalises this channel and uses the model to study policy counterfactuals.

**Figure 3.1: RICS Tenant Demand and Landlord Instruction Survey**




**Notes:** The figure plots RICS net-balance survey measures for tenant demand (3.1a) and new landlord leasing instructions (3.1b). A positive value indicates that a larger share of respondents reported an increase than a decrease, while a negative value indicates the reverse.

The model integrates search-and-matching frictions in the spirit of Michaillat and Saez (2015) with endogenous migration decisions in rental housing markets. The economy is composed of a continuum of cities. Each city is inhabited by agents who are endowed with both income and housing stock. Agents demand housing services, which is the only consumption good, and also supply housing stock. To obtain housing services, agents must visit rental properties, incurring a fixed cost with each visit. Crucially, not all visits are successful—each carries a probability of matching that is strictly less than one, reflecting the search frictions observed empirically. On the supply side, housing services are produced via a constant returns to scale matching function, combining housing stock and home visits. Spatial equilibrium is achieved through the free movement of agents across cities, with migration ensuring that utility from housing consumption remains equalised at the level of the outside option, following

the framework of Rosen (1979a) and Roback (1982).

In equilibrium, higher search costs reduce housing consumption in tight markets. As search costs rise, agents must devote a larger share of their resources to the search process itself, leaving less available for actual consumption. This reduction in effective consumption pushes agents to migrate, as their utility falls below the outside option. Migration, in turn, eases local search frictions by reducing competition: with fewer agents remaining, fewer visits are required to successfully match with a rental property. Agents continue to out-migrate until housing consumption is restored to the outside option level, reestablishing spatial equilibrium.

Moreover, the relationship between search costs and migration is non-linear. In looser housing markets, an increase in search costs has a smaller impact on out-migration. In fact, in sufficiently loose markets, higher search costs can even attract in-migration. In the model, higher search costs are associated with greater search effort (i.e., more home visits), which improves match creation. When markets are loose, the positive effect of improved matching outweighs the negative congestion effects, raising housing consumption above the outside option and drawing migrants from other cities.

Empirically validating these insights is challenging, given the limited availability of granular housing market data across Europe. To address this, I rely on a unique dataset compiled by Property Market Analysis (PMA) LLP, an independent real estate research consultancy established in 1981. PMA analysts collect, harmonise, and standardise data from a wide range of secondary sources—including national statistical agencies, brokerage firms, and commercial data providers—and supplement it with extensive primary research, such as site visits and consultations with key market stakeholders. The dataset covers the period from 2009 to 2021 and includes 34 major European cities, encompassing capital cities, large metropolitan areas, and key regional hubs. It focuses specifically on the rental housing sector, providing detailed annual city-level information on average rental prices, the number of rental transactions, and the stock of rental properties. Data quality is validated by cross-checking aggregate measures against figures from national statistical agencies.

Utilising the PMA dataset, I show that the model's novel predictions are supported empirically. First, the correlation between rental housing search costs and internal emigration is positive, even after controlling for rent levels, local prosperity, and local labour market conditions. Second, this relationship is non-linear, with the effect being strongest in the tightest

housing markets.

Having established the model's positive implications, I then assess the consequences of commonly used demand- and supply-side housing policies. I show that implementing a demand-side policy, such as rental subsidies, exacerbates search frictions in a tight housing market and reduces agents' housing consumption, leading to greater out-migration and lower consumption-based aggregate welfare. By contrast, supply-side interventions, such as expanding the housing stock, alleviate search frictions by lowering the number of visits required to secure housing services. This evaluation provides a formalisation of the argument that demand-side policies are often ineffective in tight housing markets (Weicher, 1990).

*Contribution and related literature.* This paper makes three contributions. First, it identifies rental search difficulty as a distinct channel through which housing markets affect internal migration. Research on housing and migration has long recognised that residential mobility is not determined by prices alone. As summarised by Jia et al. (2022), existing work emphasises homeownership and the associated *lock-in* effect (Ferreira et al., 2010; Head and Lloyd-Ellis, 2012; Sterk, 2015), as well as differences in housing costs across locations (Ganong and Shoag, 2017; Plantinga et al., 2013; Jeanty et al., 2010; Cannari et al., 2000; Cameron et al., 2005; Muellbauer and Cameron, 1998; Nenov, 2015; Stawarz et al., 2021). The lock-in mechanism, however, is less applicable to the setting studied here, which focuses on renters in major European cities. This paper highlights a separate non-price margin: even conditional on rents, the time and effort required to secure rental accommodation can reduce effective housing consumption and induce households to leave tight urban markets. The paper is most closely related to Bergman et al. (Forthcoming), who provide experimental evidence that reducing housing-search frictions affects neighbourhood choice. I complement their empirical evidence by developing a general equilibrium framework in which rental search costs shape internal migration.

Second, the paper proposes an alternative way of modelling housing market microstructure by introducing an explicit resource cost of search. Most existing housing search models build on the Diamond-Mortensen-Pissarides (DMP) framework, in which buyers and sellers meet through a matching function and transactions occur with probability less than one (Stein, 1995; Genesove and Han, 2012; Ngai and Tenreyro, 2014; Ngai and Sheedy, 2020a,b; Novy-Marx, 2009; Diaz and Jerez, 2013; Han and Strange, 2015). These models capture delays in

matching, but generally do not explicitly model the resources households expend through repeated property visits. Building on the microstructure approach of Michaillat and Saez (2015), I instead make each housing visit explicitly costly. This allows rental search frictions to affect households not only through the probability of securing accommodation, but also by directly reducing the resources available for consumption.

Third, the paper uncovers a new channel through which demand- and supply-side housing policies affect households. The longstanding policy debate generally evaluates these interventions through their effects on rents and housing supply (Apgar Jr, 1990; Galster, 1997; Yates and Whitehead, 1998). In the framework developed here, policies also change the resources dissipated through the search process. A rental subsidy raises demand and, when housing supply is tight, intensifies competition for available properties. Part of the subsidy is therefore absorbed through additional search effort rather than translated into greater housing consumption. Expanding the housing stock instead reduces the number of visits required to secure accommodation, alleviating both the quantity constraint and the associated search friction.

*Road map.* The rest of the paper is organised as follows. Section 3.2 presents the model. Section 3.3 shows and validates the proprietary data used in this research. Section 3.4 validates the model's findings. Section 3.5 studies the implications of place-based housing policies, and Section 3.6 concludes.

## 3.2 Model

This section introduces a stylised model that describes how housing search costs influence inter-regional relocation.

### 3.2.1 Primitives and Housing Markets

#### 3.2.1.1 Primitives

Time is static. The economy is composed of a continuum of cities. Each city is endowed with a fixed housing stock $\bar{K}$ that is equally divided among $N$ identical agents, so each agent receives an endowment of $\frac{\bar{K}}{N}$ units of housing. Agents derive utility from consuming housing services $c$ and from holding real money balances $\frac{m}{p}$. To finance these expenditures, they supply their

endowed housing stock on the market and receive an additional income endowment $\bar{\mu}$.

Agents migrate costlessly across cities until housing consumption is equalized at the outside option $\underline{c}$, following the logic of Rosen (1979a) and Roback (1982). A key modelling assumption is that the number of potential destinations is large enough such that $\underline{c}$ is fixed: no matter how conditions change in any individual city, the outside option does not adjust. This allows the analysis to focus on a representative city without explicitly modelling the full migration network.[5]

Finally, for expositional clarity, I use the terms *buying* and *renting* interchangeably to denote the acquisition of housing services. Likewise, *selling* and *leasing* are used interchangeably to denote supplying housing services to the market.

#### 3.2.1.2 Matching Function

Motivated by the evidence showing that search frictions are prevelant in the housing market, I model its microstructure using search-and-matching frictions. This aligns with a broad real estate literature emphasizing the presence of search-and-matching frictions in housing markets (e.g., Genesove and Han, 2012; Ngai and Tenreyro, 2014; Han and Strange, 2015).

Specifically, I assume that prospective renters endogenously visit $v$ landlords, each of whom can let up to $\frac{K}{N}$ units of housing stock, in order to obtain housing services. The number of rental housing transactions per agent $y$ follows a constant returns to scale matching function: $y = [(v)^{-\gamma} + (\frac{\bar{K}}{N})^{-\gamma}]^{-\frac{1}{\gamma}}$, where $\gamma$ governs the elasticity of substituition. Therefore, the total transactions satisfies

$$Y = [(vN)^{-\gamma} + (\bar{K})^{-\gamma}]^{-\frac{1}{\gamma}}. \tag{3.1}$$

Define the housing market tightness $\theta$ as aggregate numbers of visits over aggregate housing stock $\theta = \frac{vN}{\bar{K}}$. Therefore, in each city, one housing service is let with probability:

$$f(\theta) = \frac{Y}{\bar{K}} = (1 + \theta^{-\gamma})^{-\frac{1}{\gamma}}, \tag{3.2}$$

[5]Because the set of alternative destinations is arbitrarily large, any single city's migrant outflows or inflows are too small to influence housing conditions in other cities. If housing conditions deteriorate in one location, migrants can always be absorbed by the vast number of other cities without affecting their equilibrium housing consumption level.

and one visit yields a successful rent with probability

$$q(\theta) = \frac{Y}{vN} = (1 + \theta^{\gamma})^{-\frac{1}{\gamma}}. \tag{3.3}$$

The function $f$ is strictly increasing on the interval $[0, +\infty]$, whilst the function $q$ is strictly decreasing. Moreover, the aggregate housing transaction, $Y$, is increasing in $\theta$.

#### 3.2.1.3 Search Cost and Amount of Visits

Search cost stems from home visits, which resonates with the anecdotal evidence. Specifically, agents face a fixed cost $\rho$ during each visit. This cost may be pecuniary (e.g., a viewing fee) or non-pecuniary (e.g., the time and effort required to complete the visit). For concreteness, I assume that $\rho$ is paid in terms of consumption.

I now derive the number of visits required for an agent. Suppose that to consume $c$ units of housing services, an agent must make $v$ viewings and obtain a total of $c + \rho v$ units of housing services. Therefore, the total housing services rented becomes $Y = (c + \rho v)N$. Substituting (3.3) into the left-hand side of this expression and dividing by $c$, the number of visits required to purchase one unit of housing services is $\frac{1}{q(\theta)-\rho}$. It is straightforward to see that number of viewings is increasing in $\theta$, highlighting that when demand is high relative to supply, more visits are required to rent a house. With the number of visits required to purchase one unit of housing services determined, the search cost for acquiring one unit of housing service is $\tau(\theta) = \frac{\rho}{q(\theta)-\rho}$. Taking stock, to consume one unit of housing service, one is required to purchase $1 + \tau(\theta)$ units of housing service in total.

### 3.2.2 Rental Housing Market Equilibrium

#### 3.2.2.1 Aggregate Rental Housing Demand

A representative agent solves the following problem taking $\theta$ as given,

$$\text{Max}_{c,\frac{m}{p}} [\chi c^{\frac{\epsilon-1}{\epsilon}} + (\frac{m}{p})^{\frac{\epsilon-1}{\epsilon}}], \tag{3.4}$$

$$\text{s.t.} \quad m + c[1 + \tau(\theta)]p = \bar{\mu} + pf(\theta)\frac{\bar{K}}{N}. \tag{3.5}$$

Equation (3.4) highlights that an agent derives utility from consuming housing services $c$ and holding real money balances $\frac{m}{p}$ [6]. The parameter $\chi$ captures the taste for housing consumption relative to money, and the parameter $\epsilon < 1$ governs the elasticity of substitution. Equation (3.5) specifies the budget constraint. The left hand side of (3.5) shows that an agent would allocate her nominal income between holding money balance $m$, consuming housing services $c$, and paying for the search cost $\tau(\theta)$. The right hand side of (3.5) shows that an agent gets income from an exogenous endowment $\bar{\mu}$ and the sale of housing services $pf(\theta)\frac{\bar{K}}{N}$.

After taking money market clearing $Nm = N\mu$ into account, the first order condition yields the following expression of an individual agent's demand $c = (\frac{\chi}{1+\tau(\theta)})^{\epsilon}\frac{\bar{\mu}}{p}$. Subsequently, since agents are identical, the aggregate demand becomes

$$\mathcal{C}^D(\theta, p) = (\frac{\chi}{1+\tau(\theta)})^{\epsilon}\frac{\bar{\mu}}{p} \times N. \tag{3.6}$$

Aggregate housing demand decreases strictly with both $\tau(\theta)$ and $p$, indicating that as housing becomes more expensive—either through higher search costs or increased prices—it becomes less attractive to consume.

#### 3.2.2.2 Aggregate Rental Housing Supply

Aggregate housing supply, $\mathcal{C}^S$, is defined as the *consumable* housing services produced within a city. Since a $\tau(\theta)$ portion of total housing services is allocated to covering search costs, the overall output of housing services satisfies $Y = \mathcal{C}^S(1+\tau(\theta))$. Recalling from the matching function that $Y = f(\theta)\bar{K}$, we can express housing supply as

$$\mathcal{C}^S(\theta) = \frac{f(\theta)\bar{K}}{1+\tau(\theta)}. \tag{3.7}$$

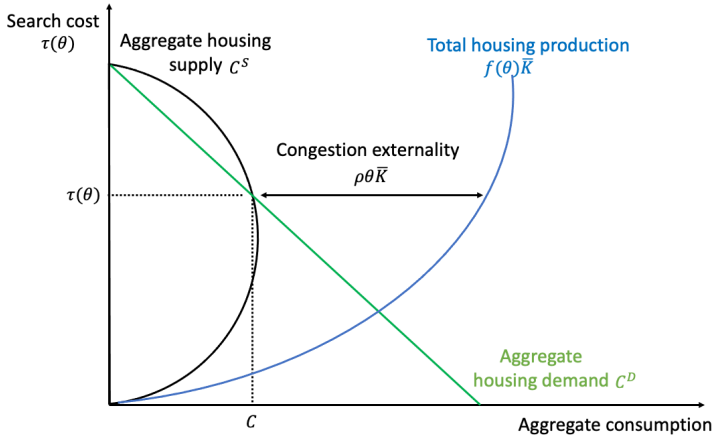
I will now derive the first order condition of aggregate supply with respect to search cost $\tau(\theta)$. Using the definition of $\tau(\theta)$ and $\theta$, (3.7) can be written as $\mathcal{C}^S(\theta) = (f(\theta) - \rho\theta)\bar{K}$. Hence,

$$\frac{\partial \mathcal{C}^S(\theta)}{\partial \tau(\theta)} = \frac{\partial \mathcal{C}^S(\theta)}{\partial \theta}\frac{\partial \theta}{\partial \tau(\theta)} = -(f'(\theta) - \rho)\frac{(q(\theta)-\rho)^2}{\rho q'(\theta)}, \tag{3.8}$$

[6]The concept of money in the utility function are also included in Barro and Grossman (1971) and Blanchard and Kiyotaki (1987). For detailed discussion of this concept, please refer to Michaillat and Saez (2015).

with $\frac{(q(\theta)-\rho)^2}{\rho q'(\theta)} < 0$. Therefore, the sign of $\frac{\partial \mathcal{C}^S(\theta)}{\partial \tau(\theta)}$ depends on the sign of $f'(\theta) - \rho$. Moreover, $f'(\theta) > 0$ while $f''(\theta) = -(1+\gamma)\theta^{\gamma-2}/(1+\theta^{-\gamma})^{1/\gamma}(\theta^{\gamma}+1)^2 < 0$, and hence, aggregate housing supply is first increasing in $\tau(\theta)$ until $f'(\theta) = \rho$, and then decreasing in $\tau(\theta)$. This relationship, together with the previously derived housing demand, is illustrated in Figure 3.2.

**Figure 3.2: Aggregate Housing Demand and Supply**




**Notes:** Figure 3.2 illustrates aggregate housing demand and supply. The former is in black, and the latter is in green. The total housing production is illustrated in blue. The difference between the total housing consumption and aggregate housing supply is the search cost.

As shown in Figure 3.2, when buyers face low search costs, a rise in these costs leads to a notable increase in total matches $f(\theta)\bar{K}$, while the increase in congestion externality is small. This, in turn, increases the supply of housing services available for consumption. In contrast, when search costs are already high, further increases in $\tau(\theta)$ substantially intensify congestion externalities and yield only a slight rise in match creation, thereby diminishing the consumable housing services.

#### 3.2.2.3 Equilibrium

Before introducing migration, I begin by analysing a *closed equilibrium* where the population in each location remains fixed. A *closed equilibrium* given $\{\mu, \bar{K}, \rho, N\}$ is a set of equilibrium outcomes $\{c, m, \theta, p\}$ that satisfies $\mathcal{C}^D(\theta, p) = \mathcal{C}^S(\theta)$. After substituting in $\mathcal{C}^D$ from (3.6) and $\mathcal{C}^S$ from (3.7), equilibrium tightness and price satisfies

$$f(\theta)(1+\tau(\theta))^{\epsilon-1} = \frac{\mu N \chi^{\epsilon}}{p\bar{K}}, \tag{3.9}$$

$$p = f(\theta)^{-1}(1+\tau(\theta))^{1-\epsilon}\frac{\mu N \chi^{\epsilon}}{\bar{K}}. \tag{3.10}$$

Naturally, the next step would be to solve for $\theta$ and $p$ using the exogenous variables. However, since we are working with a single equilibrium condition ( $\mathcal{C}^D(\theta, p) = \mathcal{C}^S(\theta)$) but two unknowns—$\theta$ and $p$—there exists an infinite set of $(\theta, p)$ pairs that satisfy the equilibrium. To resolve this indeterminacy, I assume that the equilibrium price only *partially* adjusts in response to changes in exogenous parameters, making it less flexible than the fully responsive competitive price defined in (3.10). While the assumption of incomplete price flexibility may initially appear restrictive, it is supported by institutional features observed in European rental markets. I outline two pieces of evidence below that justify this modeling choice.

***Evidence 1:*** *European rental markets display persistent downward rigidity.*

Data from PMA indicate that over the past 15 years, 85.3% of nominal rent changes and 67.1% of real rent changes in 34 major European cities have been non-negative. This rigidity is partly driven by contractual mechanisms such as Upward Only Rent Reviews, which prohibit rent reductions during lease renegotiations. Anecdotal evidence suggests that this clause is *"overwhelmingly the most common form in UK leases"*[7].

***Evidence 2:*** *Rental indexation has become widespread in Europe.*

Indexation has become a common feature in rental agreements across Europe in recent years. For instance, approximately 70% of residential rents in Munich are now indexed to changes in the Consumer Price Index (CPI) (REFIRE (2022)). Indexation constrains landlords from raising rents arbitrarily, introducing a predictable adjustment mechanism. In France, rental adjustments are tied to the government-published *Indice de Référence des Loyers*, which reflects local CPI changes. Similarly, in Scotland, *Rent Pressure Zones* are subject to government-imposed limits on CPI-indexed rent increases.

Motivated by these institutional features, I formalise the rental housing price as follows

$$p = p_0 \left( \frac{\mu N \chi^{\epsilon}}{\bar{K}} \right)^{\xi}, \tag{3.11}$$

where $p_0$ is a fixed *price level*, and $\xi \in (0, 1)$ determines the *degree of price flexibility* in response to shocks. When $\xi = 1$, price is proportional to and as flexible as the competitive price. When $0 < \xi < 1$, prices still respond in the same direction as the competitive price to

[7] See Williams Ellis.

changes in primitives, but to a less extent. Substituting (3.11) into (3.9), $\theta$ can be expressing using exogenous variables and price level $p_0$,

$$f(\theta)(1+\tau(\theta))^{\epsilon-1} = \left(\frac{\mu N \chi^{\epsilon}}{\bar{K}}\right)^{1-\xi} \frac{1}{p_0}, \tag{3.12}$$

implying that an equilibrium becomes fully determined with respect to $\theta$.

With the equilibrium determined, we can show that the aggregate rental housing consumption satisfies (3.13) after substituting in the definition of $\tau(\theta)$,

$$\mathcal{C}(\theta) = (f(\theta) - \rho\theta)\bar{K}, \tag{3.13}$$

and Appendix C.2.1 discusses comparative statics of $\mathcal{C}(\theta)$ with respect to changes in location fundamentals $\mu$, $\chi$ and $\bar{K}$.

### 3.2.3 Migration

I now allow agents to migrate following the Rosen (1979a) and Roback (1982) framework, which means that they will migrate until their individual housing consumption equal to their outside option $\underline{c}$. Hence, an *equilibrium with migration* given $\{\mu, \bar{K}, \rho, p_0, \underline{c}\}$ is a set of equilibrium outcomes $\{c, m, \theta, p, N\}$ that satisfies $\mathcal{C}^D(\theta, p) = \mathcal{C}^S(\theta)$ and $c(\theta) = \underline{c}$.

From (3.13), each agent consumes $c(\theta) = (f(\theta) - \rho\theta)\frac{\bar{K}}{N}$ housing. Substituting $c(\theta) = \underline{c}$, the number of agents in a city satisfies

$$N = (f(\theta) - \rho\theta)\bar{K}\underline{c}^{-1}. \tag{3.14}$$

The first order condition of (3.14) with respect to search cost $\tau(\theta)$ is

$$\frac{\partial N}{\partial \tau(\theta)} = -(f'(\theta) - \rho)\bar{K}\underline{c}^{-1}\frac{(q(\theta)-\rho)^2}{\rho q'(\theta)}, \tag{3.15}$$

where $q'(\theta) < 0$. The model delivers two key predictions. First, in tight housing markets—where $(f'(\theta)-\rho)$ is negative—higher search costs lead to greater out-migration. Second, because $(f'(\theta) - \rho)$ can differ across markets, the relationship between search costs and migration is non-linear. In loose markets, where $(f'(\theta) - \rho)$ is positive, higher search costs can instead promote in-migration. In the model, an increase in search cost reflects greater

search effort (more home visits), which creates additional renter-landlord matches without substantially raising congestion when the market is loose. This raises per capita rental housing consumption and makes the location more attractive to migrants.

In summary, Section 3.2 develops a simple model of the housing market. I show that in cities with tight markets, rising search costs can lead to out-migration. This occurs because congestion externalities reduce housing consumption below the level of the outside option, prompting agents to migrate until consumption is restored to that level. The subsequent sections empirically test the model's predictions using a proprietary dataset.

## 3.3 Data

Section 3.3 outlines the data used for the validation of the model.

### 3.3.1 Primary Data Source

In this section, I introduce the main dataset used in the analysis and explain the procedures undertaken to validate its quality.

#### 3.3.1.1 Description of the Main Data

In Europe, detailed and granular local housing market data are often not publicly available. Moreover, assembling consistent, unified, and standardised data across countries is challenging due to differences in currencies, data recording practices, and institutional frameworks. To address these limitations, I rely on a unique dataset provided by Property Market Analysis (PMA) LLP—a global, independent real estate research consultancy established in 1981. PMA analysts collect, clean, and harmonise data from a wide range of secondary sources, including national accounts, brokerage firms, and commercial data providers. This is further supplemented by extensive primary research, such as site visits and consultations with key market stakeholders.

The dataset spans the period from 2009 to 2021 and covers 34 major European cities. These include capital cities, large urban centres, and key regional hubs[8]. The dataset focuses

[8]The cities included are: Amsterdam, Barcelona, Berlin, Birmingham, Bremen, Bristol, Cologne, Copenhagen, Dortmund, Dresden, Duisburg, Dusseldorf, Edinburgh, Essen, Frankfurt am Main, Glasgow, Hamburg, Hannover, Helsinki, Leeds, Leipzig, London, Madrid, Manchester, Milan, Munich, Nuremberg, Rome, Rotterdam,

specifically on rental residential properties, offering detailed annual city-level information, including average rental prices, the number of rental transactions, and the stock of rental properties.

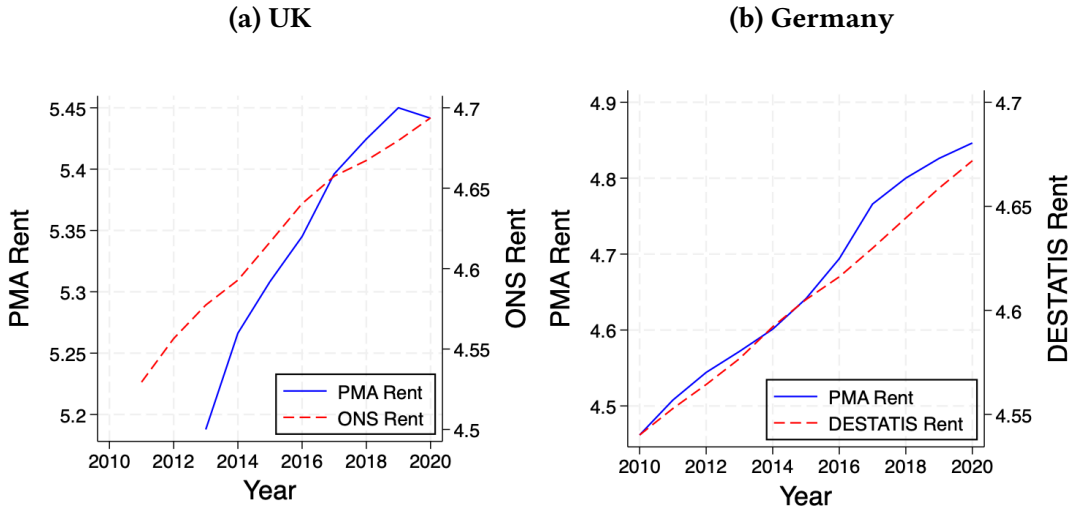
#### 3.3.1.2 Validation of Data Quality

Given the limited availability of detailed local housing market data, I assess the quality of PMA's dataset by comparing it with national-level statistics on rental rates, rental transactions, and rental property stock. I focus on the United Kingdom and Germany, as these two countries have the most comprehensive coverage within PMA's dataset.

***Validation 1:*** *Rental price.*

Figure 3.3 compares rental prices from the PMA dataset with those reported by official sources. Panel 3.3a is for the UK, and Panel 3.3b is for Germany. PMA rent is computed as a weighted average across cities in the UK and Germany, using housing stock as the weighting factor. Unsurprisingly, rental prices from PMA are higher than those reported by the ONS and DESTATIS, reflecting PMA's focus on major residential hubs. However, the trends are highly consistent across sources, with correlation coefficients of 0.98 for the UK and 0.99 for Germany.

**Figure 3.3: Rent Validation: PMA VS Official Sources**



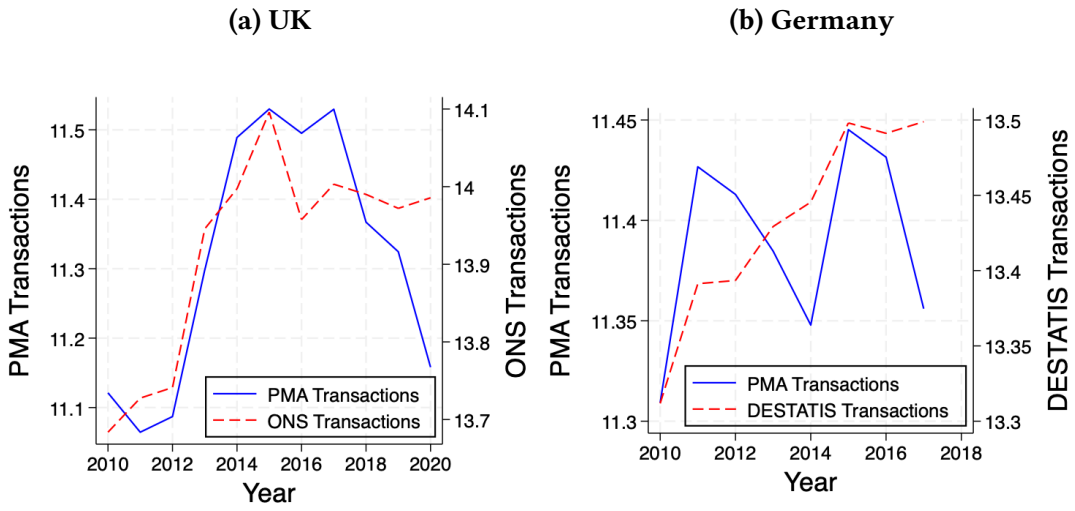

**Notes:** Figure 3.3 compares PMA's rent with national aggregates in the UK (Panel 3.3a) and Germany (Panel 3.3b). PMA rents, in blue solid lines, are computed as weighted averages across cities in the UK and Germany, using housing stock as the weighting factor. Rental rate from official sources are in red dotted lines.

Stuttgart, The Hague, Turin, Utrecht, and Vienna.

***Validation 2:*** *Rental property transactions.*

Figure 3.4 compares rental property transactions from the PMA dataset with those reported by official sources. Panel 3.4a shows the results for the UK, while Panel 3.4b presents those for Germany. The aggregate rental transaction data from PMA exhibits a respectable correlation with official figures—0.39 for the UK and 0.24 for Germany.

**Figure 3.4: Rental Property Transactions Validation: PMA VS Official Sources**




**Notes:** Figure 3.4 compares PMA's rental property transactions with national aggregates in the UK (Panel 3.4a) and Germany (Panel 3.4b). Aggregated PMA rental transactions are in blue solid lines. Rental transactions from official sources are in red dotted lines.

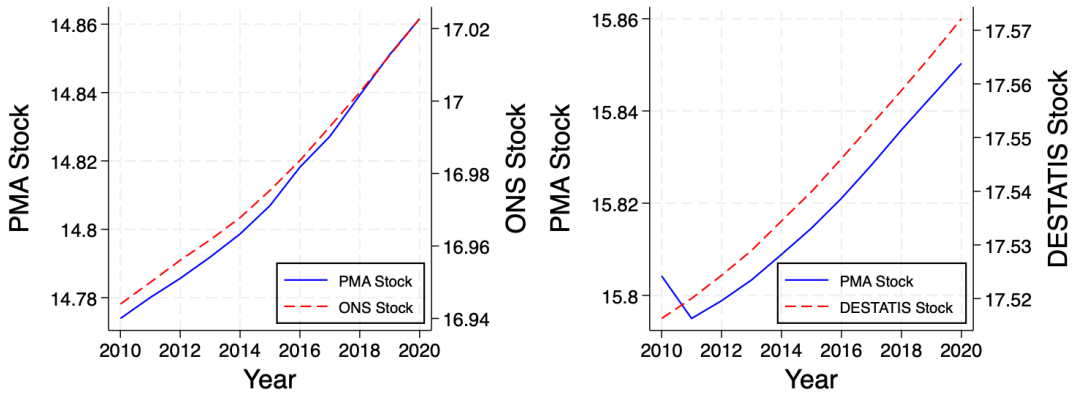
***Validation 3:*** *Rental property stock.*

Figure 3.5 compares the rental property stock from the PMA dataset with that reported by official sources. Since the ONS and DESTATIS do not provide data specifically for rental properties, I use the total residential dwelling stock as a proxy for the official sources. Panel 3.5a shows the results for the UK, while Panel 3.5b presents those for Germany. The aggregate rental property stock is broadly consistent between the PMA and official data, with correlations of 0.99 for the UK and 0.97 for Germany.

Overall, the robust correlations between the aggregated PMA data and official sources suggest that the PMA data is reliable. Additional validation exercises are provided in Appendix C.3.1.

**Figure 3.5: Rental Property Stock Validation: PMA VS Official Sources**

**(a) UK** **(b) Germany**




**Notes:** Figure 3.5 compares PMA's rental property stock with national housing stock in the UK (Panel 3.5a) and Germany (Panel 3.5b). Aggregated PMA rental property stock are in blue solid lines. Housing stock from official sources are in red dotted lines.

### 3.3.2 Additional Data Sources

We complement PMA's housing market data with economic indicators sourced from official databases. Local migration flow data are obtained from national statistical agencies. Examples include the UK's *Internal migration: detailed estimates by origin and destination local authorities, age and sex* and Austria's *STATcube: Migration within Austria 2002 to 2023*—datasets that are representative of standard practices across statistical agencies. These sources are also used to obtain official local population data, enabling the calculation of migration rates. In addition, I collect information on local unemployment rates, real GDP, and disposable incomes from Eurostat's *Regional Statistics by NUTS Classification* and the UK's *Regional Datasets* from the Office for National Statistics (ONS). These variables are included as controls.

### 3.3.3 Measuring Search Cost in the Data

Section 3.3.3 outlines how housing search costs are measured and characterized in the data. In the model, the cost of searching for a rental property is given by $\tau(\theta) = \frac{\rho}{q(\theta)-\rho}$. Estimating this expression empirically poses two key challenges. First, assigning a precise value to the per-visit cost of viewing a property, $\rho$, is difficult. Second, measuring $\theta$ is complicated by the absence of data on the number of housing visits at the city level. Due to these limitations, the most reliable proxy available in the data is the probability that a rental unit is successfully let,

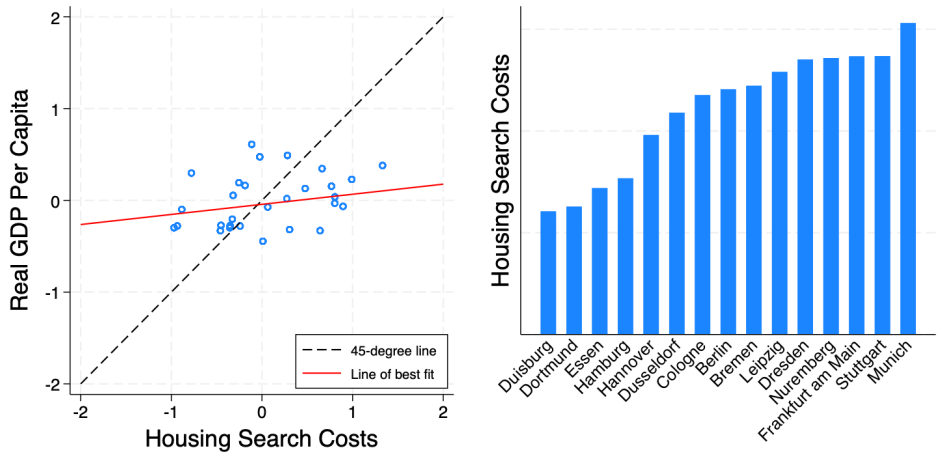
denoted as $f(\theta)$ in the model. This measure increases monotonically with search costs: when properties are rented out quickly, households must search more intensively—visiting multiple units—to secure housing, which raises the overall cost of search. In what follows, I present two stylised facts from the data regarding housing market search costs.

***Fact 1:*** *Housing rental market search costs are higher in more affluent places.*

Figure 3.6 presents the relationship between rental housing search costs and local economic prosperity. Panel 3.6a indicates that search costs tend to be higher in more affluent areas, while Panel 3.6b focuses on Germany to offer additional evidence: wealthier cities such as Munich and Frankfurt exhibit higher housing search costs compared to less prosperous cities like Dortmund and Essen.

**Figure 3.6: Rental Housing Search Cost Over Time**

**(a) Correlation with GDP Per Capita** **(b) Search Costs in German Cities**

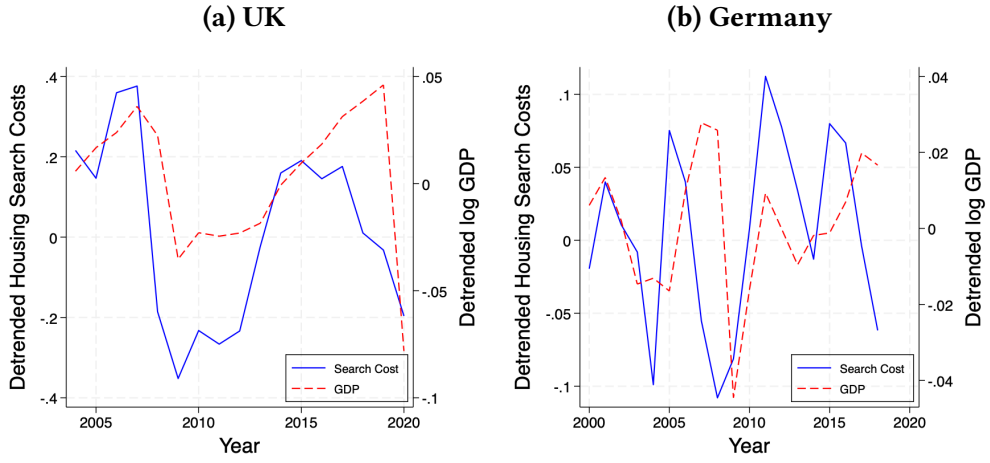



**Notes:** Figure 3.6 illustrates the relationship between housing market search costs and local prosperity. Panel 3.6a scatterplots the reationship between housing search costs and real GDP per capita across all cities in the dataset. The dashed black line is the 45-degree line, while the solid red line represents the line of the best fit. Panel 3.6b compares average housing search costs across cities in Germany.

***Fact 2:*** *Housing rental market search costs are pro-cyclical.*

Figure 3.7 demonstrates that my measure of housing market search costs is strongly pro-cyclical, exhibiting an overall correlation of 0.535. This finding is consistent with the evidence reported by Ioannides and Zabel (2018).

**Figure 3.7: Rental Housing Search Cost Over Time**




**Notes:** Figure 3.7 illustrates the relationship between cyclical components of rental housing market search costs and GDP for the UK (Panel 3.7a) and Germany (Panel 3.7b). Cyclical components are extracted using the Hodrick-Prescott (HP) Filter. are In both panels, search costs are depicted by the blue lines, while GDP is represented by the red lines.

## 3.4 Empirical Validations of the Model

In this section, I empirically examine the insights from the model.

### 3.4.1 Housing Search Costs and Inter-regional Migration

The model shows that (1) the relationship between housing search cost and out-migration is positive for cities with tight housing markets, and (2) this relationship is non-linear. I investigate whether these results hold empirically.

#### 3.4.1.1 Rental housing search cost and out-migration in tight housing markets

I run the following regression,

$$\text{net out-migration rate}_{it} = \alpha + \beta_1 \text{rental housing search cost}_{it} + C'_{it}\Gamma + \eta_i + \gamma_t + \epsilon_{it}, \quad (3.16)$$

where the dependent variable, net out-migration rate$it$, is defined as the ratio of net internal emigration to the mid-year population in city $i$ at time $t$. The variable rental housing search cost$it$ is approximated by the probability that a rental property is successfully let. The coefficient of interest, $\beta_1$, captures the semi-elasticity outlined in equation (3.15). The control variables, denoted by $C_{it}$, include real rental prices, real disposable income per capita, and local un-

employment rates. The corresponding vector of coefficients is represented by $\Gamma$. City fixed effects, $\eta_i$, account for time-invariant local characteristics such as school quality, while time fixed effects, $\gamma_t$, control for common shocks. The error term is denoted by $\epsilon_{it}$.

Panel A of Table 3.1 reports the estimation results for Equation (3.16). Columns (1) shows the coeffient of interest. The findings reveal a positive association between the housing search cost experienced by renters and the net out-migration rate. Since the PMA sample focuses on cities with the tightest housing markets within their respective countries, the model-implied semi-elasticity between housing search costs and out-migration is also positive. This suggests that the empirical results are consistent with the theoretical model's predictions.

**Table 3.1: Out-Migration and Rental Housing Search Cost**

| Dep. Variable: | Net Out-migration Rate | | | | |
|---|---|---|---|---|---|
| | Panel A | Panel B | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Rental Housing Search Cost | 0.200*** | | | | |
| | (0.0535) | | | | |
| Rental Housing Search Cost $1^{st}$ Quartile | | -0.359** | | | |
| | | (0.179) | | | |
| Rental Housing Search Cost $2^{nd}$ Quartile | | | -0.026 | | |
| | | | (0.054) | | |
| Rental Housing Search Cost $3^{rd}$ Quartile | | | | 0.168 | |
| | | | | (0.166) | |
| Rental Housing Search Cost $4^{th}$ Quartile | | | | | 0.155$^{+}$ |
| | | | | | (0.107) |
| $N$ | 266 | | 266 | | |
| adj. $R^2$ | 0.31 | | 0.41 | | |
| City & country FE | ✓ | | ✓ | | |
| Time FE | ✓ | | ✓ | | |
| Cluster robust SE | ✓ | | ✓ | | |
| Controls | ✓ | | ✓ | | |

Standard errors in parentheses

$^{+}\ p < 0.20$, $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

**Notes:** Panel A of Table 3.1 presents the estimation result from equation (3.16). Column (1) reports the baseline estimate of $\beta_1$, capturing the correlation between housing market congestion and net out-migration. Panel B reports results from equation (3.17), with columns (2)–(5) displaying heterogeneous effects by market tightness quartile. All regressions include controls for real housing rental rate, real disposable income per capita and local unemployment rates.

#### 3.4.1.2 Non-linearity

Moreover, I show that the relationship between housing search cost and out-migration is non-linear using the following specification,

$$\begin{aligned}\text{net out-migration rate}_{it} = \alpha + \sum_{q} \beta_{1q} \left(\text{rental housing search cost}_{it} \times \mathbb{1}\{\overline{\text{tightness}_i} = q\}\right) \\ + \sum_{q} \Gamma_q \left(C_{it} \times \mathbb{1}\{\overline{\text{tightness}_i} = q\}\right) + \eta_i + \gamma_t + \epsilon_{it},\end{aligned} \tag{3.17}$$

where $\mathbb{1}\{\overline{\text{tightness}_i} = q\} = 1$ if city $i$'s average rental housing market tightness falls within the $q^{\text{th}}$ quartile, and 0 otherwise. Housing market tightness is measured using search cost. Accordingly, $\beta_{1q}$ represents the semi-elasticity of the net out-migration rate with respect to rental housing search cost for cities in the $q^{\text{th}}$ quartile. The remaining variables are as defined in equation (3.16).

Panel B of Table 3.1 presents the estimation results from equation (3.17). Columns (2) to (5) show the association between rental housing search costs and out-migration for cities, moving from the loosest to the tightest housing markets. The relationship appears to be non-linear: in cities with the loosest housing markets, out-migration is negatively associated with search cost, whereas in cities with the tightest housing markets, the relationship is positive. These insights confirm the findings from (3.15).

Appendix C.3.2 presents additional robustness tests that support the validity of the empirical results. The first test re-estimates equations (3.16) and (3.17) using bootstrap standard errors to account for the limited number of observations. The second test uses alternative proxies for rental market tightness in (3.17), specifically the average rental rate and real GDP per capita.

In conclusion, Section 3.4 confirms the model's two key insights: (1) in cities with tight housing markets, higher housing search costs are associated with increased out-migration, and (2) this relationship is non-linear. With the model empirically validated, I apply its theoretical framework to policy analysis in Section 3.5.

## 3.5 Policy

Using the theoretical framework developed in Section 3.2, I evaluate widely adopted housing market policies on both the demand and supply sides. Before detailing the policy experiments, I first present real-world examples of such interventions.

Demand-side policies typically involve rent subsidies, with notable examples including the *Housing Benefit (HB)* in the United Kingdom and the *Mietzuschuss* in Germany. These programs have long been used to support renters by reducing their housing costs. In recent years, however, there has been a growing policy emphasis on supply-side interventions. For instance, the 2019 Conservative Government in the UK pledged to "sustain efforts to continually increase the number of homes being constructed" (Wilson, 2021), a goal echoed by housing strategies in Ireland (Armstrong, 2022) and the Netherlands (Oostveen, 2022).

Motivated by these real-world examples, I examine how rental subsidies and housing stock expansions affect aggregate welfare within a city. Since housing is the only consumption good in this framework, changes in aggregate welfare can be viewed as changes in total housing consumption following the implementation of these policies.

### 3.5.1 Demand-side Policy

The aggregate welfare in a city is given by $\mathcal{W} = \underline{c}N$, where $\underline{c}$ is the constant per capita housing consumption ensured by spatial equilibrium. As a result, aggregate welfare depends entirely on the number of agents $N$ residing in the city. To assess the impact of housing policies, I therefore focus on characterising how $N$ responds to policy interventions.

Suppose that the government introduces a rental subsidy $\mathbf{s}$ to each agent. Therefore, from (3.12), the equilibrium tightness can be expressed as

$$f(\theta)(1+\tau(\theta))^{\epsilon-1} = \left(\frac{(\mu+\mathbf{s})N\chi^{\epsilon}}{\bar{K}}\right)^{1-\xi}\frac{1}{p_0}, \tag{3.18}$$

Moreover, the number of agents in a location follows (3.14), that is, $N = (f(\theta)-\rho\theta)\bar{K}\underline{c}^{-1}$. Differentiating $N$ with respect to the subsidy $\mathbf{s}$ yields the first-order condition:

$$\frac{\partial N}{\partial \mathbf{s}} = (f'(\theta)-\rho)\bar{K}\underline{c}^{-1}\frac{\partial \theta}{\partial \mathbf{s}}, \tag{3.19}$$

with

$$\frac{\partial\theta}{\partial \mathbf{s}} = \frac{(1-\xi)\left(\frac{(\mu+\mathbf{s})N\chi^{\epsilon}}{\bar{K}}\right)^{-\xi}\frac{N\chi^{\epsilon}}{p_0\bar{K}}}{f'(\theta)(1+\tau(\theta))^{\epsilon-1}+f(\theta)(\epsilon-1)(1+\tau(\theta))^{\epsilon-2}\tau'(\theta)} > 0. \tag{3.20}$$

Thus, the sign of $\frac{\partial N}{\partial \mathbf{s}}$ depends on the term $f'(\theta)-\rho$. In cities where the housing market is tight, we have $f'(\theta)-\rho<0$. In this case, the number of agents $N$ decreases in response to the rental subsidy. Consequently, aggregate welfare, measured by $\underline{c}N$, also declines. The underlying intuition is that demand-side policies such as rental subsidies reduce aggregate consumption in already tight markets, as shown in Appendix C.2.1. This, in turn, causes per capita housing consumption to fall below the outside option $\underline{c}$, prompting agents to leave the city.

### 3.5.2 Supply-side Policy

Suppose that the government expands the total housing stock by $\mathbf{K}$, the equilibrium tightness is now

$$f(\theta)(1+\tau(\theta))^{\epsilon-1} = \left(\frac{(\mu+\mathbf{s})N\chi^{\epsilon}}{\bar{K}+\mathbf{K}}\right)^{1-\xi}\frac{1}{p_0}. \tag{3.21}$$

Moreover, using the same derivation as described in Appendix C.2.2, per agent housing consumption can be expressed as $c(\theta) = \frac{\chi^{\epsilon}\bar{\mu}}{p_0}(1+\tau(\theta))^{-\epsilon}\left(\frac{\mu N\chi^{\epsilon}}{\bar{K}+\mathbf{K}}\right)^{-\xi}$. Therefore, in a spatial equilibrium, the number of agent in a city equals

$$N = \left[\frac{\chi^{\epsilon}\bar{\mu}}{p_0}(1+\tau(\theta))^{-\epsilon}\left(\frac{\mu\chi^{\epsilon}}{\bar{K}+\mathbf{K}}\right)^{-\xi}\underline{c}^{-1}\right]^{\frac{1}{\xi}}. \tag{3.22}$$

Differentiating with respect to $\mathbf{K}$ yields the first-order condition:

$$\frac{\partial N}{\partial \mathbf{K}} = \mathcal{A}\frac{\chi^{\epsilon}\bar{\mu}}{\underline{c}p_0}\left[-\epsilon(1+\tau(\theta))^{\epsilon-1}\left(\frac{\mu N\chi^{\epsilon}}{\bar{K}+\mathbf{K}}\right)^{-\xi}N\tau'(\theta)\frac{\partial\theta}{\partial\mathbf{K}} + (1+\tau(\theta))^{-\epsilon}\left(\mu\chi^{\epsilon}\right)^{-\xi}\xi(\bar{K}+\mathbf{K})^{\xi-1}\right], \tag{3.23}$$

where $\mathcal{A} \equiv \frac{1}{\xi}\left[\frac{\chi^{\epsilon}\bar{\mu}}{p_0}(1+\tau(\theta))^{-\epsilon}\left(\frac{\mu\chi^{\epsilon}}{\bar{K}+\mathbf{K}}\right)^{-\xi}\underline{c}^{-1}\right]^{\frac{1}{\xi}-1} > 0$. As is evident from (3.21), an increase in $\mathbf{K}$ reduces market tightness, i.e., $\frac{\partial\theta}{\partial\mathbf{K}} < 0$. Therefore, $\frac{\partial N}{\partial\mathbf{K}} > 0$ for all values of $\theta$. That is, expanding the housing stock increases the number of agents in the city, thereby raising aggregate housing consumption $\underline{c}N$.

In conclusion, while I acknowledge the limitations of the framework—namely, the exclusion of other consumption goods, the absence of a labour market, and the lack of an explicit

migration network—the normative analysis remains primarily explanatory. Nonetheless, the mechanism introduced offers valuable insight into the effects of housing market policies. In particular, it highlights that rental subsidies, though well-intentioned, may unintentionally exacerbate search difficulty, ultimately making it more difficult for individuals to secure housing.

## 3.6 Conclusion

This paper proposes that search frictions in rental housing markets are an important driver of internal migration, motivated by compelling anecdotal evidence from European cities. It develops a novel model of rental housing market microstructure with endogenous migration decisions, showing that rising search costs lead to out-migration from tight housing markets by absorbing resources and reducing effective housing consumption. The model also predicts a non-linear relationship: the migration response is strongest in the tightest markets, while in looser markets, improved matching efficiency mitigates the negative effects of higher search costs.

The model's predictions are validated using a proprietary dataset, addressing the limited availability of granular public housing data. The framework is then used to evaluate policy implications, showing that demand-side interventions, such as rental subsidies, are ineffective in tight markets because they exacerbate search frictions and accelerate out-migration. By contrast, supply-side policies that expand the housing stock alleviate search costs and enhance market efficiency.

These findings are preliminary and subject to several limitations. First, the quantitative impact of congestion on migration is not estimated and may be modest. Second, the model abstracts from labour market dynamics, which could offset search-driven outflows in cities offering strong employment opportunities. Third, extending the framework to model discrete migration choices would provide a richer analysis of bilateral migration patterns, though this is beyond the current scope. Fourth, the empirical analysis is restricted to major European cities; broader datasets covering all urban areas would allow a more comprehensive validation. Nonetheless, this paper provides the first systematic analysis of how housing search frictions shape internal migration and highlights the importance of incorporating housing search costs into models of urban mobility.

# Appendices

# Chapter A

# Appendices for Unemployed Capital in Space

## A.1 Data Appendix

### A.1.1 Data Cleaning and Summary Statistics

We leverage a dataset sourced from PMA encompassing office, industrial, and logistic buildings at the city level from 1981 to 2022.[1] To get a comprehensive picture of spatial capital allocations, we combine all commercial real estate within each city.

Additionally, we define the investment rate as investment over the capital stock and calculate investment based on equation (1.5). We derive the finding rate and separation rate according to equations (1.6) and (1.7). To ensure data quality, instances where the finding rate and separation rate exceed 0.99 or fall below 0.01 are treated as anomalies and are consequently excluded from our analysis. Moreover, we restrict our analysis to data from 1990 onwards, as this marks a point when the data collection process of the company appears to have reached a sufficiently advanced stage. Table A.1 presents the summary statistics after cleaning the data.

[1] For London and Paris, PMA data are reported at the submarket level, which we aggregate to the city (market) level to ensure consistency across cities.

**Table A.1: Summary Statistics (1990-2022)**

| *Variables* | **Mean** | **S.D.** | **P25** | **P50** | **P75** | **N** |
|---|---|---|---|---|---|---|
| | | | **United Kingdom** | | | |
| *Unemployment Rate* | 0.10 | 0.04 | 0.06 | 0.09 | 0.12 | 987 |
| *Employment Rate* | 0.90 | 0.04 | 0.87 | 0.91 | 0.93 | 987 |
| *Investment Rate* | 0.11 | 1.26 | 0.01 | 0.02 | 0.03 | 986 |
| *Finding Rate* | 0.40 | 0.21 | 0.24 | 0.38 | 0.53 | 987 |
| *Separation Rate* | 0.04 | 0.02 | 0.02 | 0.03 | 0.05 | 987 |
| *Stock* | 2645 | 5343 | 571 | 1402 | 2797 | 987 |
| | | | **European Union** | | | |
| *Unemployment Rate* | 0.09 | 0.04 | 0.06 | 0.09 | 0.12 | 358 |
| *Employment Rate* | 0.91 | 0.04 | 0.88 | 0.91 | 0.94 | 358 |
| *Investment Rate* | 0.03 | 0.22 | 0.03 | 0.04 | 0.05 | 357 |
| *Finding Rate* | 0.52 | 0.20 | 0.35 | 0.50 | 0.67 | 358 |
| *Separation Rate* | 0.03 | 0.02 | 0.02 | 0.03 | 0.04 | 358 |
| *Stock* | 9489 | 8901 | 4622 | 7468 | 10568 | 358 |

Note: Table A.1 presents summary statistics of the capital unemployment rate, employment capital rate, investment rate, finding rate, separation rate, and total capital stock at the city level between 1990 and 2022 for the United Kingdom and Europe. The unit for stock is thousands of square meters.

### A.1.2 Data Validation

This section conducts additional validations of the capital stock measures reported by PMA, comparing this data with Ottonello (2021) and across space and over time with well-established measures from UK national accounting provided by the Office of National Statistics (ONS).

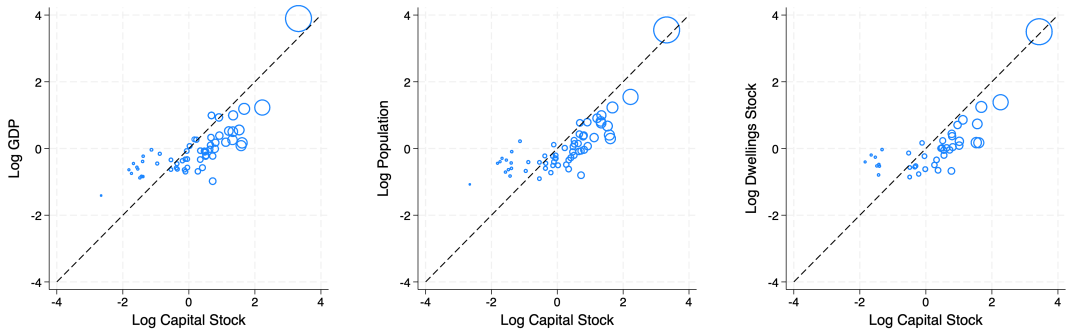
First, we notice that Table A.1 reports summary statistics in line with those reported by Ottonello (2021). In particular, we find that our capital unemployment rate is also 10 percent and that our standard deviation is 4 percent, close to the 2.4 percent found in their study.

Second, we compare our capital stock measure with other measures of location size such as GDP, population, and dwelling stocks. The ONS defines a dwelling as a unit of accommodation that may comprise one or more household spaces (a household space is the accommodation used or available for use by an individual household).[2] Figure A.1 presents the scatterplots of local GDP, population, and dwellings against local capital stock from PMA in the cross-section of UK cities. A visual analysis confirms the expectation that areas with higher GDP, population, and dwellings tend to exhibit higher levels of capital stock.

Finally, we follow Ottonello (2021) and compare the behavior over time of the capital

[2]See: ONS definitions.

**Figure A.1: Spatial Correlations Between PMA Capital Stock and GDP, Population, and Dwellings in the UK**

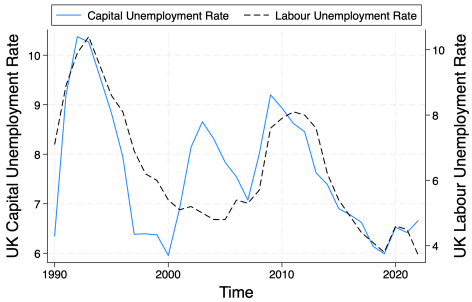



**(a) GDP** **(b) Population** **(c) Dwellings**

Note: Figure 1.1 presents the spatial correlation between the capital stock from the PMA dataset and key economic indicators of location size, namely GDP (Figure A.1a), population (Figure A.1b), and residential dwellings (Figure A.1c) in the UK. All observations are in logs and time-averaged. Cross-sectional averages have been removed. The relative size of each location within the UK is represented by the size of the circles in the figures.

unemployment rate with the normal unemployment labor rate. Figure A.2 illustrates this comparison over time. Overall, we observe that the dynamics over time of the capital unemployment rate closely mirror those of the unemployment labor rate, a pattern consistent with standard intuition related to unemployment rates and with the findings depicted in Figure 1 of Ottonello (2021). Moreover, we find that regressing capital unemployment rates on labor unemployment rate leads to a positive correlation ranging 0.696-0.742, further confirming their similar behavior.

**Figure A.2: Time Series of Capital Unemployment and Labor Rates**




Note: Figure A.2 shows the time series of the capital unemployment rate and unemployment labor rate in the United Kingdom between 1990 and 2022. Labor unemployment data is obtained from ONS. The blue line represents the capital unemployment rate, whereas the dotted black line depicts the labor unemployment rate.

### A.1.3 More on The Distribution and Spatial Persistence of Capital Unemployment Rates

Here, we present additional evidence on the distribution and spatial persistence of capital unemployment rates in our data.

#### A.1.3.1 Additional Scatterplots

Figure A.3 displays binscatters of the capital unemployment rate against itself with 5- and 10-year lags, both with and without time fixed effects. The light blue circles represent group averages, while the dashed black line represents the 45-degree line.

Overall, we find that the binscatter group averages align closely with the 45-degree line, reaffirming the strong persistence of this variable. Additionally, we observe that controlling for time fixed effects does not significantly alter this result, suggesting that persistent nationwide shocks do not seem to drive the persistence. If anything, the persistence appears stronger after accounting for this.[3]

#### A.1.3.2 Evidence from Europe

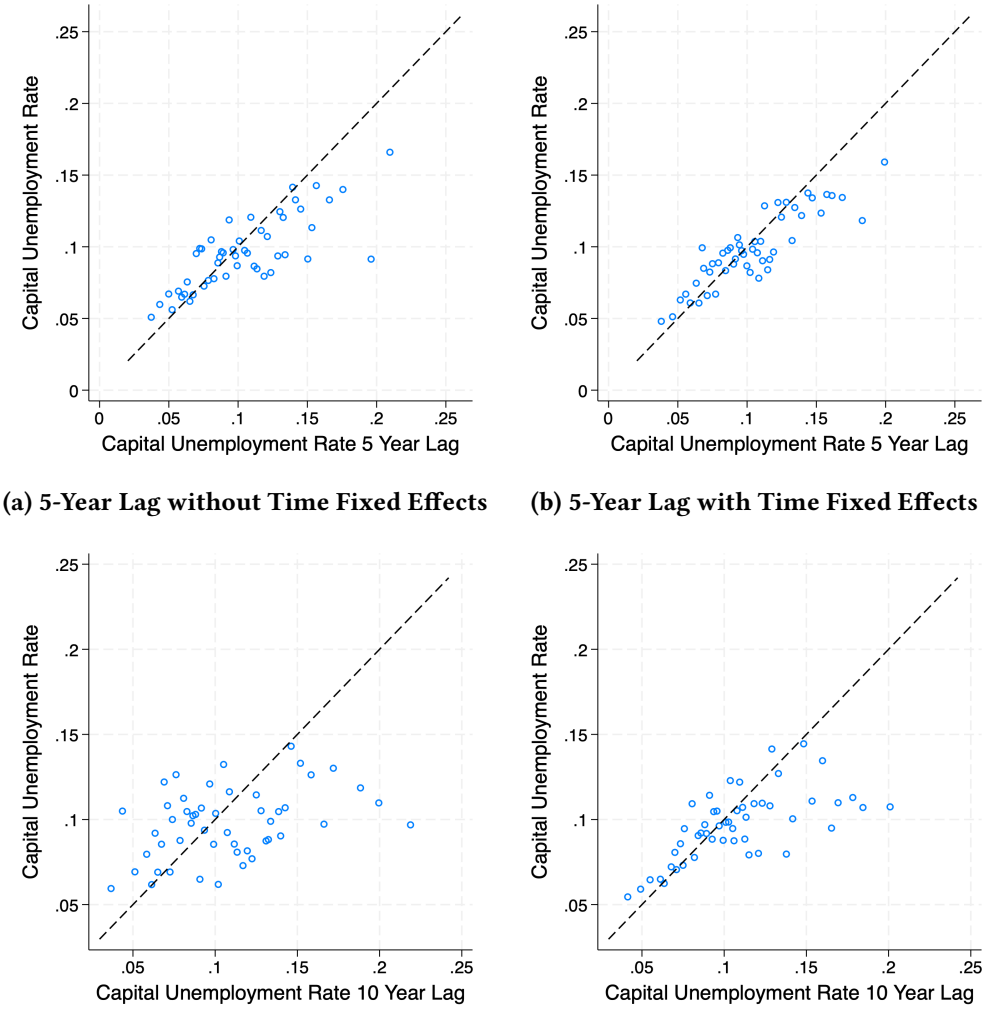
In Section 1.2.2, we show that capital unemployed rates exhibit significant persistence over time across UK cities. In this section of the appendix, we assess the robustness of this finding by examining the persistence of this measure within European cities.

To assess the persistence of spatial differentials in the capital unemployment rate, we split the sample into two sub-periods: one before and the other after 2006. Figure A.4 plots the capital unemployment rate in the second subperiod against the capital unemployment rate in the first subperiod for every city in Europe. Notably, the capital unemployment rate across European cities also exhibits a high degree of persistence, aligning closely around the dashed black 45-degree reference line.

Overall, our findings suggest that persistence in the spatial distribution of capital unemployment rates seems to be a robust feature of local capital markets and does not appear to depend on the specific country of analysis.

[3] Controlling for location-specific exposure to economy-wide industry cycles, as explained in Appendix A.1.3, yields very similar results, which are available upon request.

**Figure A.3: Additional Evidence on the Persistence of Capital Unemployment Rate**




**(a) 5-Year Lag without Time Fixed Effects**

**(b) 5-Year Lag with Time Fixed Effects**

**(c) 10-Year Lag without Time Fixed Effects**

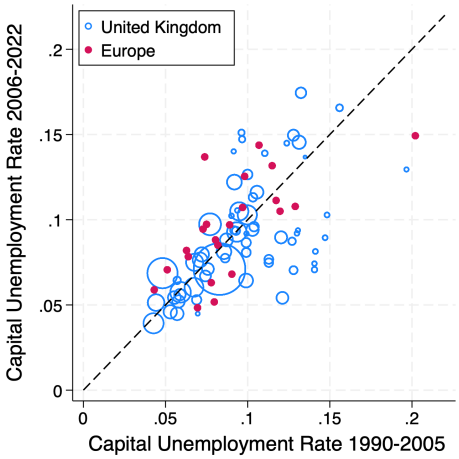
**(d) 10-Year Lag with Time Fixed Effects**

Note: Figure A.3 displays binscatters of the capital unemployment rate against itself with 5- and 10-year lags, both with and without time fixed effects. Light blue circles represent group averages. The dashed black line represents the 45-degree line.

### A.1.3.3 Accounting for Labor Unemployment Rates and Persistent Shocks

This section of the Appendix explores the potential role of local labor unemployment rates and persistent shocks in the documented persistence of capital unemployment rate gaps. While labor unemployment rates may influence the behavior of other market, such as capital market, persistent shocks, driven by the deindustrialization process experienced by the UK, may create a mismatch between the existing local supply of capital and the changing demand due to evolving local sectoral composition.

**Figure A.4: Spatial Persistence of Capital Unemployment Rates in UK and Europe**




**(a) Persistence of Capital Unemployment Rate in UK and Europe**

Note: Figure A.4 plots the capital unemployment rate in the UK and European cities in two subperiods of the sample. The blue open circles represent cities in the UK, and the size of each circle corresponds to the total capital within that city. The red circles represent cities in Europe. The dashed line represents the 45-degree line.

While labor unemployment rates are readily available from the data, we construct a location-specific exposure measure to economy-wide industry cycles. In particular, we define exposure as follows:

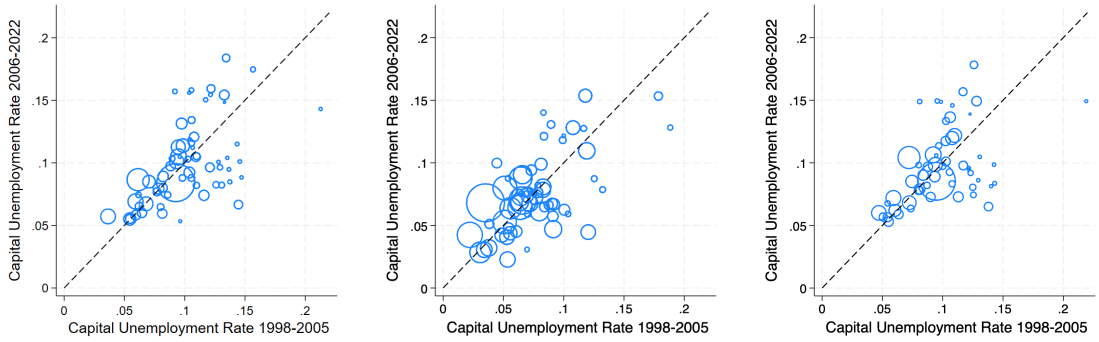
$$E_{jt-1990} = \sum_i \omega_{ij1990} \times \Delta_{t-1990} \log Y_{it}, \tag{A.1}$$

where $i$ defines the industry, $j$ the city, and $t$ time. Thus, exposure is defined as the weighted average, with weights given by the 1990 (initial) industry output share of total output in a given location, of cumulative changes since 1990 in industry output $Y$.

Figure A.5 plots capital unemployment rates in UK cities in two subperiods of the sample after controlling for time fixed effects (Figure A.5a), time fixed effects and industry cycles simultaneously (Figure A.5b), and time fixed effects and and labor unemployment rates simultaneously (Figure A.5c). The blue circles represent cities in the UK, and the size of each circle corresponds to the total capital within that city. The dashed line represents the 45-degree line. Overall, we find that accounting for time fixed effects, local labor unemployment rates, and industry cycles does not significantly affect the persistent patterns documented in the main text.[4] Thus, we conclude that, while the UK economy has large labor unemployment rate

[4]Figure A.5b is slightly less neat because controlling for industry cycles results in some loss of observations,

**Figure A.5: Spatial Persistence Accounting for Persistent Shocks**




**(a) Without Time Fixed Effects**

**(b) Without Time Fixed Effects and Industry Cycles**

**(c) Without Time Fixed Effects and Labour Unemployment Rate**

Note: Figure A.5 plots capital unemployment rates in UK cities in two subperiods of the sample after controlling for time fixed effects (Figure A.5a), time fixed effects and industry cycles simultaneously (Figure A.5b), and time fixed effects and labor unemployment rates simultaneously (Figure A.5c). The blue circles represent cities in the UK, and the size of each circle corresponds to the total capital within that city. The dashed line represents the 45-degree line.

differences and has witnessed a slow-moving deindustrialization process, our data suggest that these factors are unlikely to be the main drivers of the observed persistence in capital unemployment rates.

### A.1.3.4 Net Capital Investment Rate from Aggregate Official Statistics

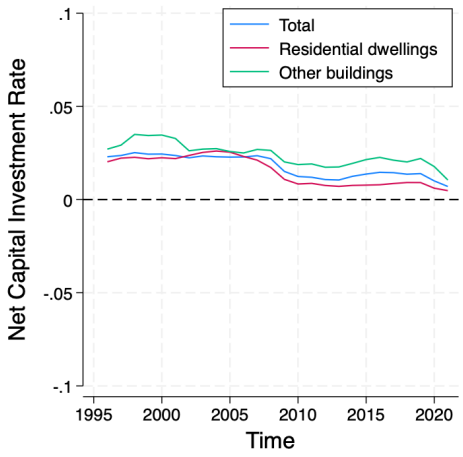
This section illustrates the evolution of net capital investment rates over time using aggregate national statistics for comparable measures of capital. To the best of our knowledge, local-level data on investment in similar types of capital are not available.

Figure A.6 displays the evolution of net capital investment rates in the UK from 1996 to 2021. Overall, we find that these rates are minimal and not far from zero, averaging around 2 percent. This finding is consistent with our results presented in the main text.[5]

as the PMA data define locations at a more granular level than the ONS.

[5]While the aggregate investment rate is similar between our data and the ONS, the latter appears to be about 1-2 percentage points higher. This discrepancy could stem from investments in the quality of buildings—not just in the quantity of new structures—which our data, focused solely on square meters, does not capture.

**Figure A.6: Net Capital Investment from ONS**




Note: Figure A.6 shows the evolution of net capital investment rates for different types of structures calculated from UK aggregate official statistics.

## A.1.4 More on The Spatial Ins and Outs of Unemployed Capital

Here, we present additional evidence on the central role of separation rates in explaining capital unemployment rate gaps in our data.

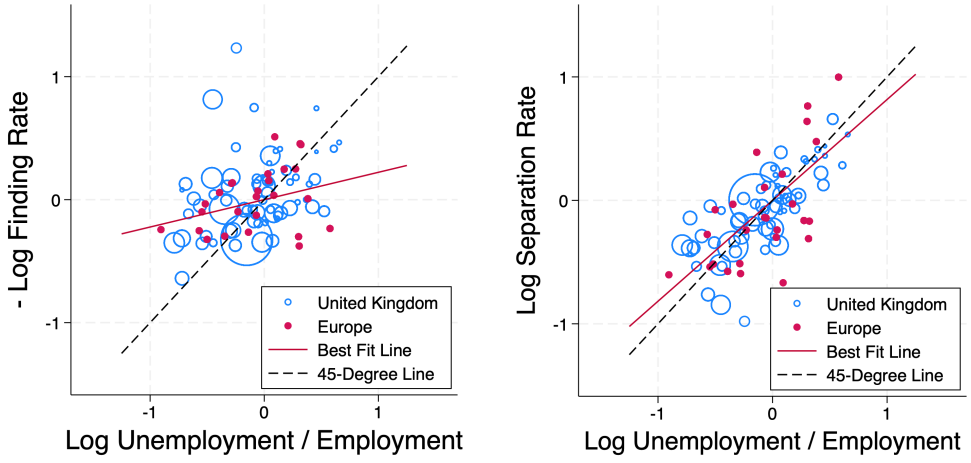
### A.1.4.1 Descriptive Evidence for Europe

In this section of the appendix, we assess whether the contributions of separation rates and finding rates to the local capital unemployment rate are comparable between UK and European cities.

Figure A.7 plots minus the log of finding rates $f_j$ and the log of separation rates $s_j$ against the log of the unemployment-employment capital rate ratio $\boldsymbol{k}_j^u/\boldsymbol{k}_j^e$ across cities in the UK (blue) and Europe (red). Figure A.7a suggests that finding rates exhibit relatively low variation across different locations, with the best-fit line notably distant from the 45-degree line (depicted in dashed black). In contrast, when examining separation rates, they emerge as the primary factor driving differences in local capital unemployment rates. Figure A.7b shows that separation rates vary substantially across locations, with their best-fit line closely aligning with the 45-degree line.

Overall, our findings suggest that the quantitative importance of separation rates in ex-

**Figure A.7: Capital Market Flows Across Space in UK and Europe**




**(a) Finding Rate** **(b) Separation Rate**

Note: Figure A.7 shows graphically the contribution of minus the log of the finding rate and the log of the separation rate to local capital unemployment rate differences across UK and European locations. Figure A.7a scatterplots minus the log of the finding rate against the log of the unemployment-employment capital ratio, across cities in the UK. Figure A.7b scatterplots the log of the separation rate against the log of the unemployment-employment capital ratio, across cities in the UK and Europe. Open blue circles represent cities in the UK, with size proportional to their total capital. Solid red circles represent cities in Europe. Each data point represents a within-city average, with cross-sectional means removed for the plot. The 45-degree line is in dashed black, and the line of best for European locations fit is in solid red.

plaining local capital unemployment rate differences seems to be a robust feature of local capital markets and does not seem to depend on the specific country we focus on.

### A.1.4.2 Expanded Decompositions

In Section 1.3.1, we presented a decomposition of the log of the unemployment-employment capital rate ratio assuming $\delta \approx 0$. In this section of the appendix, we instead present an expanded decomposition holding for any value of $\delta$, assessing its impact on our empirical findings.

In particular, we can generalize equation (1.8) in the main text to the case with $\delta \neq 0$ yielding the following decomposition of the log of the unemployment-employment capital rate:

$$\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right) = \log(s_j) - \log(f_j) + \log\left(\left(\frac{s_j(1-\delta)+(1-f_j)\delta/\boldsymbol{k}_j^e}{\delta + f_j(1-\delta)}\right)\frac{f_j}{s_j}\right). \tag{A.2}$$

The first two terms in equation (A.2) mirror those in equation (1.8), capturing the transitions in and out of the unemployment state for capital. The third term is new to this decomposition, specifically accounting for the extensive margin of unemployed capital associated with newly invested capital.

From equation (A.2), we arrive at a spatial decomposition of the variance of the log of the unemployment-employment capital rate ratio, given by:

$$\begin{aligned}\operatorname{Var}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right)\right) &= \operatorname{Cov}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), \log(s_j)\right) + \operatorname{Cov}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), -\log(f_j)\right) \\ &+ \operatorname{Cov}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), \log\left(\left(\frac{s_j(1-\delta)+(1-f_j)\delta/\boldsymbol{k}_j^e}{\delta+f_j(1-\delta)}\right)\frac{f_j}{s_j}\right)\right) \\ &+ \operatorname{Cov}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), \varepsilon_j\right),\end{aligned} \tag{A.3}$$

where the last term can be calculated as the difference between the left-hand side and the first three terms of the decomposition, and is meant to capture measurement error in the data or departures from the steady-state assumption adopted in the analysis, as in the main text.

Thus, we can use equation (A.3) to inspect if our empirical findings from Section 1.3.2 are robust to allow for the extensive margin. Table A.2 presents the results from this expanded decomposition for the UK and Europe and compares them with the results from the decomposition outline by equation (1.9) in the main text.

**Table A.2: Variance Decomposition of Local Unemployment-Employment Capital Ratio**

| | **UK** | | **Europe** | |
|---|---|---|---|---|
| *Direct flows: separation and finding rates (%)* | 98 | 98 | 104 | 104 |
| *Separation rate (%)* | 68 | 68 | 82 | 82 |
| *Finding rate (%)* | 30 | 30 | 22 | 22 |
| *Extensive margin due to investment (%)* | – | -11 | – | -10 |
| *Measurement error (%)* | 2 | 13 | -4 | 6 |

Note: This table shows the variance decomposition of the log unemployment-employment capital ratio for the UK and Europe. Columns 2 and 4 show the variance decomposition in equation (1.9), while columns 3 and 5 show the variance decomposition in equation (A.3). Direct flows represent the contributions of separation and finding rates. All numbers are reported in percent.

We recover moderate values for measurement error, ranging from 2 to 13 percent, sug-

gesting a modest role for measurement error or the the steady-state assumption adopted in the analysis. Additionally, we find that the extensive margin of unemployed capital accounts for approximately -11 percent in the UK and -10 percent in Europe. While the contribution of the extensive margin to changes in local unemployed capital is not zero, this augmented decomposition confirm that the predominant source of variation comes again from direct flows, with the separation rate playing a predominant quantitative role.

## A.2 Model Appendix

### A.2.1 Household Euler Equation Derivation

Here we derive the household's Euler equation (1.13). The household solves the following problem:

$$\mathcal{W}(K_j, K_j^e) = \max_{\{K_j'\}} \mathcal{A}_j \log \left( W_j L_j + \int_{z \geq z_j^c} r_j(z) dF(z) K_j^e + (1-\delta)K_j + \Pi_j - p_j^r K_j - p_j^h L_j - K_j' \right) + \beta \mathcal{W}\left(K_j', (1-s_j)(1-\delta)K_j^e + f_j(K_j' - (1-\delta)K_j^e)\right). \tag{A.4}$$

The first order condition with respect to $K_j'$ can be written as

$$\frac{\partial \mathcal{W}_j}{\partial K_j'} = -\frac{\mathcal{A}_j}{C_j} + \beta \left( \frac{\partial \mathcal{W}_j'}{\partial K_j'} + f_j \frac{\partial \mathcal{W}_j'}{\partial K_j^{e'}} \right) = 0. \tag{A.5}$$

Moreover, from the envelope condition, we have $\frac{\partial \mathcal{W}_j'}{\partial K_j'} = (1 - \delta - p_j^{r'})\frac{\mathcal{A}_j}{C_j'}$, which substituted back in the FOC yields the following equation:

$$\frac{\mathcal{A}_j}{C_j} = \beta \left[ (1 - \delta - p_j^{r'}) \frac{\mathcal{A}_j}{C_j'} + f_j \frac{\partial \mathcal{W}_j'}{\partial K_j^{e'}} \right]. \tag{A.6}$$

Define $Q_j \equiv \frac{\mathcal{A}_j}{C_j}$ and $\eta \mathbb{E} S_j \equiv \partial \mathcal{W}(K_j', K_j^{e'}) / \partial K_j^{e'}$ and we have derived the following:

$$Q_j = \beta \left[ Q_j'(1 - \delta - p_j^{r'}) + f_j \eta \mathbb{E} S_j \right], \tag{A.7}$$

which corresponds to equation (1.13).

### A.2.2 Rental Rate of Capital Derivation

Here we derive the rental rate of capital in equation (1.19). Nash bargaining implies

$$\eta V_j^p(z) = (1-\eta)(V_j^e(z) - V_j^u), \tag{A.8}$$

while the free entry condition on (1.18) implies

$$Q_j \frac{\kappa}{q(\theta_j)} = \beta(1-d)\mathbb{E}[V_j^p(z')]^+. \tag{A.9}$$

Combining these two equation together with equations (1.14)-(1.17) yields the following expressions:

$$\begin{aligned} V_j^e(z) - V_j^u &= Q_j r_j(z) + (1-\delta)(1-p(\theta_j))\beta(1-d)\mathbb{E}[V_j^e(z') - V_j^u]^+ && \text{(A.10)} \\ &= Q_j r_j(z) + (1-\delta)(1-p(\theta_j))\beta(1-d)\frac{\eta}{1-\eta}\mathbb{E}[V_j^{p'}]^+, && \text{(A.11)} \\ &= Q_j \left[ r_j(z) + (1-\delta)(1-p(\theta_j))\frac{\eta}{1-\eta}\frac{\kappa}{q(\theta_j)} \right]; && \text{(A.12)} \end{aligned}$$

and

$$V_j^p(z) = Q_j \left( \pi_j(z) - c - r_j(z) + (1-\delta)\frac{\kappa}{q(\theta_j)} \right). \tag{A.13}$$

Substituting these values back in the Nash bargaining equation gives

$$Q_j \eta \left( \pi_j(z) - c - r_j(z) + (1-\delta)\frac{\kappa}{q(\theta_j)} \right) = Q_j(1-\eta) \left[ r_j(z) + (1-\delta)(1-p(\theta_j))\frac{\eta}{1-\eta}\frac{\kappa}{q(\theta_j)} \right], \tag{A.14}$$

which simplifies to

$$r_j(z) = \eta \left( \pi_j(z) - c + (1-\delta)\kappa\theta_j \right). \tag{A.15}$$

### A.2.3 Tightness and Separation Cutoff Elasticities Derivations

#### A.2.3.1 Derivation of Elasticity to Location Fundamentals

We begin by deriving $\frac{\partial \mathcal{W}(K_j', K_j^{e'})}{\partial K_j^{e'}}$, which represents the average surplus accrued to the household from a match with a capital unit, averaged over the idiosyncratic realization of the firm's

productivity shock. This is given by the following expression:

$$\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j \mathbb{E} r_j + \left[(1-s_j)(1-\delta) - f_j(1-\delta)\right] \beta \frac{\partial \mathcal{W}_j'}{\partial K_j^{e'}}. \tag{A.16}$$

The free entry condition, combined with the Nash bargaining solution for the division of total surplus, implies that:

$$\frac{\partial \mathcal{W}_j'}{\partial K_j^{e'}} = \frac{\eta}{1-\eta} \frac{1}{\beta(1-d)(1-F(z_j^c))} Q_j \frac{\kappa}{q(\theta_j)}, \tag{A.17}$$

Combining equations (A.16) and (A.17), the identities $s_j = 1 - (1-d)\left(1-F(z_j^c)\right)$ and $f_j = p(\theta_j)(1-d)\left(1-F(z_j^c)\right)$, and the expression for the rental rate, we obtain:

$$\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j \left( \mathbb{E} r_j + \frac{\eta}{1-\eta}(1-\delta)(1-p(\theta_j)) \frac{\kappa}{q(\theta_j)} \right), \tag{A.18}$$

Substituting this back into the free entry condition yields the following match creation equation:

$$Q_j \frac{\kappa}{q(\theta_j)} = \beta Q_j'(1-d)(1-F(z_j^c))(1-\eta) \left( \mathbb{E}\pi_j(z') - c + (1-\delta) \frac{1-\eta p(\theta_j')}{1-\eta} \frac{\kappa}{q(\theta_j')} \right). \tag{A.19}$$

Imposing steady state and using $\mathbb{A} \equiv \beta(1-d)(1-\delta)$, $\mathbb{E}\pi_j(z') = \mathbb{B} W_j^{-\frac{1-\alpha}{\alpha}} \mathcal{Z}_j \mathbb{E} z'$, and $\mathbb{B} \equiv \frac{\alpha}{1-\alpha}(1-\alpha)^{\frac{1}{\alpha}}$, we obtain the following:

$$\eta \mathbb{A}(1-F(z_j^c))\theta_j + \frac{1-\mathbb{A}(1-F(z_j^c))}{q(\theta_j)} = \frac{1}{1-\delta} \frac{1-\eta}{\kappa} \mathbb{A}(1-F(z_j^c))(\mathbb{B} W_j^{-\frac{1-\alpha}{\alpha}} \mathcal{Z}_j \mathbb{E} z' - c). \tag{A.20}$$

After implicit differentiating the LHS of equation (A.20) with respect to $\mathcal{Z}_j$ the following is obtained:

$$\left( \eta \mathbb{A}(1-F(z_j^c)) + \frac{(1-\mathbb{A}(1-F(z_j^c)))\varepsilon_{q,\theta}}{\theta_j q(\theta_j)} \right) \frac{\partial \theta_j}{\partial \mathcal{Z}_j} + \mathbb{A} \left( \eta \theta_j - \frac{1}{q(\theta_j)} \right) \frac{\partial (1-F(z_j^c))}{\partial z_j^c} \frac{\partial z_j^c}{\partial \mathcal{Z}_j}. \tag{A.21}$$

While implicitly differentiating the RHS of equation (A.20) with respect to $\mathcal{Z}_j$ the following is obtained:

$$\frac{(1-\eta)(1-F(z_j^c))\mathbb{A}\mathbb{B}}{(1-\delta)\kappa}\left(W_j^{-\frac{1-\alpha}{\alpha}}\mathbb{E}z' + W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\frac{\partial\mathbb{E}z_j'}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j} - \frac{1-\alpha}{\alpha}W_j^{-\frac{1}{\alpha}}\frac{\partial W_j}{\partial z_j^c}\mathcal{Z}_j\mathbb{E}z' + \frac{1}{\mathbb{B}}\frac{\mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\mathbb{E}z' - c}{1-F(z_j^c)}\frac{\partial(1-F(z_j^c))}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j}\right). \tag{A.22}$$

Equating (A.21) and (A.22) and rearranging we obtain the following:

$$\begin{aligned}\frac{\partial\theta_j}{\partial\mathcal{Z}_j} &= \frac{\theta_j q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta_j q(\theta_j) + (1-\mathbb{A}(1-F(z_j^c))\varepsilon_{q,\theta}}\frac{(1-\eta)(1-F(z_j^c))\mathbb{A}}{(1-\delta)\kappa}\\ &\times\left(\mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathbb{E}z' + \mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\frac{\partial\mathbb{E}z'}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j} - \mathbb{B}\frac{1-\alpha}{\alpha}W_j^{-\frac{1}{\alpha}}\frac{\partial W_j}{\partial\mathcal{Z}_j}\mathcal{Z}_j\mathbb{E}z' + \frac{\mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\mathbb{E}z' - c}{1-F(z_j^c)}\frac{\partial(1-F(z_j^c))}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j}\right)\\ &- \frac{\theta_j q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta_j q(\theta_j) + (1-\mathbb{A}(1-F(z_j^c))\varepsilon_{q,\theta}}\mathbb{A}\left(\eta\theta_j - \frac{1}{q(\theta_j)}\right)\frac{\partial(1-F(z_j^c))}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j}.\end{aligned} \tag{A.23}$$

We can simplify this expression using the following steps. Rearranging (A.20),

$$\frac{(1-\eta)\mathbb{A}(1-F(z_j^c))}{(1-\delta)\kappa} = \left[\eta\mathbb{A}(1-F(z_j^c))\theta_j + \frac{1-\mathbb{A}(1-F(z_j^c))}{q(\theta_j)}\right]\frac{1}{\mathbb{E}\pi_j(z')-c}, \tag{A.24}$$

and therefore,

$$\begin{aligned}&\frac{\theta q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta q(\theta_j) + (1-\mathbb{A}(1-F(z_j^c)))\varepsilon_{q,\theta}}\frac{(1-\eta)(1-F(z_j^c))\mathbb{A}}{(1-\delta)\kappa}\\ &= \frac{\theta_j q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta_j q(\theta_j) + (1-\mathbb{A}(1-F(z_j^c)))\varepsilon_{q,\theta}}\left[\eta\mathbb{A}(1-F(z_j^c))\theta_j + \frac{1-\mathbb{A}(1-F(z_j^c))}{q(\theta_j)}\right]\frac{1}{\mathbb{E}\pi_j(z')-c},\\ &= \frac{\left[\eta\mathbb{A}(1-F(z_j^c))q(\theta)\theta_j + 1 - \mathbb{A}(1-F(z_j^c))\right]}{\eta\mathbb{A}(1-F(\mathcal{Z}))\theta q(\theta) + (1-\mathbb{A}(1-F(\mathcal{Z})))\varepsilon_{q,\theta}}\frac{\theta}{\mathbb{E}\pi_j(z')-c},\\ &= \Upsilon\frac{\theta}{\mathbb{E}\pi_j(z')-c}.\end{aligned} \tag{A.25}$$

where

$$\begin{aligned}\Upsilon &\equiv \frac{\left[\eta\mathbb{A}(1-F(z_j^c))q(\theta)\theta_j + 1 - \mathbb{A}(1-F(z_j^c))\right]}{\eta\mathbb{A}(1-F(z_j^c))\theta q(\theta) + (1-\mathbb{A}(1-F(z_j^c)))\varepsilon_{q,\theta}},\\ &\equiv \frac{(1-\delta)\beta(1-d)(1-F(z_j^c))\eta p(\theta_j) + (1-(1-\delta)\beta(1-d)(1-F(z_j^c)))}{(1-\delta)\beta(1-d)(1-F(z_j^c))\eta p(\theta_j) + (1-(1-\delta)\beta(1-d)(1-F(z_j^c)))\mu}.\end{aligned} \tag{A.26}$$

Moreover, we get

$$\frac{\theta q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta q(\theta_j)+(1-\mathbb{A}(1-F(z_j^c)))\varepsilon_{q,\theta}}=\Upsilon\frac{\theta_j}{\mathbb{E}\pi_j(z')-c}\times\frac{\kappa}{(1-\eta)(1-F(z_j^c))\mathbb{A}}. \tag{A.27}$$

Substituting everything back (A.23), and expressing in terms of elasticity,

$$\begin{aligned}\varepsilon_{\theta_j,\mathcal{Z}_j}=&\Upsilon\frac{1}{\mathbb{E}\pi_j(z')-c}\times\left(\mathbb{E}\pi_j(z')+\mathbb{E}\pi_j(z')\varepsilon_{\mathbb{E}z',z_j^c}\varepsilon_{z_j^c,\mathcal{Z}_j}-\frac{1-\alpha}{\alpha}\mathbb{E}\pi(z_j')\varepsilon_{W_j,\mathcal{Z}_j}+(\mathbb{E}\pi(z_j')-c)\varepsilon_{1-F(z_j^c),z_j^c}\varepsilon_{z_j^c,\mathcal{Z}_j}\right)\\&+\Upsilon\frac{1}{\mathbb{E}\pi_j(z')-c}\times\frac{\kappa(1-\eta p(\theta_j))}{(1-\eta)q(\theta_j)}\varepsilon_{1-F(z_j^c),z_j^c}\varepsilon_{z_j^c,\mathcal{Z}_j}.\end{aligned} \tag{A.28}$$

Collecting terms, we get

$$\varepsilon_{\theta_j,\mathcal{Z}_j}=\Upsilon_j\frac{\mathbb{E}\pi_j(z')}{\mathbb{E}\pi_j(z')-c}\left[1+\Omega_j\varepsilon_{z_j^c,\mathcal{Z}_j}-\frac{1-\alpha}{\alpha}\varepsilon_{W_j,\mathcal{Z}_j}\right], \tag{A.29}$$

where $\Omega_j$ take the following form:

$$\Omega_j\equiv\varepsilon_{\mathbb{E}z',z_j^c}+\frac{\mathbb{E}\pi_j(z')-c}{\mathbb{E}\pi_j(z')}\left(1+\frac{\kappa(1-\eta p(\theta_j))}{q(\theta_j)(1-\eta)(\mathbb{E}\pi_j(z')-c)}\right)\varepsilon_{1-F(z_j^c),z_j^c}. \tag{A.30}$$

#### A.2.3.2 Derivation of Elasticity to Separation Threshold

Firm's profit maximization problem, (1.16), states that

$$\pi_j(z)=\max_{\ell_j(z)}(\mathcal{Z}_jz)^\alpha\ell_j(z)^{1-\alpha}-W_j\ell_j(z). \tag{A.31}$$

The first-order condition solves:

$$(1-\alpha)(\mathcal{Z}_jz)^\alpha\ell_j(z)^{-\alpha}=W_j, \tag{A.32}$$

which implies:

$$\pi_j(z)=\frac{\alpha}{1-\alpha}(1-\alpha)^{\frac{1}{\alpha}}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_jz. \tag{A.33}$$

Hence, the cut-off threshold from (1.22) can be expressed as

$$0=\frac{\alpha}{1-\alpha}(1-\alpha)^{\frac{1}{\alpha}}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_jz_j^c-c+(1-\delta)\frac{1-\eta p(\theta)}{1-\eta}\frac{\kappa}{q(\theta_j)}. \tag{A.34}$$

Rearranging,

$$z_j^c = \frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}}\frac{1}{\mathcal{Z}_j}W_j^{\frac{1-\alpha}{\alpha}}\left(c + \frac{(1-\delta)\eta}{1-\eta}\kappa\theta - \frac{\kappa}{1-\eta}\frac{1}{q(\theta)}\right). \tag{A.35}$$

Differentiating it with respect to $\mathcal{Z}$ and rearranging it yields the following expressions:

$$\begin{aligned}
\frac{\partial z_j^c}{\partial \mathcal{Z}_j} &= -\frac{1}{\mathcal{Z}_j}z_j^c + \frac{1-\alpha}{\alpha W_j}z_j^c\frac{\partial W_j}{\partial \mathcal{Z}_j} + \frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}}\frac{1}{\mathcal{Z}_j}W_j^{\frac{1-\alpha}{\alpha}}\left(\frac{\eta}{1-\eta} + \frac{1}{1-\eta}\frac{1}{q(\theta)^2}q'(\theta)\right)\kappa(1-\delta)\frac{\partial\theta}{\partial\mathcal{Z}_j}, \\
&= -\frac{1}{\mathcal{Z}_j}\left(\frac{\kappa(1-\delta)}{1-\eta}\frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}}W_j^{\frac{1-\alpha}{\alpha}}\left(-\frac{q'(\theta)}{q(\theta)^2} - \eta\right)\frac{\partial\theta_j}{\partial\mathcal{Z}_j} + z_j^c - \frac{1-\alpha}{\alpha W_j}z_j^c\frac{\partial W_j}{\partial\mathcal{Z}_j}\mathcal{Z}_j\right), \\
&= -\frac{1}{\mathcal{Z}_j}\left(\frac{\kappa(1-\delta)}{1-\eta}\left(-\frac{q'(\theta)}{q(\theta)^2} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j}\theta_j\left(\frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}}W_j^{\frac{1-\alpha}{\alpha}}\mathcal{Z}_j^{-1}\right) + z_j^c - \frac{1-\alpha}{\alpha}z_j^c\varepsilon_{W_j,\mathcal{Z}_j}\right), \\
&= -\frac{1}{\mathcal{Z}_j}\left(\frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(-\frac{q'(\theta)}{q(\theta)^2} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j}z_j^c + z_j^c - \frac{1-\alpha}{\alpha}z_j^c\varepsilon_{W_j,\mathcal{Z}_j}\right), \\
&= -\frac{1}{\mathcal{Z}_j}\left(\frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(\frac{\mu}{p(\theta_j)} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j}z_j^c + z_j^c - \frac{1-\alpha}{\alpha}z_j^c\varepsilon_{W_j,\mathcal{Z}_j}\right),
\end{aligned} \tag{A.36}$$

where the fourth equal sign uses the fact that $\frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}}W_j^{\frac{1-\alpha}{\alpha}}\mathcal{Z}^{-1} = \frac{1}{\pi_j(z_j^c)}z_j^c$. The fifth equal sign uses the fact that $-\frac{q'(\theta)}{q(\theta)^2} = \frac{\varepsilon_{q,\theta}}{p(\theta_j)} \equiv \frac{\mu}{p(\theta_j)}$.

Expressing the above as elasticity, we get

$$\begin{aligned}
\varepsilon_{z_j^c,\mathcal{Z}_j} &= -\frac{1}{\mathcal{Z}}\left(\frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(\frac{\mu}{p(\theta_j)} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j}z_j^c + z_j^c - \frac{1-\alpha}{\alpha}z_j^c\varepsilon_{W_j,\mathcal{Z}_j}\right)\frac{\mathcal{Z}_j}{z_j^c} \\
&= -1 - \frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(\frac{\mu}{p(\theta_j)} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j} + \frac{1-\alpha}{\alpha}\varepsilon_{W_j,\mathcal{Z}_j}.
\end{aligned} \tag{A.37}$$

### A.2.4 Social Planner Derivations

This section solves the social planner's problem discussed in Section 1.4.4. The social planner solves the following optimization problem:

$$\mathcal{W}^{SP}(K_j, K_j^e, z_j^c) = \max_{\{K_j', E_j^k, z_j^{c'}, \ell_j(z), L_j\}} \mathcal{A}_j\log(C_j) + \beta\mathcal{W}^{SP}(K_j', K_j^{e'}, z_j^{c'}), \tag{A.38}$$

subject to the following constraints:

$$C_j = \left[\frac{1}{1-F(z_j^c)}\int_{z\geq z_j^c}\left[(\mathcal{Z}_j z)^\alpha \ell_j(z)^{1-\alpha} - c\right] f(z)dz\right] K_j^e + (1-\delta)K_j - \left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1}{\phi}} - (L_j)^{\frac{1}{\gamma}} - \kappa E_j^k - K_j', \tag{A.39}$$

$$K_j^{e'} = (1-d)(1-F(z_j^{c'}))(1-\delta)K_j^e + p(\theta_j)(1-d)(1-F(z_j^{c'}))(K_j' - (1-\delta)K_j^e), \tag{A.40}$$

$$\theta_j = \frac{E_j^k}{K_j' - (1-\delta)K_j^e}, \tag{A.41}$$

$$L_j = \int_{z\geq z_j^c} \ell_j(z) f(z) dz K_j^e, \tag{A.42}$$

$$\sum_j L_j = \overline{L} \tag{A.43}$$

First order conditions are as follows:

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j'} = -Q_j + \beta\left[\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j'} + \frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}}\frac{\partial K_j^{e'}}{\partial K_j'}\right] = 0, \tag{A.44}$$

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial E_j^k} = -Q_j\kappa + \beta\left[\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}}\frac{\partial K_j^{e'}}{\partial E_j^k}\right] = 0, \tag{A.45}$$

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial z_j^{c'}} = \beta\left(\frac{\partial \mathcal{W}^{\mathcal{SP}'}{}_j}{\partial K_j^{e'}}\frac{\partial K_j^{e'}}{\partial z_j^{c'}} + \frac{\partial \mathcal{W}_j^{SP'}}{\partial z_j^{c'}}\right) = 0, \tag{A.46}$$

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial \ell_j(z)} = Q_j K_j^e \frac{1}{1-F(z_j^r)}\left((1-\alpha)(\ell_j(z))^{-\alpha}(Z_j\mathbb{E}z)^\alpha - W_j\right) = 0, \tag{A.47}$$

$$\frac{\partial W_j}{\partial L_j} = Q_j\left(W_j - \frac{1}{\gamma}(L_j)^{\frac{1-\gamma}{\gamma}}\right) - \mathbb{L} = 0. \tag{A.48}$$

#### A.2.4.1 Derivation of Euler Equation and Capital Creation Equation

Take the first two FOCs, we have

$$Q_j = \beta\left[\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j'} + \frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}}\frac{\partial K_j^{e'}}{\partial K_j'}\right], \tag{A.49}$$

$$Q_j\kappa = \beta\left[\frac{\partial \mathcal{W}_j^{SP\prime}}{\partial K_j^{e\prime}}\frac{\partial K_j^{e\prime}}{\partial E_j^k}\right]. \tag{A.50}$$

We then express each component of these expressions in the following,

$$\frac{\partial K_j^{e\prime}}{\partial K_j'} = (1-d)(1-F(z_j^{c\prime}))\varepsilon_{q,\theta}p(\theta_j), \tag{A.51}$$

and

$$\frac{\partial K_j^{e\prime}}{\partial E_j^k} = (1-d)(1-F(z_j^{c\prime}))(1-\varepsilon_{q,\theta})q(\theta_j). \tag{A.52}$$

and,

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j} = Q_j\left(1-\delta-\frac{1}{\phi\mathcal{P}_j}\left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1-\phi}{\phi}}\right), \tag{A.53}$$

and

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j^e} = Q_j\left(\mathbb{E}\pi_i - c\right) + \beta\left[(1-d)(1-F(z_j^{c\prime}))(1-\delta)\left[1-\varepsilon_{q,\theta}p(\theta_j)\right]\frac{\partial \mathcal{W}_j^{SP\prime}}{\partial K_j^{e\prime}}\right]. \tag{A.54}$$

Taking stock,

$$Q_j = \beta\left[Q_j'\left(1-\delta-\frac{1}{\phi\mathcal{P}_j}\left(\frac{K_j'}{\mathcal{P}_j}\right)^{\frac{1-\phi}{\phi}}\right) + (1-d)(1-F(z_j^{c\prime}))\varepsilon_{q,\theta}p(\theta_j)\frac{\partial \mathcal{W}_j^{SP\prime}}{\partial K_j^{e\prime}}\right], \tag{A.55}$$

and

$$Q_j\kappa = \beta\left[(1-d)(1-F(z_j^{c\prime}))(1-\varepsilon_{q,\theta})q(\theta_j)\frac{\partial \mathcal{W}_j^{SP\prime}}{\partial K_j^{e\prime}}\right], \tag{A.56}$$

and

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j^e} = Q_j\left(\mathbb{E}\pi_i - c\right) + \beta\left[(1-d)(1-F(z_j^{c\prime}))(1-\delta)\left[1-\varepsilon_{q,\theta}p(\theta_j)\right]\frac{\partial \mathcal{W}_j^{SP\prime}}{\partial K_j^{e\prime}}\right]. \tag{A.57}$$

We first examine (A.55), using the fact that $f_j \equiv (1-d)(1-F(z_j^{c\prime}))p(\theta_j)$, $A$, as well as $p_j^{r\prime} = \frac{1}{\phi\mathcal{P}_j}\left(\frac{K_j'}{\mathcal{P}_j}\right)^{\frac{1-\phi}{\phi}}$, (A.55) can be expressed as

$$Q_j = \beta\left[Q_j'(1-\delta-p_j^{r\prime}) + f_j\varepsilon_{q,\theta}\mathbb{E}S_j\right]. \tag{A.58}$$

This expression is identical to 1.13 if $\varepsilon_{q,\theta} = \eta$.

We move on to construct the capital creation equation. Substituting (A.56) into (A.57),

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j^e} = Q_j \left( \mathbb{E}\pi_j - c + (1-\delta)\frac{1-\varepsilon_{q,\theta}p(\theta_j)}{1-\varepsilon_{q,\theta}}\frac{\kappa}{q(\theta_j)} \right), \tag{A.59}$$

rolling one period forward,

$$\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} = Q'_j \left( \mathbb{E}\pi'_j - c + (1-\delta)\frac{1-\varepsilon_{q,\theta}p(\theta'_j)}{1-\varepsilon_{q,\theta}}\frac{\kappa}{q(\theta'_j)} \right). \tag{A.60}$$

Finally, substituting (A.60) back into (A.56)

$$Q_j \frac{\kappa}{q(\theta_j)} = \beta Q'_j (1-d)(1-F(z_j^{c'}))(1-\varepsilon_{q,\theta}) \left( \mathbb{E}\pi'_j - c + (1-\delta)\frac{1-\varepsilon_{q,\theta}p(\theta'_j)}{1-\varepsilon_{q,\theta}}\frac{\kappa}{q(\theta'_j)} \right), \tag{A.61}$$

which is capital creation equation in the decentralized equilibrium (A.19) if $\varepsilon_{q,\theta} = \eta$.

#### A.2.4.2 Derivation of Separation Threshold

The first order condition with respect to the separation threshold is written as

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial z_j^{c'}} = \beta \left( \frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} \frac{\partial K_j^{e'}}{\partial z_j^{c'}} + \frac{\partial \mathcal{W}_j^{SP'}}{\partial z_j^{c'}} \right) = 0. \tag{A.62}$$

As before, we will derive each component of the expression above individually. First, it can be shown that

$$\frac{\partial K_j^{e'}}{\partial z_j^{c'}} = \frac{\partial (1-F(z_j^{c'}))}{\partial z_j^{c'}} \frac{1}{1-F(z_j^{c'})} K_j^{e'}. \tag{A.63}$$

Moreover,

$$\begin{aligned}
\frac{\partial \mathcal{W}_j^{SP'}}{\partial z_j^{c'}} &= Q'_j K_j^{e'} \frac{\partial}{\partial z_j^{c'}} \left[ \frac{1}{1-F(z_j^{c'})} \int_{z_j^{c'}}^{z^{\max}} \left[ \left( (\mathcal{Z}_j z')^{\alpha} \ell_j(z')^{1-\alpha} - W_j \ell_j(z') \right) - c \right] f(z') dz' \right], \\
&= Q'_j K_j^{e'} \left[ -\frac{1}{(1-F(z_j^{c'}))^2} \frac{\partial (1-F(z_j^{c'}))}{\partial z_j^{c'}} \int_{z_j^{c'}}^{z^{\max}} \left[ \left( (\mathcal{Z}_j z')^{\alpha} \ell_j(z')^{1-\alpha} - W_j \ell_j(z') \right) - c \right] f(z') dz' \right] \\
&\quad + Q'_j K_j^{e'} \left[ \frac{1}{1-F(z_j^{c'})} \frac{\partial}{\partial z_j'^{c}} \int_{z_j^{c'}}^{z^{\max}} \left[ \left( (\mathcal{Z}_j z')^{\alpha} \ell_j(z')^{1-\alpha} - W_j \ell_j(z') \right) - c \right] f(z') dz' \right].
\end{aligned} \tag{A.64}$$

Using the Leibniz integral rule,

$$\frac{\partial}{\partial z_j^{c'}} \int_{z_j^{c'}}^{z^{\max}} \left[ \left( (\mathcal{Z}_j z')^{\alpha} \ell_j(z')^{1-\alpha} - W_j \ell_j(z') \right) - c \right] = \frac{\partial (1 - F(z_j^{c'}))}{\partial z_j^{c'}} \left( \pi_j^{c'} - c \right). \tag{A.65}$$

Hence,

$$\begin{aligned} \frac{\partial \mathcal{W}_j^{SP'}}{\partial z_j^{c'}} &= Q_j' K_j^{e'} \left[ -\frac{1}{(1 - F(z_j^{c'}))} \frac{\partial (1 - F(z_j^{c'}))}{\partial z_j^{c'}} (\mathbb{E}\pi_j' - c) + \frac{1}{(1 - F(z_j^{c'}))} \frac{\partial (1 - F(z_j^{c'}))}{\partial z_j^{c'}} (\pi_j^{c'} - c) \right] \\ &= Q_j' K_j^{e'} \frac{1}{1 - F(z_j^{c})} \frac{\partial (1 - F(z_j^{c'}))}{\partial z_j^{c'}} (\pi_j^{c'} - \mathbb{E}\pi_j'). \end{aligned} \tag{A.66}$$

Finally, substituting (A.63), (A.66) as well as the previously derived (A.60) into (A.62),

$$\begin{aligned} 0 &= \frac{\partial (1 - F(z_j^{c'}))}{\partial z_j^{c'}} \frac{1}{1 - F(z_j^{c'})} K_j^{e'} \frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} + Q_j' K_j^{e'} \frac{1}{1 - F(z_j^{c})} \frac{\partial (1 - F(z_j^{c'}))}{\partial z_j^{c'}} (\pi_j^{c'} - \mathbb{E}\pi_j') \\ &= Q_j' \left( \mathbb{E}\pi_j' - c + (1 - \delta) \frac{1 - \varepsilon_{q,\theta'} p(\theta_j)}{1 - \varepsilon_{q,\theta}} \frac{\kappa}{q(\theta_j')} + (\pi_j^{c'} - \mathbb{E}\pi_j') \right), \\ &= \pi_j^{c'} - c + (1 - \delta) \frac{1 - \varepsilon_{q,\theta'} p(\theta_j)}{1 - \varepsilon_{q,\theta}} \frac{\kappa}{q(\theta_j')}. \end{aligned} \tag{A.67}$$

This expression would be the same as 1.22 if $\varepsilon_{q,\theta'} = \eta$.

#### A.2.4.3 Derivation of Labor Wage

The first order condition of firm-level labor demand yields

$$0 = K_j^e \left( (1 - \alpha)(\ell_j(z))^{-\alpha} (\mathcal{Z}_j \mathbb{E}z)^{\alpha} - W_j \right), \tag{A.68}$$

rearranging,

$$\ell_j(z) = \left( \frac{1 - \alpha}{W_j} \right)^{\frac{1}{\alpha}} \mathcal{Z}_j \mathbb{E}z, \tag{A.69}$$

which is identical to the firm-level demand in the decentralized equilibrium as shown in (A.32).

#### A.2.4.4 Derivation of Spatial Equilibrium

The first order condition of aggregate labor demand yields

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial L_j} = Q_j \left( W_j - \frac{1}{\gamma} (L_j)^{\frac{1-\gamma}{\gamma}} \right) = \mathbb{L} \tag{A.70}$$

for all locations, where $\mathbb{L}$ is the Lagrangian multiplier. Recall that from (1.27) $p_j^h = \frac{1}{\gamma} L_j^{\frac{1-\gamma}{\gamma}}$, the above can be written as

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial L_j} = Q_j \left( W_j - p_j^h \right) = \mathbb{L} \tag{A.71}$$

This means that $Q_j \left( W_j - p_j^h \right)$ must be the same for all location. This coincides with the Rosen-Roback spatial equilibrium.

### A.2.5 Optimal Taxation

We derive equation (1.43) in this section. Suppose we give a placed-based subsidy to the unemployed capitalists, so that $\theta_j^{SP} = \theta_j^{DE}$. The representative family solves the following problem:

$$\begin{aligned} \mathcal{W}(K_j K_j^e) = \max_{\{K_j'\}} \mathcal{A}_j \log \Bigg( & W_j L_j + \int_{z \geq z_j^c} r_j(z) dF(z) K_j^e + (1-\delta) K_j + \Pi_j - p_j^r K_j - p_j^h L_j - K_j' + \tau_j \left( K_j - K_j^e \right) \Bigg) \\ & + \beta W \left( K_j', (1-s_j)(1-\delta) K_j^e + f_j(K_j' - (1-\delta) K_j^e) \right). \end{aligned} \tag{A.72}$$

and therefore,

$$\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j \left( \mathbb{E} r_j - \tau_j + \frac{\eta}{1-\eta} (1-\delta)(1-p(\theta_j)) \frac{\kappa}{q(\theta_j)} \right). \tag{A.73}$$

Moreover, household's value functions are now

$$V_j^u = -Q_j(p_j^k - \tau_j) + (1-\delta)\beta \left\{ V_j^u + p(\theta_j)(1-d) \mathbb{E}[V_j^e(z') - V_j^u]^+ \right\}, \tag{A.74}$$

$$V_j^e(z) = Q_j(r_j(z) - p_j^k) + (1-\delta)\beta \left\{ V_j^u + (1-d) \mathbb{E}[V_j^e(z') - V_j^u]^+ \right\}; \tag{A.75}$$

and therefore, the rental rate becomes

$$\mathbb{E}r_j(z) = \eta(\mathbb{E}\pi_j(z) - c + (1-\delta)\kappa\theta_j) + (1-\eta)\tau_j. \tag{A.76}$$

Substituting the rental rate into the expression of $\frac{\partial \mathcal{W}_j}{\partial K_j^e}$,

$$\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j\eta\left(\mathbb{E}\pi_j(z) - c - \tau_j + (1-\delta)\frac{1-\eta p(\theta_j)}{1-\eta}\frac{\kappa}{q(\theta_j)}\right). \tag{A.77}$$

Therefore, the total surplus becomes

$$S_j^{DE}(z) = \frac{1}{\eta}\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j\left(\mathbb{E}\pi_j(z) - c - \tau_j + (1-\delta)\frac{1-\eta p(\theta_j)}{1-\eta}\frac{\kappa}{q(\theta_j)}\right). \tag{A.78}$$

The total surplus under social planner's problem is derived in (A.59), which is restated below,

$$S_j^{SP}(z) = \frac{\partial \mathcal{W}_j^{SP}}{\partial K_j^e} = Q_j\left(\mathbb{E}\pi_j - c + (1-\delta)\frac{1-\varepsilon_{q,\theta}p(\theta_j)}{1-\varepsilon_{q,\theta}}\frac{\kappa}{q(\theta_j)}\right), \tag{A.79}$$

Taking stock, we have the following expressions for the surplus

$$\begin{aligned} DE: \quad & S_j^{DE}(z) = Q_j\left(\mathbb{E}\pi_j(z) - c - \tau_j + (1-\delta)\frac{1-\eta p(\theta_j)}{1-\eta}\frac{\kappa}{q(\theta_j)}\right), \\ SP: \quad & S_j^{SP}(z) = Q_j\left(\mathbb{E}\pi_j(z) - c + (1-\delta)\frac{1-\varepsilon_{q,\theta}p(\theta_j)}{1-\varepsilon_{q,\theta}}\frac{\kappa}{q(\theta_j)}\right). \end{aligned} \tag{A.80}$$

Therefore for $S_j^{DE} = S_j^{SP}$,

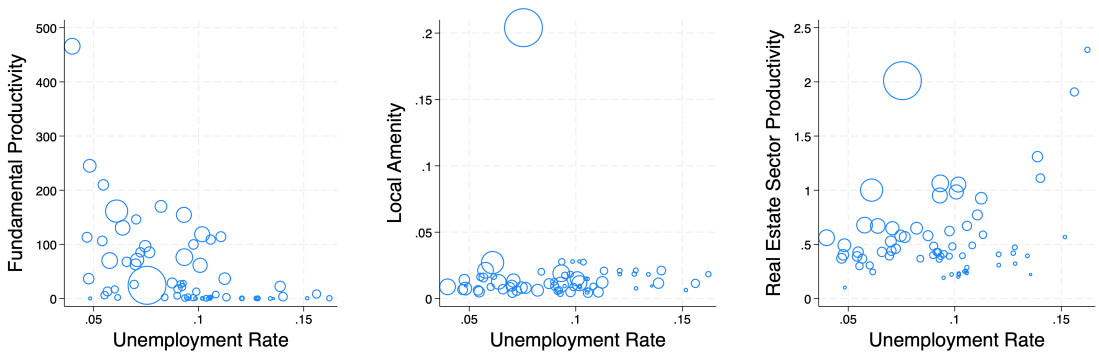
$$\begin{aligned} \tau_j &= \frac{\varepsilon_{q,\theta} - \eta}{1-\eta}\left(\mathbb{E}\pi_j(z) - c + (1-\delta)\kappa\theta_j\right), \\ &= \frac{\mu - \eta}{1-\eta}\left(\mathbb{E}\pi_j(z) - c + (1-\delta)\kappa\theta_j\right). \end{aligned} \tag{A.81}$$

## A.3 Quantitative Appendix

### A.3.1 Location-Specific Parameters

Here, we present the differences in location-specific fundamentals $\{\mathcal{Z}_j, \mathcal{A}_j, \mathcal{P}_j\}_{j=1}^{\infty}$ retrieved from our calibration strategy, as discussed in Table 1.1. In particular, Figure A.8 plots capital unemployment against local productivity, amenity, and real estate sector productivity.

**Figure A.8: Labor productivity, Amenities, and Real Estate Productivity**



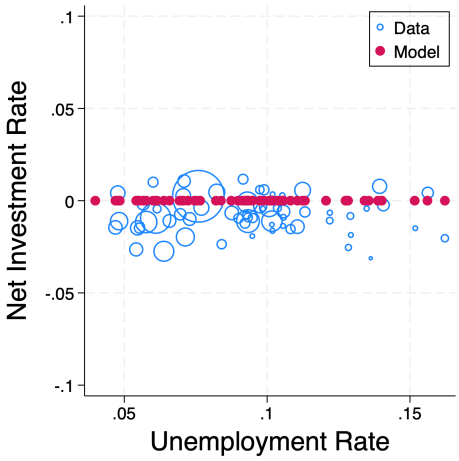

**(a) Local Productivity** **(b) Amenity** **(c) Real Estate Productivity**

Note: Figure A.8 shows the correlations between capital unemployment rate with local fundamental productivity, amenity, and real estate sector productivity in the model. Each circle represents a city in the UK, and the size of it corresponds to the total capital within that city.

## A.3.2 Investment Rates

Here, we validate the investment behavior implied by the model with the findings in the data. Figure A.9 shows the scatterplot of net investment rates from the data and the model against capital unemployment rates. Overall, we find a close fit between the two.

**Figure A.9: Net Investment Rate: Model vs. Data**




Note: Figure A.9 scatterplots net investment rate across cities in the UK against capital unemployment rate from the model (blue) and data (red). The blue open circles represent cities in the UK, and the size of each circle corresponds to the total capital within that city.

### A.3.3 Correlations Between Capital Unemployment Rates and Untargeted Observables

Here, we correlate the local capital unemployment rate with the GDP per capita, GDP per unit of capital, rental rates, and household income. Table A.3 shows the results. Overall, although none of these moments were targeted in the calibration, the model matches them satisfactorily both qualitatively and quantitatively.

**Table A.3: Capital Unemployment Rate and Its Correlates: Model vs Data**

| *Dependent variable* | **Capital Unemployment Rate** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Data | | Model | Data | | Model | Data | | Model | Data | | Model |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| GDP per capita | -0.03 | -0.05$^{+}$ | -0.02*** | | | | | | | | | |
| | (0.02) | (0.03) | (0.00) | | | | | | | | | |
| GDP per unit of capital | | | | -0.12$^{+}$ | -0.19* | -0.03*** | | | | | | |
| | | | | (0.08) | (0.10) | (0.00) | | | | | | |
| Rental Rate | | | | | | | -0.01 | -0.04* | -0.03*** | | | |
| | | | | | | | (0.01) | (0.02) | (0.00) | | | |
| Household Income | | | | | | | | | | -0.02$^{+}$ | -0.01 | -0.01*** |
| | | | | | | | | | | (0.01) | (0.02) | (0.00) |
| *Fixed Effects* | | | | | | | | | | | | |
| City | ✗ | ✓ | | ✗ | ✓ | | ✗ | ✓ | | ✗ | ✓ | |
| Time | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | |
| *Controls* | | | | | | | | | | | | |
| City-specific Time Trend | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | |
| Local capital composition | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | |
| Observations | 855 | 854 | 67 | 855 | 854 | 67 | 987 | 986 | 67 | 538 | 535 | 67 |

Note: Dependent variable is the capital unemployment rate. All independent variables are in logs and are standardized. Standard errors in parentheses are clustered at city level. $^{+}$, *, **, and *** denote 15%, 10%, 5%, and 1% significance respectively.

### A.3.4 Amenities

Here, we correlate the estimated amenities with the local amenity score provided by PMA, as well as with the ONS data on the location's amenity provision per 10,000 people. We standardize all variables to ensure the comparability of units. Table A.4 shows the results. Overall, a higher amenity is positively associated with higher estimated amenities.

### A.3.5 Extensive Margin

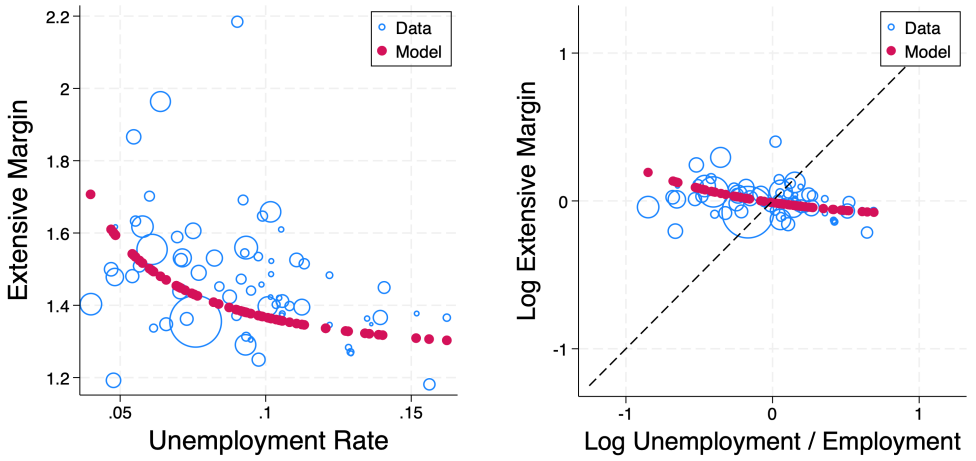
In this section, we compare the contribution of the extensive margin to spatial capital unemployment rate differences in the model and the data.

**Table A.4: Correlation of Estimated Amenities with Observables**

| *Dependent Variable* | **Amenities** | | | | | |
|---|---|---|---|---|---|---|
| Amenity index | 0.225 | | | | | 0.47 |
| | (0.213) | | | | | (0.35) |
| Establishments per 10,000 people | | | | | | |
| General practitioner | | 0.094 | | | | 0.063 |
| | | (0.104) | | | | (0.12) |
| Dentists | | | 0.400 | | | 0.17* |
| | | | (0.280) | | | (0.093) |
| Sports facilities | | | | 0.125** | | 0.69+ |
| | | | | (0.047) | | (0.49) |
| Supermarkets | | | | | 0.081 | 0.54 |
| | | | | | (0.15) | (0.49) |
| Observations | 64 | 53 | 53 | 51 | 57 | 51 |
| $R^2$ | 0.05 | 0.007 | 0.13 | 0.012 | 0.006 | 0.28 |

Note: All variables are standardized to ensure comparability of units. Observations are weighted by location relative size. Robust standard errors are reported in parentheses. +, *, **, and *** denote 15%, 10%, 5%, and 1% statistical significance, respectively.

**Figure A.10: Extensive Margin and Capital Unemployment Gap Differences**




**(a) Raw Data** **(b) Contribution to Decomposition** (A.3)

Note: Figure A.10 illustrates the extensive margin and its contribution to local capital unemployment rate differences in the model (blue) and data (red), across UK locations. In Figure A.10a, the extensive margin is plotted against the local unemployment rate, along with the dashed black 45-degree line. Figure A.10b displays the demeaned log of the extensive margin against the demeaned log of the unemployment-employment capital ratio, also with the dashed black 45-degree line. The size of the circles is proportional to the size of the location.

Figure A.10 presents our results related to the extensive margin. Figure A.10a shows the extensive margin across locations with different capital unemployment rates both in the data

(blue) and the model (red). The model captures well both the decline of the extensive margin with the capital unemployment rate as well as its quantitative magnitude. We recall that none of this has been targeted in our calibration strategy, making it a successful result of the model. Figure A.10b displays the demeaned log of the extensive margin against the demeaned log of the unemployment-employment capital ratio both in the data (blue) and the model (red), as required by the augmented decomposition (A.3) in Appendix A.1.4.

**Table A.5: Variance Decomposition of Local Unemployment-Employment Capital Ratio**

| | **Data** | | **Model** | |
|---|---|---|---|---|
| *Direct flows: separation and finding rates (%)* | 100 | 112 | 100 | 117 |
| *Separation rate (%)* | 69 | 78 | 68 | 79 |
| *Finding rate (%)* | 31 | 34 | 32 | 38 |
| *Extensive margin due to investment (%)* | – | -12 | – | -17 |

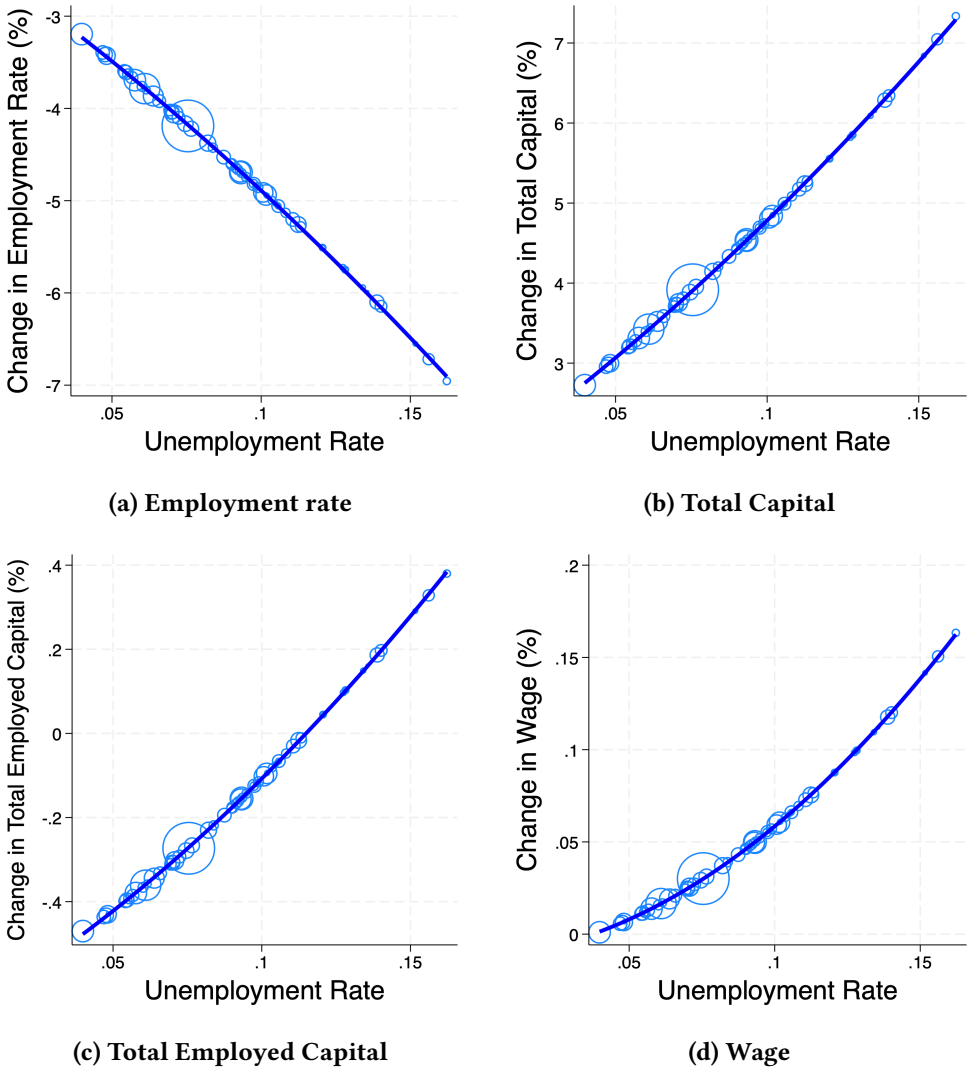
Note: This table compares the variance decomposition of log unemployment-employment capital ratio between data and model. Columns 1 and 3 show the variance decomposition in equation (1.9), while columns 2 and 4 show the variance decomposition in equation (A.3) without measurement error. Direct flows represent the contributions of separation and finding rates. All numbers are reported in percent.

Table A.5 compares the variance decomposition of log unemployment-employment capital ratio between data and model. Columns 1 and 3 show the variance decomposition in equation (1.9) in the model and the data as discussed in the main text, while columns 2 and 4 show the variance decomposition in equation (A.3) without measurement error in the model and the data. The model captures well quantitatively the major contribution of the separation rate and the minor one of the finding rate, as well as the negative contribution of the extensive margin.

### A.3.6 Social Planner Solution

Figure A.11 presents the differences between the social planner's allocation and the decentralized equilibrium across locations, with respect to the capital employment rate, total capital, employed capital, and wages.

**Figure A.11: Changes in Capital Employment Rate, Total Capital, Total Employed Capital and Wage in Social Planner Solution**




**(a) Employment rate** **(b) Total Capital**

**(c) Total Employed Capital** **(d) Wage**

Notes: Figure A.11 plots changes in capital employment rate, total capital, total employed capital, and unemployment rate from the decentralized equilibrium to the social planner's solution. Each circle represents a city, and the size of the circle corresponds to the capital stock. The thick blue line is the quadratic line of the best fit.

# Chapter B

# Appendices for Labor Markets and Migration

## B.1 Model Appendix

### B.1.1 Solving for the Continuous Value of Unemployment

In this section we derive the continuous value of unemployment $\Phi^c_{at}$. To ease notation, the derivations assume that worker types remain fixed, but we note that extending these derivations to allow for changing types is straightforward. Recall that the expression for $v^{U,c}_{at}(\boldsymbol{\varepsilon})$ is,

$$v^{U,c}_{at}(\boldsymbol{\varepsilon}) = b^c_{at} + \beta \max\left\{V^{S,c}_{at} + \nu\varepsilon^c_{at}, \max_{c'\neq c}\{V^{S,c'}_{For,t} - \tau^{c,c'}_a + \nu\varepsilon^{c'}_{at}\}\right\}, \tag{B.1}$$

Therefore, the expression of expected value of unemployment satisfies

$$V^{U,c}_{at}(\boldsymbol{\varepsilon}) = b^c_{at} + \beta\mathbb{E}\left[\max\left\{V^{S,c}_{at} + \nu\varepsilon^c_{at}, \max_{c'\neq c}\{V^{S,c'}_{For,t} - \tau^{c,c'}_a + \nu\varepsilon^{c'}_{at}\}\right\}\right]. \tag{B.2}$$

To simplify the notation, this expression can be written as

$$V^{U,c}_{at} = b^c_{at} + \beta\mathbb{E}\left[\max_{c'}\left\{V^{S,c'}_{at} - \tau^{c,c'}_a + \nu\varepsilon^{c'}_{at}\right\}\right], \tag{B.3}$$

and we seek to solve

$$\Phi_{at}^{c} = \mathbb{E}\left[\max_{c'}\left[V_{at}^{S,c'} - \tau_{a}^{c,c'} + \nu\varepsilon_{at}^{c'}\right]\right]. \tag{B.4}$$

We follow the standard procedure as seen in Caliendo et al. (2019). Define $\frac{(V_a^{S,c'} - V_a^{S,\tilde{c}}) - (\tau_{at}^{c,c'} - \tau_{c,\tilde{c}})}{\nu} = \varepsilon_{-c',\tilde{c}}$. Therefore, the equation above can be re-expressed as

$$\Phi_{at}^{c} = \sum_{c'=1}^{C}\sum_{=0}^{S}\int_{-\infty}^{\infty}\left[V_{at}^{S,c'} - \tau_{a}^{c,c'} + \nu\varepsilon_{at}^{c'}\right] f(\varepsilon_{at}^{c'})\left[\Pi_{\tilde{c}\neq c}F\left(\varepsilon_{-c',\tilde{c}} + \varepsilon_{at}^{c'}\right)\right] d\varepsilon_{at}^{c'}. \tag{B.5}$$

Since $\varepsilon_{at}^{c'}$ are drawn from a Type-I Extreme Value Distribution, $F(\varepsilon_{at}^{c'}) = \exp(-\exp(-\varepsilon_{at}^{c'} - \overline{\gamma}))$, where $\overline{\gamma} \equiv \int_{-\infty}^{\infty} x\exp(-x - \exp(-x))dx$ is the Euler constant. Hence,

$$f(\varepsilon_{at}^{c'}) = \partial F/\partial\varepsilon = \exp(-\varepsilon_{at}^{c'} - \overline{\gamma})\exp[-\exp(-\varepsilon_{at}^{c'} - \overline{\gamma})]. \tag{B.6}$$

Furthermore, after substituting in the definition of $F(.)$,

$$\Pi_{\tilde{c}\neq c}F\left(\varepsilon_{-c',\tilde{c}} + \varepsilon_{c}\right) = \exp\left[-\exp(-\varepsilon_{at}^{c'} - \overline{\gamma}) \times \sum_{\tilde{c}=1}^{C}\text{-}\exp(-\varepsilon_{-c',\tilde{c}})\right] \tag{B.7}$$

Combine the two expressions from the above,

$$f(\varepsilon_{at}^{c'})\Pi_{\tilde{c}\neq c}F\left(\varepsilon_{-c',\tilde{c}} + \varepsilon_{c}\right) = \exp(-\varepsilon_{at}^{c'} - \overline{\gamma})\exp\left[-\exp(-\varepsilon_{at}^{c'} - \overline{\gamma}) \times \sum_{\tilde{c}=1}^{C}\text{-}\exp(-\varepsilon_{-c',\tilde{c}})\right]. \tag{B.8}$$

Define $\lambda_c \equiv \log\sum_{\tilde{c}=1}^{C}\exp(-\varepsilon_{-c',\tilde{c}})$, and $\varsigma_{c'} = \varepsilon_{c'} + \overline{\gamma}$, then

$$\Phi_{at}^{c} = \sum_{c'=1}^{C}\int_{-\infty}^{\infty}\left[V_{at}^{S,c'} - \tau_{a}^{c,c'} + \nu(\varsigma_{c',} - \overline{\gamma})\right]\exp\left\{-\varsigma_{c',} - \exp[-(\varsigma_{c',} - \lambda_{c',})]\right\} d\varsigma_{c',}. \tag{B.9}$$

Define $\tilde{\mathcal{Y}}_{c'} = \varsigma_{c'} - \lambda_{c',}$. The expression above becomes

$$\Phi_{at}^{c} = \sum_{c'=1}^{C}\exp(-\lambda_{c'})\left[V_{at}^{S,c'} - \tau_{a}^{c,c'} + \nu\lambda_{c',}\right]. \tag{B.10}$$

where we use the fact that $\int_{-\infty}^{\infty} \exp\left\{-\tilde{\mathcal{Y}}_{c',} - \exp(-\tilde{\mathcal{Y}}_{c',})\right\} = 1$, and the last equal sign is due to the definition of $\overline{\gamma}$. After substituting in the definition of $\lambda_{c'}$,, the expression above can be written as

$$\Phi_{at}^{c} = \sum_{c'=1}^{C} \exp\left[-\log \sum_{\tilde{c}=1}^{C} \exp(-\varepsilon_{-c',\tilde{c}})\right]\left[V_{at}^{S,c'} - \tau_{at}^{c,c'} + \nu \log \sum_{\tilde{c}=1}^{C} \exp(-\varepsilon_{-c',\tilde{c}})\right]. \quad \text{(B.11)}$$

Moreover,

$$\exp\left(-\log \sum_{\tilde{c}=1}^{C} \exp(-\varepsilon_{-c',\tilde{c}})\right) = \frac{\exp(V_{at}^{S,c'} - \tau_{a}^{c,c'})^{\frac{1}{\nu}}}{\sum_{\tilde{c}=1}^{C} \exp(V_{at}^{S,\tilde{c}} - \tau_{a}^{c,\tilde{c}})^{\frac{1}{\nu}}}. \quad \text{(B.12)}$$

Therefore,

$$\Phi_{at}^{c} = \sum_{c'=1}^{C} \frac{\exp(V_{at}^{S,c'} - \tau_{a}^{c,c'})^{\frac{1}{\nu}}}{\sum_{\tilde{c}=1}^{C} \exp(V_{at}^{S,\tilde{c}} - \tau_{a}^{c,\tilde{c}})^{\frac{1}{\nu}}}\left[V_{at}^{S,c'} - \tau_{a}^{c,c'} + \nu \log \sum_{\tilde{c}=1}^{C} \exp(-\varepsilon_{-c',\tilde{c}})\right]. \quad \text{(B.13)}$$

Moreover,

$$\nu \log \sum_{\tilde{c}=1}^{C} \exp(-\varepsilon_{-c',\tilde{c}}) = -(V_{at}^{S,c'} - \tau_{a}^{c,c'}) + \nu \log \sum_{\tilde{c}=1}^{C} \exp(V_{at}^{S,\tilde{c}} - \tau_{a}^{c,\tilde{c}})^{\frac{1}{\nu}}. \quad \text{(B.14)}$$

Substitute this expression into the expression of $\Phi_{at}^{c'}$, we have

$$\Phi_{at}^{c} = \nu\left[\log \sum_{c'}\left(\exp\left(V_{at}^{S,c'} - \tau_{a}^{c,c'}\right)\right)^{1/\nu}\right]. \quad \text{(B.15)}$$

Given that the household's type is $a' = For$ if they migrate, and the cost of staying in the same country is zero,

$$\Phi_{at}^{c} = \nu \log\left[\exp\left(V_{at}^{S,c}\right)^{1/\nu} + \sum_{c' \neq c}\left(\exp\left(V_{For,t}^{S,c'} - \tau_{a}^{c,c'}\right)\right)^{1/\nu}\right]. \quad \text{(B.16)}$$

### B.1.2 Derivation of Wage

In this section we derive the wage rate from (2.10). Let $\eta$ be worker's bargaining power, the Nash Bargaining Solution and the free-entry condition imply that

$$V_{at}^{W,c}(z) - V_{at}^{U,c} = \frac{\eta}{1-\eta} V_{at}^{J,c}(z). \tag{B.17}$$

After Substituting in (2.2), (2.5) and (2.8), (B.17) can be written as

$$\begin{aligned} & w_{at}^{c}(z) - (1-\beta)b_{at}^{c} - \beta(1-\beta)\Phi_{at}^{c} + \beta(1-\delta_{at}^{c})\mathbb{E}_{z'|z}\max\{V_{at}^{W,c}(z') - V_{at}^{U,c}, 0\} \\ & = \frac{\eta}{1-\eta}\left[y_{at}^{c}(z) - w_{at}^{c}(z) + \beta(1-\delta_{at}^{c})\mathbb{E}_{z'|z}\max\{V_{at}^{J,c}(z'), 0\}\right]. \end{aligned} \tag{B.18}$$

Nash Bargaining Solution implies $\mathbb{E}_{z'|z}\max\{V_{at}^{W,c}(z') - V_{at}^{U,c}, 0\} = \frac{\eta}{1-\eta}\mathbb{E}_{z'|z}\max\{V_{at}^{J,c}(z'), 0\}$, and therefore,

$$\begin{aligned} & w_{at}^{c}(z) - (1-\beta)b_{at}^{c} - \beta(1-\beta)\Phi_{at}^{c} + \beta(1-\delta_{at}^{c})\frac{\eta}{1-\eta}\mathbb{E}_{z'|z}\max\{V_{at}^{J,c}(z'), 0\} \\ & = \frac{\eta}{1-\eta}\left[y_{at}^{c}(z) - w_{at}^{c}(z) + \beta(1-\delta_{at}^{c})\mathbb{E}_{z'|z}\max\{V_{at}^{J,c}(z'), 0\}\right] \end{aligned} \tag{B.19}$$

Rearranging, the wage rate $w_{at}^{c}(z)$ solves

$$w_{at}^{c}(z) = (1-\eta)(1-\beta)\left[b_{at}^{c} + \beta\Phi_{at}^{c}\right] + \eta y_{at}^{c}(z). \tag{B.20}$$

### B.1.3 Derivation of the Migration Flows

In this section, we solve the fraction of workers who reallocate from labor market $c$ to $c'$. This fraction is equal to the probability that the utility of moving to $c'$ is higher than the utility of moving to any other labor market. Let $\mu_{at}^{c,c'}$ as the fraction of workers who reallocate from labor market $c$ to $c'$. Then

$$\begin{aligned} \mu_{at}^{c,c'} &= \Pr\left(V_{at}^{S,c'} - \tau_{at}^{c,c'} + \nu\varepsilon_{at}^{c'} \geq \max_{\tilde{c}\neq c}\left\{V_{at}^{S,\tilde{c},} - \tau_{a}^{c,\tilde{c}} + \nu\varepsilon_{at}^{\tilde{c}}\right\}\right), \\ &= \Pr\left(\varepsilon_{at}^{\tilde{c}} \leq \frac{(V_{at}^{S,c'} - V_{at}^{S,\tilde{c}}) - (\tau_{a}^{c,c'} - \tau_{a}^{c,\tilde{c}})}{\nu} + \varepsilon_{at}^{c'}\right) \text{ for all } \tilde{c} \neq c'. \end{aligned} \tag{B.21}$$

Because the taste shocks are i.i.d., and recall the definition of $\varepsilon_{-c',\tilde{c}\tilde{s}}$,

$$\begin{aligned}\mu_{at}^{c,c'} &= \int_{-\infty}^{\infty} f(\varepsilon_c)\Pi_{\tilde{c}\neq c}F\left(\varepsilon_{-c',\tilde{c}}+\varepsilon_{at}^{c'}\right)d\varepsilon_{at}^{c'},\\ &= \int_{-\infty}^{\infty}\exp(-\varepsilon_{at}^{c'}-\overline{\gamma})\times\exp\left[-\exp(-\varepsilon_{at}^{c'}-\overline{\gamma})\times\sum_{\tilde{c}=1}^{C}\text{-}\exp(-\varepsilon_{-c',\tilde{c}})\right]d\varepsilon_{at}^{c'},\end{aligned} \tag{B.22}$$

where the second equal sign is derived in Section B.1.1.Recall that we have defined $\lambda_{c',} \equiv \log\sum_{\tilde{c}=1}^{C}\exp(-\varepsilon_{-c',\tilde{c}})$, and $\varsigma_{c'} = \varepsilon_{c'}+\overline{\gamma}$. Then, the equation above can be re-expressed as

$$\mu_{at}^{cs,c'} = \int_{-\infty}^{\infty}\exp\left\{-\varsigma_{c',}-\exp[-(\varsigma_{c',}-\lambda_{c',})]\right\}d\varsigma_{c',}. \tag{B.23}$$

Moreover, recall that $\tilde{\mathcal{Y}}_{c'} = \varsigma_{c'}-\lambda_{c'}$, Then, we expression above can be written as

$$\begin{aligned}\mu_{at}^{c,c'} &= \int_{-\infty}^{\infty}\exp\left[-(\tilde{\mathcal{Y}}_{c'}+\lambda_{c'})-\exp(-\tilde{\mathcal{Y}}_{c'})\right]d\varsigma_{c'}\\ &= \exp(-\lambda_{c',})\left\{\exp\left[-\exp(-\tilde{\mathcal{Y}}_{c'})\right]\right\}_{-\infty}^{\infty}\\ &= \exp(-\lambda_{c'}).\end{aligned} \tag{B.24}$$

Substitute in the definition $-\lambda_{c'}$,

$$\mu_{at}^{c,c'} = \exp\left(-\log\sum_{\tilde{c}=1}^{C}\exp(-\varepsilon_{-c',\tilde{c}})\right). \tag{B.25}$$

This expression has been derived in (B.12) from Section B.1.1, and therefore,

$$\mu_{at}^{c,c'} = \frac{\exp(V_{at}^{S,c'}-\tau_a^{c,c'})^{\frac{1}{\nu}}}{\sum_{\tilde{c}=1}^{C}\exp(V_{at}^{S,\tilde{c}}-\tau_a^{c,\tilde{c}})^{\frac{1}{\nu}}}. \tag{B.26}$$

Recall that $\tilde{a}$ takes value $Dom$ if $c'=c$ and value $For$ if $c'\neq c$, the expression above can be written as

$$\mu_{at}^{c,c'} = \frac{\exp(V_{\tilde{a}t}^{S,c'}-\tau_a^{c,c'})^{1/\nu}}{\exp(V_{at}^{S,c})^{1/\nu}+\sum_{\tilde{c}\neq c}\exp(V_{For,t}^{S,\tilde{c}}-\tau_a^{c,\tilde{c}})^{1/\nu}}. \tag{B.27}$$

### B.1.4 Derivation of Migration Flows Using the Outside Option

Migration flows from a submarket $c$ to $c'$ can be written as

$$\mu_{at}^{c,c'} = \frac{\exp(V_{\tilde{a}t}^{S,c'} - \tau_a^{c,c'})^{1/\nu}}{\exp(V_{at}^{S,c})^{1/\nu} + \sum_{\tilde{c}\neq c}\exp(V_{For,t}^{S,\tilde{c}} - \tau_a^{c,\tilde{c}})^{1/\nu}}, \tag{B.28}$$

Therefore, the total out-migration rate from into a submaet $c$ becomes

$$\sum_{c'}\mu_{at}^{c,c'} = \frac{\sum_{\tilde{c}\neq c}\exp(V_{at}^{S,c'} - \tau_a^{c,c'})^{1/\nu}}{\sum_{\tilde{c}\neq c}\exp(V_{at}^{S,\tilde{c}} - \tau_a^{c,\tilde{c}})^{1/\nu} + \exp(V_{at}^{S,c})^{1/\nu}} \tag{B.29}$$

given that the migration cost of staying in the same submarket $\tau_a^{c,c} = 0$. Let $\exp\left(\overline{V}_{at}^{c}\right)^{1/\nu} \equiv \sum_{\tilde{c}\neq c}\exp(V_{at}^{S,\tilde{c}} - \tau_a^{c,\tilde{c}})^{1/\nu}$, and define the total out-migration rate $\sum_{c'}\mu_{at}^{c,c'} \equiv \underline{\mu}_{at}^{c}$, we have

$$\underline{\mu}_{at}^{c} = \frac{\exp\left(\overline{V}_{at}^{c}\right)^{1/\nu}}{\exp\left(V_{at}^{S,c}\right)^{1/\nu} + \exp\left(\overline{V}_{at}^{c}\right)^{1/\nu}}. \tag{B.30}$$

Moreover, we have

$$\Phi_{at}^{c} = \nu\left[\log\sum_{c'}\left(\exp\left(V_{at}^{S,c'} - \tau_a^{c,c'}\right)\right)^{1/\nu}\right], \tag{B.31}$$

and after substituting in the definition of $\overline{V}_{at}^{c}$, we have

$$\Phi_{at}^{c} = \nu\log\left[\exp\left(V_{at}^{S,c}\right)^{1/\nu} + \exp\left(\overline{V}_{at}^{c}\right)^{1/\nu}\right].$$

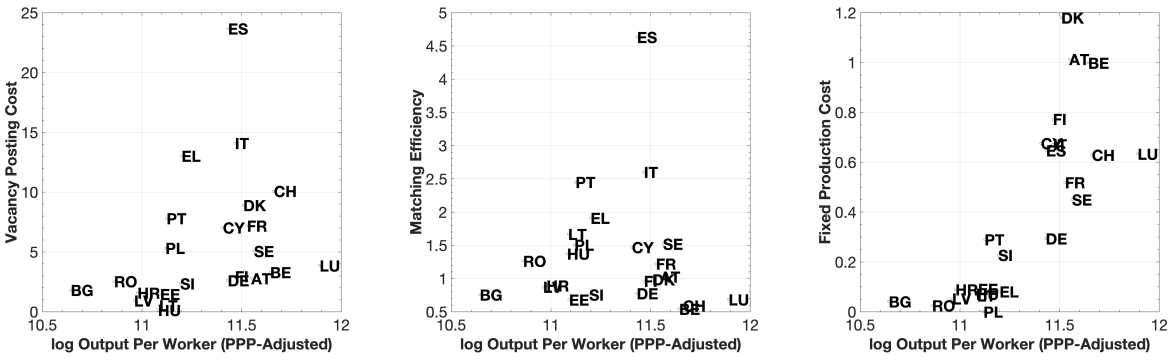
## B.2 Quantitative Appendix

### B.2.1 Calibrated Parameters

In this section, we plot the additional parameters calibrated internally against log output per worker. Figure B.1a to B.1c plot vacancy posting cost $\kappa^c$, matching efficiency $m^c$ and fixed production cost $\chi^c$ against log of output per worker.

Figure B.2 displays the adjusted bilateral migration flows for all origin-destination pairs, where each cell reports the ratio of migrants moving from origin $c$ to destination $c'$ relative

**Figure B.1: Calibrated Parameters**

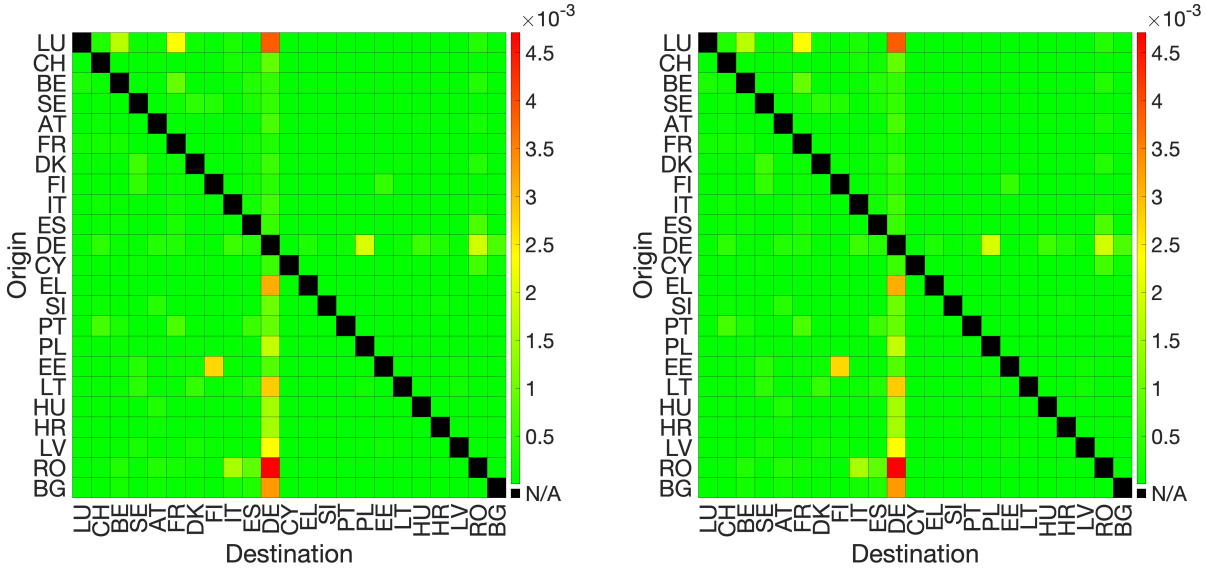



**(a) Vacancy Posting Cost** **(b) Matching Efficiency** **(c) Fixed Production Cost**

Note: Figure B.1a to B.1c plot vacancy posting cost $\kappa^c$, matching efficiency $m^c$ and fixed production cost $\chi^c$ against PPP-adjusted log of output per worker.

to non-migrants remaining in $c$. Countries are ordered by output per worker from highest to lowest. Green cells correspond to low flow intensities and red cells to high flow intensities. Figures B.2a and B.2b present the corresponding matrices implied by the model and observed in the data, respectively.

**Figure B.2: Separation and Finding Rate Differences**




**(a) Bilateral Migration Flow Model** **(b) Bilateral Migration Flow Data**

Note: Figure B.2 displays the adjusted bilateral migration flows for all origin-destination pairs, where each cell reports the ratio of migrants moving from origin $c$ to destination $c'$ relative to non-migrants remaining in $c$. Countries are ordered by PPP-adjusted output per worker from highest to lowest. Green cells correspond to low flow intensities and red cells to high flow intensities. Figures B.2a and B.2b present the corresponding matrices implied by the model and observed in the data, respectively.

# Chapter C

# Appendices for Searching Costs in the Rental Housing Market and Internal Migration

## C.1 Institutional Background in the European Rental Housing Market

Appendix C.1 provides information on the institutional backgrounds in European housing market.

### C.1.1 United kingdom

The United Kingdom's rental housing market is highly intermediated, with letting agents controlling many stages of the rental process. In 2024, 72% of landlords let their properties through agents (OpenRent, 2024). As a result, tenants typically must schedule viewings around agents' availability. Although the Tenant Fees Act 2019 prohibits charging for viewings, some agents have sought to circumvent the rule by introducing a guarantee fee, according to multiple reports. Agents have also been reported to initiate bidding wars, pushing rents above advertised levels (Evening Standard, 2024). Beyond matching tenants and landlords, agents manage essential compulsory administrative tasks, such as anti-money laundering checks.

### C.1.2 Germany

With 57% of households renting their homes, the rental housing market constitutes a major segment of Germany's housing sector. It is also a market characterized by substantial intermediation. Private landlords control between 65% and 70% of rental properties, and around 70% of them rely on real estate agents to manage their lettings (ProFido Consulting, 2024). Agents play a critical intermediary role, handling tenant selection, contract negotiations, and legal compliance. Although the Bestellerprinzip (Ordering Principle) prohibits landlords from passing agent commissions directly onto tenants, these costs can be indirectly transferred through higher rents (Makler-Vergleich.de, 2024).

### C.1.3 Netherlands

The Netherlands' rental housing market faces severe challenges due to a critical shortage of supply, amplifying the role of real estate agents, who now facilitate over 50% of rental transactions (NVM, 2024). Tenants typically must go through agents to arrange viewings and negotiate lease terms. Although regulations are in place to protect tenants, some agents have been involved in unlawful practices, including illegal eviction attempts. In addition, agents handle key administrative tasks, such as verifying income and identity documents, further reinforcing their central role in the rental process.

Beyond the cases discussed, the heavy involvement of intermediaries is also a common feature in other European countries. This reliance increases search costs for tenants, who must work through agent-controlled processes to access and secure rental housing.

## C.2 Model Appendix

### C.2.1 Comparative Statics of Aggregate Consumption

In this section, I derive the comparative statics of aggregate consumption with respect to location primitives. Aggregate housing consumption can be expressed solely as a function of $\theta$:

$$\mathcal{C}(\theta) = (f(\theta) - \rho\theta)\bar{K}. \tag{C.1}$$

Given that the search cost $\tau(\theta)$ depends only on $\theta$, aggregate housing supply can equivalently be expressed as a function of search costs.

From equation (3.12), it is clear that variations in endowment $\mu$, housing preference $\chi$, and housing stock $\bar{K}$ influence market tightness $\theta$, which in turn affects aggregate consumption. In what follows, I derive the comparative statics of aggregate consumption with respect to changes in these fundamental parameters. The first order condition of $\mathcal{C}$ with respect to endowment $\mu$ and housing taste parameter $\chi$ are as follows:

$$\frac{\partial \mathcal{C}(\theta)}{\partial \mu} = (f'(\theta) - \rho)\bar{K}\frac{\partial \theta}{\partial \mu}, \tag{C.2}$$

$$\frac{\partial \mathcal{C}(\theta)}{\partial \chi} = (f'(\theta) - \rho)\bar{K}\frac{\partial \theta}{\partial \chi}. \tag{C.3}$$

Moreover, C.2.2 shows that (C.1) is identical to $\mathcal{C}(\theta) = \frac{\chi^\epsilon \bar{\mu}}{p_0}(1+\tau(\theta))^{-\epsilon}\left(\frac{\mu N \chi^\epsilon}{\bar{K}}\right)^{-\xi} N$, and hence, the first order condition with respect to housing stock $\bar{K}$ satisfies

$$\frac{\partial \mathcal{C}(\theta)}{\partial \bar{K}} = \frac{\chi^\epsilon \bar{\mu}}{p_0}\left[-\epsilon(1+\tau(\theta))^{\epsilon-1}\left(\frac{\mu N \chi^\epsilon}{\bar{K}}\right)^{-\xi} N\tau'(\theta)\frac{\partial \theta}{\partial \bar{K}} + (1+\tau(\theta))^{-\epsilon}\left(\mu N \chi^\epsilon\right)^{-\xi} N\bar{K}^{\xi-1}\xi\right]. \tag{C.4}$$

From (3.12)

$$\frac{\partial \theta}{\partial \mu} = \frac{(1-\xi)\left(\frac{\mu N \chi^\epsilon}{\bar{K}}\right)^{-\xi}\frac{N\chi^\epsilon}{p_0 \bar{K}}}{f'(\theta)(1+\tau(\theta))^{\epsilon-1} + f(\theta)(\epsilon-1)(1+\tau(\theta))^{\epsilon-2}\tau'(\theta)} > 0, \tag{C.5}$$

$$\frac{\partial \theta}{\partial \chi} = \frac{(1-\xi)\left(\frac{\mu N \chi^\epsilon}{\bar{K}}\right)^{-\xi}\frac{\mu N}{p_0 \bar{K}}\epsilon\chi^{\epsilon-1}}{f'(\theta)(1+\tau(\theta))^{\epsilon-1} + f(\theta)(\epsilon-1)(1+\tau(\theta))^{\epsilon-2}\tau'(\theta)} > 0, \tag{C.6}$$

and from the definition of $\theta$, $\frac{\partial \theta}{\partial \bar{K}} < 0$. Substituting the partial derivatives into equations (C.2), (C.3), and (C.4), and noting that $\epsilon > 1$, it follows that $\frac{\partial \mathcal{C}(\theta)}{\partial \mu} < 0$ and $\frac{\partial \mathcal{C}(\theta)}{\partial \xi} < 0$ whenever $f'(\theta) - \rho < 0$, and the opposite holds when $f'(\theta) - \rho > 0$. Additionally, $\frac{\partial \mathcal{C}(\theta)}{\partial \bar{K}} > 0$ for all values of $\theta$.

Since $\tau'(\theta) > 0$, these results highlight that the effect of demand-side factors—namely $\mu$ and $\xi$—on aggregate housing consumption is non-linear and mediated by the level of search cost $\tau(\theta)$. When $f'(\theta) - \rho < 0$, indicating a high search cost environment, an increase in housing demand reduces consumption due to heightened congestion effects. Conversely, when search costs are low, an increase in demand leads to higher consumption. In contrast, ex-

panding housing supply unambiguously raises housing consumption by increasing productive capacity.

### C.2.2 Alternative Expression of Aggregate and Per Capita Consumption

In this section, I show that aggregate consumption can be expressed alternatively, which helps us to derive the first order condition with respect to housing stock. Multiplying $(1+\tau(\theta))^{-\epsilon}\bar{K}$ on both sides of (3.12),

$$\frac{f(\theta)\bar{K}}{1+\tau(\theta)} = \frac{\chi^{\epsilon}\bar{\mu}}{p_0}(1+\tau(\theta))^{-\epsilon}\left(\frac{\mu N\chi^{\epsilon}}{\bar{K}}\right)^{-\xi} N, \tag{C.7}$$

where the left hand side of the equation above is exactly the aggregate consumption derived in (3.7). Therefore, we can express aggregate and per capita housing consumption as

$$\mathcal{C}(\theta) = \frac{\chi^{\epsilon}\bar{\mu}}{p_0}(1+\tau(\theta))^{-\epsilon}\left(\frac{\mu N\chi^{\epsilon}}{\bar{K}}\right)^{-\xi} N; \tag{C.8}$$

$$c(\theta) = \frac{\chi^{\epsilon}\bar{\mu}}{p_0}(1+\tau(\theta))^{-\epsilon}\left(\frac{\mu N\chi^{\epsilon}}{\bar{K}}\right)^{-\xi}. \tag{C.9}$$

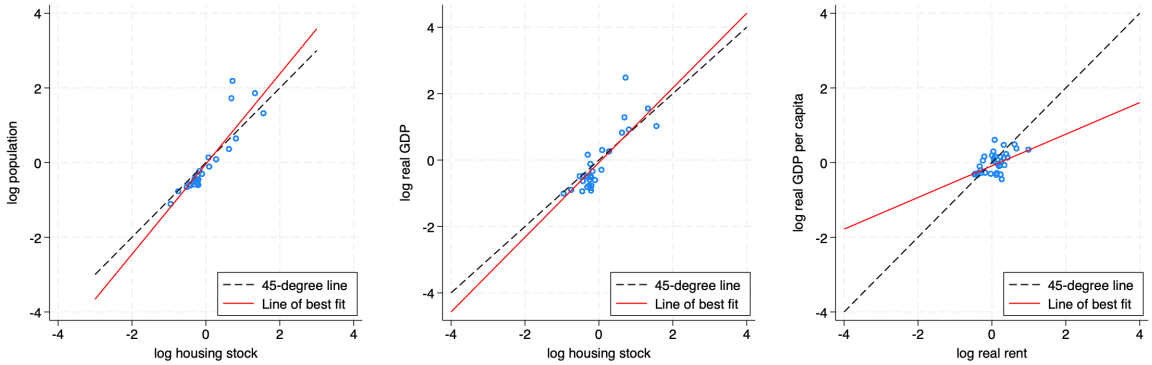
## C.3 Data Appendix

### C.3.1 Data Validation

Here, I conduct additional data validation exercises. First, C.1 presents scatterplots of PMA's rental property stock and rental rate against local economic indicators, with each circle representing a city. The solid red lines show the best fit, while the dotted black lines are 45-degree lines. Panels C.1a and C.1b display the relationship between demeaned log rental property stock and both demeaned log population and demeaned log real GDP. These panels highlight the well-known fact that larger cities, in terms of population and economic activity, tend to have more rental properties. Panel C.1c illustrates the correlation between demeaned log real rent and demeaned log real GDP per capita, confirming the commonly observed trend that more prosperous areas tend to have higher rental prices (OECD and Eurostat (2012)).

**Figure C.1: Cross-sectional Validation**

**(a)** Housing stock and population **(b)** Housing stock and local GDP **(c)** Housing rent and GDP per capita




**Notes:** Figure C.1 scatterplots granular housing data provided by PMA against local economic data. Each circle represents a city. The solid red lines depict the line of best fit, where the dotted black lines are the 45-degree lines. Panels C.1a and C.1b depict the relationship between demeaned log rental property stock and both demeaned log population, as well as demeaned log real GDP. Panel C.1c illustrates the correlation between demeaned log real rent and demeaned log real GDP per capita.

### C.3.2 Baseline Regression Robustness Check

Appendix C.3.2 performs two robustness tests. The first robustness test estimates equation (3.16) and (3.17) using bootstrap standard errors. The second robustness test uses average rental rate and real GDP per capita as proxies of the rental housing market tightness in (3.17).

Table C.1 demonstrates that the main results remain robust when using bootstrap standard errors, although the statistical significance of some estimates is reduced. Table C.2 further supports the non-linear relationship between housing search cost and out-migration, as the signs of the point estimates vary across the spectrum from the loosest to the tightest housing markets.

**Table C.1: Out-Migration and Rental Housing Search Cost - Bootstrap SE**

| Dep. Variable: | Net Out-migration Rate | | | | |
|---|---|---|---|---|---|
| | Panel A | Panel B | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Rental Housing Search Cost | 0.200*** | | | | |
| | (0.0521) | | | | |
| Rental Housing Search Cost $1^{st}$ Quartile | | -0.359$^{+}$ | | | |
| | | (0.226) | | | |
| Rental Housing Search Cost $2^{nd}$ Quartile | | | -0.026 | | |
| | | | (0.060) | | |
| Rental Housing Search Cost $3^{rd}$ Quartile | | | | 0.168 | |
| | | | | (0.168) | |
| Rental Housing Search Cost $4^{th}$ Quartile | | | | | 0.155 |
| | | | | | (0.211) |
| $N$ | 266 | 266 | | | |
| adj. $R^2$ | 0.31 | 0.41 | | | |
| City & country FE | ✓ | ✓ | | | |
| Time FE | ✓ | ✓ | | | |
| Bootstrap SE | ✓ | ✓ | | | |
| Controls | ✓ | ✓ | | | |

Standard errors in parentheses

$^{+}$ $p < 0.20$, $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Notes:** Panel A of Table C.1 presents the estimation result from equation (3.16). Column (1) reports the baseline estimate of $\beta_1$, capturing the correlation between housing market congestion and net out-migration. Panel B reports results from equation (3.17), with columns (2)–(5) displaying heterogeneous effects by market tightness quartile. All regressions include controls for real housing rental rate, real disposable income per capita and local unemployment rates.

**Table C.2: Out-Migration and Rental Housing Search Cost - Alternative Specifications of Tightness**

| Dep. Variable: | Net Out-migration Rate | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Panel A | | | | Panel B | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Rental Housing Search Cost $1^{st}$ Quartile | -0.416** | | | | -0.177 | | | |
| | (0.174) | | | | (0.140) | | | |
| Rental Housing Search Cost $2^{nd}$ Quartile | | 0.144* | | | | 0.141$^{+}$ | | |
| | | (0.078) | | | | (0.105) | | |
| Rental Housing Search Cost $3^{rd}$ Quartile | | | 0.009 | | | | 0.183 | |
| | | | (0.058) | | | | (0.216) | |
| Rental Housing Search Cost $4^{th}$ Quartile | | | | 0.134 | | | | 0.186*** |
| | | | | (0.104) | | | | (0.041) |
| $N$ | 268 | | | | 268 | | | |
| adj. $R^2$ | 0.40 | | | | 0.36 | | | |
| City & country FE | ✓ | | | | ✓ | | | |
| Time FE | ✓ | | | | ✓ | | | |
| Cluster Robust SE | ✓ | | | | ✓ | | | |
| Controls | ✓ | | | | ✓ | | | |

Standard errors in parentheses

$^{+}$ $p < 0.20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Notes:** Panel A of Table C.2 presents the estimation results from equation (3.17) using average housing rental rate as a proxy of housing market tightness. Panel B estimates the same equation but uses real GDP per capita as a proxy of housing market tightness. All regressions include controls for real housing rental rate, real disposable income per capita, and local unemployment rates.

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