Unemployed Capital in Space*

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This paper uses a unique dataset to highlight a set of novel facts about the importance, determinants, and persistence of spatial differences in capital unemployment—defined as idle units searching to be traded. The data show that these differences are primarily driven by variations in separation rates between capital and firms across locations. We demonstrate that a spatial search-and-matching model of local capital markets can quantitatively account for these patterns. Frictions in local capital markets significantly reduce aggregate output and reveal that the social planner's allocation does not necessarily align with the decentralized equilibrium, highlighting potential welfare gains from place-based policies.

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

JEL Codes: E20, E22, E60, R12, R13, R30, R33

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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).[1] 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, important for local prosperity, 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, thereby underscoring the potential for significant welfare gains through 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

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

and covers 67 UK cities, contributing approximately 46 percent of the total UK GDP in 2021.[2] 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: *More prosperous locations exhibit lower local capital unemployment rates.*

Fact 2: *Differences in local capital unemployment rates are large and persistent.*

Fact 3: *Local net investment rates are at the replacement rate level and do not move to close the local capital unemployment rate gaps.*

The large and persistent differences in local capital unemployment rates cannot be easily attributed to persistent shocks from deindustrialization. While 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, these patterns are consistent with long-run forces, as indicated by the strong association between local prosperity and capital unemployment differences, as well as by net investment rates remaining close to the replacement rate without adjusting to close these gaps, as one would expect if persistent shocks were the primary 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

[2]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 text provide a detailed discussion on this.

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

Fact 4: *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 5: *Local capital unemployment rate gaps are mostly driven 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 help explain the limited explanatory power of persistent deindustrialization shocks, 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.

To examine the aggregate implications of this phenomenon, we develop a dynamic spatial model of capital accumulation that incorporates search-and-matching frictions à la Pissarides (2000) in local capital markets, capturing equilibrium mismatches between unfulfilled demand and unexhausted supply (Fact 4). 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 (1979) 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 5). 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. However, while the model clarifies the underlying mechanisms and identifies key parameters that must be disciplined through calibration, it does not impose ex-ante restrictions on the relative strength of these forces, leaving their quantitative relevance to be resolved in the calibration exercise.

Therefore, to assess whether the model quantitatively aligns with empirical observations, we calibrate it 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 differences between the local markets with the highest and lowest unemployment rates. However, we leave the relative importance of finding and separation rates in explaining capital unemployment rate gaps untargeted. We then evaluate the model's quantitative performance by analyzing its fit with several untargeted moments. The model successfully captures the relative importance of capital and its unemployment rate in explaining income per capita differences (Fact 1), as well as the fact that the investment rate equals the replacement rate and does not adjust to close these gaps (Fact 3). Additionally, the model is in line with GDP differences across locations, the rental rate elasticity of local capital unemployment rates, and empirically observable amenities.

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, as indicated by the two key elasticities governing the role of finding and separation rates, 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 67 percent of spatial capital unemployment rate differences to the separation rate and 33 percent to the finding rate, closely aligning with the empirical data (Fact 5).

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 raising matching efficiency to a level that reduces the capital unemployment rate by one-fourth leads to an approximately 5 percent increase in aggregate output. The rationale for the second exercise is that our calibration indicates a failure of the generalized Hosios (1990) condition, which the model requires for efficiency. Solving for the planner's allocation, which we show can be implemented through place-based subsidies to the stock of unemployed capital, results 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 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 literature emphasizing frictions associated with physical capital inputs, including frictional investment dynamics (Cooper and Haltiwanger, 2006; Asker et al., 2014), capital misallocation (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008, and subsequent contributions), and capital reallocation (Ramey and Shapiro, 1998; Eisfeldt and Rampini, 2006; Gavazza, 2011; Lanteri, 2018).[3,4] Particularly close to our work is Ottonello (2021), who emphasizes the role of search frictions in generating capital unemployment and their implications

[3]Other contributions to the literature on frictional investment dynamics include Abel and Eberly (1994, 1996), Caballero et al. (1995), Doms and Dunne (1998), Caballero (1999), Khan and Thomas (2008), Clementi and Palazzo (2019), Winberry (2021), and Baley and Blanco (2021), among others.

[4]Evidence of friction in 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.

for business cycle dynamics.[5] Differences in capital unemployment across locations can be interpreted as an extreme form of misallocation driven by market frictions, wherein some capital units remain idle while actively searching for trading opportunities. 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 a novel dynamic spatial model of capital accumulation that incorporates realistic trading frictions in local physical capital markets. By grounding the model in search-and-matching frictions, we are able to directly account for our novel empirical evidence on the spatial distribution of capital unemployment. Our analysis 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. (2021), 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 (1979) and Roback (1982).[6] 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 that justify place-based policies with potentially large welfare gains. 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

[5] Other works with search frictions in capital markets include Wright et al. (2018, 2020) and Cao and Shi (2023), among others.

[6] 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).

in imperfections in local capital markets.

Outline. Section 2 introduces our dataset. Section 3 details our stylized facts. Section 4 introduces the model, while Section 5 provides a quantitative assessment and presents the positive implications of the model. Section 6 presents the main counterfactual analysis. Finally, Section 7 offers concluding remarks.

2 Data

This section outlines the data used for the empirical analysis.

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.

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.[7] The quality of this data is central to PMA's core business, which is property forecasting.[8] Analysts there gather and scrutinize data from various secondary sources like

[7]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.

[8]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 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.

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.[9] 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, industrial 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.[10]

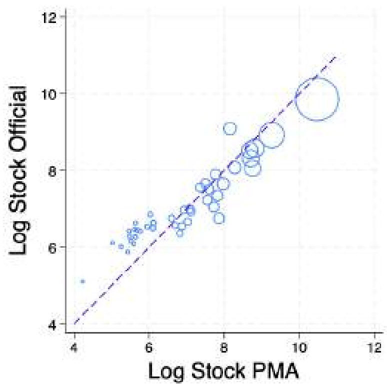
2.1.2 Validation of Data Quality. We gauge data quality by correlating our capital measure with official sources (Figure 1). The official capital stock data is obtained from the *Energy Performance of Buildings* project, initiated by the Department for Levelling Up, Housing & Communities. This project 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 and A.2.

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.

[9] 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.

[10] 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.

Figure 1: Official vs. PMA Capital Stock



Note: Figure 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.

2.2 Additional Data Sources

We complement the PMA data with information from the 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 density are obtained by combining the *Population Profiles for Local Authorities* dataset and area information from the *Open Geography Portal*. Additionally, we obtain crime rates and health indices—two supplementary measures of local prosperity used in our analysis—from the *Recorded Crime Data by Community Safety Partnership Area* dataset and the *Health Index Scores* dataset, respectively. Finally, local labor unemployment rates are sourced from the *Regional Labour Market: Local Indicators for ITL3 Geography* dataset.

3 Empirical Analysis

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

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 three regularities.

Fact 1: *More prosperous locations exhibit lower local capital unemployment rates.*

Table 1 illustrates this point by correlating the local capital unemployment rate with various observables related to a location's prosperity. To account for unobservable city-specific characteristics and time-varying aggregate shocks, we control for city- and time-fixed effects. In Appendix A.3.1, we demonstrate that removing city-fixed effects, thus relying on longer-run variation, does not alter the main takeaway. Additionally, we include city-specific trends to capture potential long-run dynamics and capital mix controls to account for differences in the composition of capital across locations.[11] The measures of prosperity considered in the analysis include labor productivity (value-added per capita), capital productivity (value-added per unit of total capital), density (population per square meter), house prices, household income, and the local labor unemployment rate. To account for spatial serial correlation, standard errors are clustered at the city level.

Columns (1) to (7) in Table 1 clearly indicate that more prosperous locations tend to have lower capital unemployment rates. Specifically, locations with higher labor and capital productivity, as well as greater density, exhibit lower capital unemployment rates. Similarly, higher rental rate, house prices, and household income are associated with lower capital unemployment.[12] On the other hand, a higher labor unemployment rate predicts a higher capital unemployment rate.

Moreover, column (8) shows how local capital unemployment rates correlate with the local capital mix. Locations with high industrial properties or logistic facilities as a share of total capital exhibit lower capital unemployment rates, albeit this is not statistically significant and is economically small. This suggests that deindustrialization shocks are unlikely to be the pri-

[11] Controlling for the capital mix means accounting for the share of industry-related and logistics-related structures as a proportion of total structures.

[12] Formally, we measure the rental rate per square meter in each location as the present value of local prices per square meter, given by $r_j = \frac{p_j}{1-(1-\delta)\beta}$.

Table 1: Capital Unemployment Rate and Its Correlates

Dependent Variable	Capital Unemployment Rate								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor Productivity	-0.181^{+}								
	(0.115)								
Capital Productivity		-0.140**							
		(0.073)							
Density			-0.105						
			(0.116)						
Rental rate				-0.072**					
				(0.030)					
House price					-0.071**				
					(0.035)				
Household income						-0.376*			
						(0.219)			
Labor Unemployment Rate							0.696*		
							(0.356)		
Capital Mix									
Industrial Property Share								-0.035	
								(0.026)	
Logistics Facilities Share								-0.054	
								(0.062)	
Net Investment Rate									0.033
									(0.105)
Fixed Effects									
City	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls									
City-specific Time Trend	✓	✓	✓	✓	✓	✓	✓	✓	✓
Capital mix	✓	✓	✓	✓	✓	✓	✓	✗	✗
Observations	827	854	856	743	811	873	887	986	553

Note: Labor productivity, capital productivity, density, rental rate, house price, and household income are in logs, the other independent variables are ratios. City-specific time trends are linear. Standard errors are clustered at the city level and reported in parentheses. $^{+}$, *, **, and *** denote 15, 10, 5, and 1% statistical significance respectively.

mary drivers of variations in local capital unemployment rates. If deindustrialization were the main driver of differences in the local capital unemployment rate, we would expect cities with many manufacturing buildings to face depressed demand for these facilities. Consequently, localities with a high number of industrial and logistics buildings would be associated with a higher local capital unemployment rate. However, this does not seem to be the case in our data. Appendix A.3.4 shows that these results are robust to using alternative measures of the location-specific exposure to economy-wide industry cycles. Finally, column (9) shows that the correlation between the net investment rate—i.e., the growth rate of capital—and the local capital unemployment rate is close to zero and statistically insignificant, a point we revisit when presenting our third fact.

To assess the quantitative relevance of spatial disparities in capital unemployment rates for local prosperity—beyond their empirical association—we assume that output in location j

at time t is given by the following production function:

$$Y_{jt} = ((1 - k^u_{jt})K_{jt})^{\alpha} L_{jt}^{1-\alpha} Z_{jt}, \tag{1}$$

where Y is real output, k^u is the capital unemployment rate, K is total capital, L is labor, and Z represents productivity. Thus, variation in output per capital can be decomposed as follows:

$$\mathbb{V}\left(\log\left(\frac{Y_{jt}}{N_{jt}}\right)\right) = \underbrace{\overbrace{\mathbb{C}\left(\log\left(\frac{Y_{jt}}{N_{jt}}\right), \alpha\log(1-k^u_{jt})\right)}^{\text{Unemployment rate contribution}} + \overbrace{\mathbb{C}\left(\log\left(\frac{Y_{jt}}{N_{jt}}\right), \alpha\log\left(\frac{K_{jt}}{N_{jt}}\right)\right)}^{\text{Total capital contribution}}}_{\text{Employed capital contribution}}$$

$$+ \underbrace{\mathbb{C}\left(\log\left(\frac{Y_{jt}}{N_{jt}}\right), (1-\alpha)\log\left(\frac{L_{jt}}{N_{jt}}\right)\right)}_{\text{Labor force participation contribution}} + \underbrace{\mathbb{C}\left(\log\left(\frac{Y_{jt}}{N_{jt}}\right), \log\left(Z_{jt}\right)\right)}_{\text{Productivity contribution}}. \tag{2}$$

Effectively, this implies that spatial variation in output per capita can be decomposed into contributions from productivity differences, labor force participation differences, and employed capital differences. The latter can further be broken down into unemployment rate differences and total capital differences. Since each element in equation (2) 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.

Table 2 presents the results in detail. We find that while variation in productivity across locations accounts for 60 percent of output per capita differences, constituting as expected the largest part, differences in employed capital account for 25 percent of these differences, and the remaining 15 percent is accounted for by differences in labor force participation.[13] Within the contribution of employed capital, differences in unemployment rate account for one-fifth of it and the remaining is due to differences in total capital stock.

Having established that local capital unemployment rates are negatively associated with measures of local prosperity, accounting for a non-negligible fraction of them, and uncorre-

[13]These results are broadly consistent with similar accounting exercises applied to cross-country settings, where productivity differences repeatedly emerge as the main driver of income per capita disparities, while capital still plays a quantitatively significant role.

Table 2: Variance Decomposition of Local Output per Capita

	Output p.c. explained
Employed capital (%)	25
Unemployment rate (%)	5
Total capital (%)	20
Labor force participation (%)	15
Productivity (%)	60

Note: This table shows the empirical variance decomposition of log output per capital as reported in equation (2). All numbers are reported in percent.

lated with the industrial composition of the location, we now present our second fact.

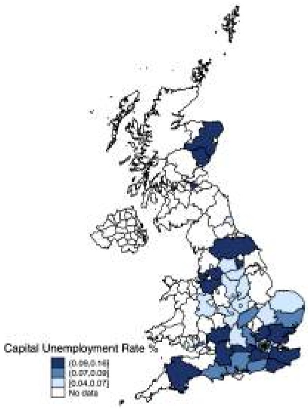
Fact 2: *Differences in local capital unemployment rates are large and persistent.*

Figure 2 shows this point. Figure 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 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.

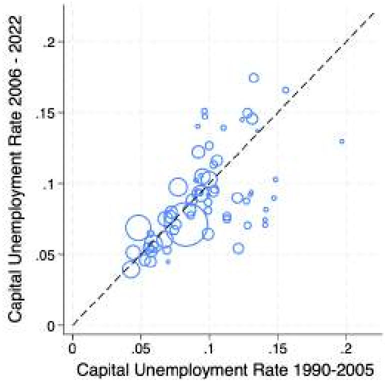
Appendix A.3 presents additional evidence that complements our findings using binscatter plots of capital unemployment rates, documenting the strong persistence of these patterns across different time horizons. Furthermore, Appendix A.3 extends this analysis to European cities, confirming the observed patterns.

One potential factor behind Fact 2 is persistent shocks, which generate a potential mismatch between the existing local supply of capital and the changing demand due to the evolving local sectoral composition, driven by the deindustrialization process experienced by the UK (Kitson and Michie, 2014; Rice and Venables, 2021). In Appendix A.3, we show that controlling for this, by netting out the contribution of time-fixed effects or the location-specific exposure to economy-wide industry cycles from local capital unemployment rates, yields a

Figure 2: Spatial Distribution and Persistence of Capital Unemployment Rate



(a) Local Capital Unemployment Rate



(b) Persistence of Capital Unemployment Rate

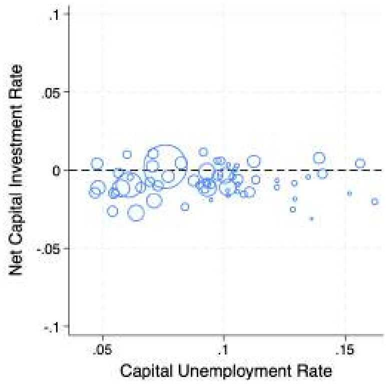
Note: Figure 2 provides an overview of the spatial distribution and persistence of the capital unemployment rate in cities across the UK. Figure 2a maps capital unemployment rates in UK cities based on the PMA dataset. Figure 2b plots capital unemployment rates in UK cities in two subperiods of the sample. The blue circles represent cities in the UK, and the size of each circle corresponds to the total capital within that city.

similar picture to Figure 2. This is consistent with our findings in Table 1, which show no association between local capital unemployment rates and the local industry mix. Thus, we conclude that persistent deindustrialization shocks do not seem enough to fully explain our findings. One plausible explanation for this finding is that our dataset, with a large fraction of offices, consists of properties that are highly substitutable across different sectors. As a result, they are not significantly affected by changing demand due to shifting sectoral composition. Having established the existence of large differences in local capital unemployment rates across locations and their persistence, we now present our third fact.

Fact 3: *Local net investment rates are at the replacement rate level and do not move to close the local capital unemployment rate gaps.*

Figure 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. The correlation is close to zero as already documented in column (8) of Table 1. 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.3.5 demonstrates that the magnitude of our net investment rate aligns with figures from aggregate national accounts.[14] Since by definition investment rate equals the net investment rate plus the depreciation rate, we conclude that most local investment is close to depreciation, i.e., at the replacement rate.

Figure 3: Local Net Investment Rates



Note: Figure 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 rate is negatively associated with measures of local prosperity (Fact 1). Moreover, differences in this measure are both large and persistent (Fact 2). Robustness exercises 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 3). Taken together, this evidence suggests that the underlying drivers of these spatial differences must be rooted in long-run, steady-state-like economic forces. 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 fourth and fifth facts.

[14] 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.

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 fifth and sixth facts.

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:

$$\boldsymbol{K}_{jt} = (1 - \delta)\boldsymbol{K}_{jt-1} + X_{jt-1}, \tag{3}$$

where δ 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.[15] The law of motions of total employed and unemployed capital is given by:

$$\boldsymbol{K}^e_{jt} = f_{jt}[(1 - \delta)\boldsymbol{K}^u_{jt-1} + X_{jt-1}] + (1 - s_{jt})(1 - \delta)\boldsymbol{K}^e_{jt-1}, \tag{4}$$

$$\boldsymbol{K}^u_{jt} = (1 - f_{jt})[(1 - \delta)\boldsymbol{K}^u_{jt-1} + X_{jt-1}] + s_{jt}(1 - \delta)\boldsymbol{K}^e_{jt-1}; \tag{5}$$

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 (4) 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:

$$\boldsymbol{M}_{jt} = f_{jt}[(1 - \delta)\boldsymbol{K}^u_{jt-1} + X_{jt-1}], \tag{6}$$

[15] 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.

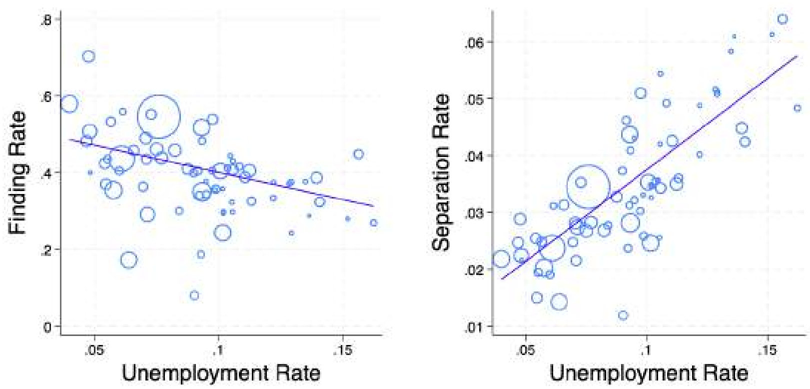
Equations (3), (4), (5), and (6) can be employed to describe total investment X_{jt}, the finding rate f_{jt}, and the separation rate s_{jt} as functions of observables and parameters denoted by:

$$X_{jt} = \boldsymbol{K}_{jt+1} - (1-\delta)\boldsymbol{K}_{jt}, \tag{7}$$

$$f_{jt} = \boldsymbol{M}_{jt}/[(1-\delta)\boldsymbol{K}^{u}_{jt-1} + X_{jt-1}], \tag{8}$$

$$s_{jt} = \{\boldsymbol{M}_{jt} - [\boldsymbol{K}^{e}_{jt} - (1-\delta)\boldsymbol{K}^{e}_{jt-1}]\}/[(1-\delta)\boldsymbol{K}^{e}_{jt-1}]. \tag{9}$$

Figure 4: Capital Market Flows Across Space



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

Note: Figure 4 shows the finding rate, separation rate, and employment margin across different UK local capital markets sorted by their capital unemployment rate. Figure 4a displays the finding rate and Figure 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 4 illustrates the relationship between the local capital unemployment rate, the finding and the separation rate. The median finding rate is 40 percent (Figure 4a) while the median separation rate is 3 percent (Figure 4b), establishing our fourth fact.

Fact 4: *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 coexisting with substantial capital unemployment rates are consistent with substantial demand for these structures, explaining why low demand or mismatch explanations associated with persistent deindustrialization shocks did not seem to have a major bite in the previous section.

Finally, we can derive the following steady-state relation for $\delta \approx 0$ using equation (5):

$$\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right) \approx \log(s_j) - \log(f_j), \tag{10}$$

where $\boldsymbol{k}_j^u$ is the capital unemployment rate and $\boldsymbol{k}_j^e$ is the employment capital rate. Equation (10) 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.4.2 generalizes equation (10) to any value of δ, showing that this approximation does not affect our conclusions.

From equation (10), we arrive at a spatial application of the unemployment decomposition formula (e.g., Fujita and Ramey, 2009), given by:

$$\mathbb{V}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right)\right) = \mathbb{C}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), \log(s_j)\right) + \mathbb{C}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), -\log(f_j)\right) + \varepsilon_j. \tag{11}$$

Equation (11) systematically breaks down the impact of each component in equation (10), 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 ε_j, which may result both from measurement error in the data or departures from the steady-state assumption imposed above.[16]

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 (10).

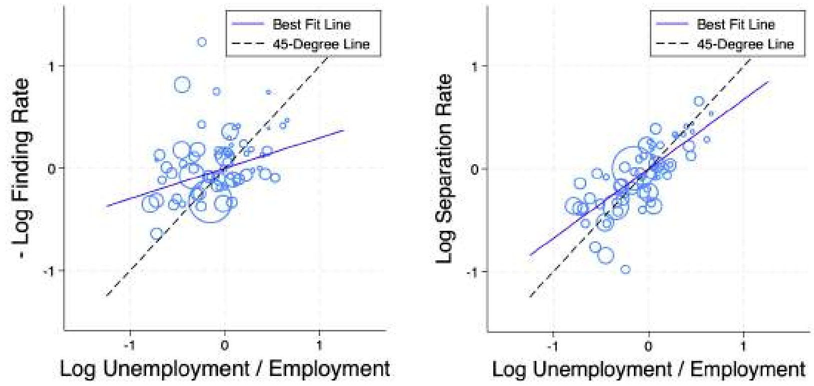
Fact 5: *Local capital unemployment rate gaps are mostly driven by differences in separation rates across locations.*

Figure 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. Figure 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

[16] In principle it could arise also form the assumption of $\delta \approx 0$. However, we generalize equation (10) to any value of δ in Appendix A.4.2, showing that this approximation does not matter significantly for our results.

the main factor driving differences in local capital unemployment rates, as indicated in Figure 5b. Separation rates vary substantially across locations, and their best-fit line closely aligns with the 45-degree line.

Figure 5: Capital Market Flows Decomposition Across Space



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

Note: Figure 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 5a scatterplots minus the log of the finding rate against the log of the unemployment-employment capital ratio, across cities in the UK. Figure 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 (11) 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 3.1.

We confirm the robustness of our findings through additional exercises. Online Appendix A.4.1 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 (10) to accommodate δ greater than zero enables us to consider the contribution of the extensive margin from newly invested capital. Online Appendix A.4.2 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.

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.

4.1 Primitives, Capital Markets, and Timing

4.1.1 Primitives. Time is discrete and indexed by t.[17] 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 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. The representative family discounts the future at rate β, derives utility $\mathcal{A}_j \log(C_j)$ from local amenities $\mathcal{A}_j$ and consumption C_j, and supplies labor L_j and capital K_j. Capital is either rented and pays a return, thus employed, or not, remaining unemployed, and it depreciates with probability δ. 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 distribution of capital. This is also consistent with anecdotal evidence suggesting that a significant portion of the UK real estate market is intermediated (see Appendix B.1). 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

[17] Given our focus on the steady-state equilibrium, as motivated by our empirical analysis, we largely omit the t subscript.

with probability $1-\rho$ from a Beta distribution with parameters (λ_1, λ_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 $y_j(z) = (\mathcal{Z}_j z)^{\alpha} \ell^{1-\alpha}$. 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 κ. It is natural to assume that firms exert search effort for capital, as is often the case in real estate markets.

4.1.2 Capital Markets and Timing.

Motivated by our evidence showing that high capital transaction rates coexist with substantial capital unemployment (Fact 4), we model the underlying market structure of local capital markets using search-and-matching frictions, which enable sustained demand to coexist with idle capacity. 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), 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).[19]

In particular, we assume that contacts between unemployed 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.[20] 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, and capital

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

[19] Anecdotal evidence further supports the presence of these friction in local commercial real estate markets (e.g., *Source 1*; *Source 2*; *Source 3*).

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

depreciates at rate δ. 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, production occurs, followed by capital depreciation with probability δ. Value functions are written in stage B.

4.2 Local Capital Market Equilibrium

4.2.1 The Representative Family. The representative family takes market tightness as given and solves the following problem:

$$\mathcal{W}(K_j, K_j^e) = \max_{\{C_j, K_j'\}} \mathcal{A}_j \log(C_j) + \beta \mathcal{W}(K_j', K_j^{e'}), \tag{12}$$

$$\text{s.t.} \quad C_j = W_j L_j + \int_{z \geq z_j^c} r_j(z) dF(z) K_j^e + (1-\delta)K_j + \Pi_j - p_j^r K_j - p_j^h L_j - K_j', \tag{13}$$

$$K_j^{e'} = (1 - s_j)(1-\delta)K_j^e + f_j(K_j' - (1-\delta)K_j^e). \tag{14}$$

Equations (12)–(14) present the recursive formulation of the representative family's problem. Equation (12) defines the family's value function, while equation (13) 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, Π_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 (14) 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 B.2—yields the following Euler equation:

$$Q_j = \beta \left[Q_j' \left(1 - \delta - p_j^{r'} \right) + f_j \eta \mathbb{E} S_j \right], \tag{15}$$

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 (15) 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 β. 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.

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:

$$V_j^u = -Q_j p_j^k + (1 - \delta)\beta \left\{ V_j^u + p(\theta_j)(1 - d)\mathbb{E}[V_j^e(z') - V_j^u]^+ \right\}, \tag{16}$$

$$V_j^e(z) = Q_j(r_j(z) - p_j^k) + (1 - \delta)\beta \left\{ V_j^u + (1 - d)\mathbb{E}[V_j^e(z') - V_j^u]^+ \right\}; \tag{17}$$

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:

$$\pi_j(z) = \max_{\ell_j(z)} (\mathcal{Z} z)^\alpha \ell_j(z)^{1-\alpha} - W_j \ell_j(z). \tag{18}$$

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

$$V_j^p(z) = Q_j(\pi_j(z) - c - r_j(z)) + (1 - \delta)\beta(1 - d)\mathbb{E}[V_j^p(z') - V_j^v]^+, \tag{19}$$

$$V_j^v = -Q_j \kappa + \beta q(\theta_j)(1 - d)\mathbb{E}[V_j^p(z') - V_j^v]^+. \tag{20}$$

As anticipated in Section 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 η representing the capital owners' bargaining power. In this protocol, the capital owners' surplus, $V_j^e(z) - V_j^u$, equals a fraction η 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 B.3, is given by:

$$r_j(z) = \eta\left(\pi_j(z) - c + (1-\delta)\kappa\theta_j\right). \tag{21}$$

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:

$$Q_j\kappa = \beta q(\theta_j)(1-d)(1-\eta)\mathbb{E}[S_j(z')]^+, \tag{22}$$

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 (19), (21), and (22) with the definition of total surplus yields:

$$S_j(z) = Q_j\left(\pi_j(z) - c + (1-\delta)\frac{1-\eta p(\theta)}{1-\eta}\frac{\kappa}{q(\theta_j)}\right), \tag{23}$$

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:

$$0 = \pi_j(z_j^c) - c + (1-\delta)\frac{1-\eta p(\theta)}{1-\eta}\frac{\kappa}{q(\theta_j)}. \tag{24}$$

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

$$s_j = 1 - (1-d)\left(1 - F(z_j^c)\right), \tag{25}$$

$$f_j = p(\theta_j)(1-d)\left(1 - F(z_j^c)\right); \tag{26}$$

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.

4.2.3 The Real Estate and Housing Sectors.

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

$$\text{Real estate sector:} \quad \Pi_j^r = \max_{K_j} \; p_j^r K_j - \left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1}{\phi}}, \tag{27}$$

$$\text{Housing sector:} \quad \Pi_j^h = \max_{L_j} \; p_j^h L_j - (L_j)^{\frac{1}{\gamma}}. \tag{28}$$

Profit maximization yields the following prices:

$$p_j^r = \frac{1}{\phi}\left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1-\phi}{\phi}} \frac{1}{\mathcal{P}_j}, \quad \text{and} \quad p_j^h = \frac{1}{\gamma} L_j^{\frac{1-\gamma}{\gamma}}; \tag{29}$$

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

4.2.4 Spatial Allocation of Workers and Equilibrium.

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

$$Q_j(W_j - p_j^h) = \underline{\mathcal{W}}, \tag{30}$$

which says that the marginal value of one extra worker to the representative family, as measure in terms of utility by the wage net of the housing costs, must equal the outside option of workers.

Therefore, using equation (30) and the aggregate constraint $\sum_j L_j = \overline{L}$, we can derive the following condition for the distribution of workers across locations:

$$L_j = \frac{\left[\gamma\left(W_j - \frac{\underline{W}}{Q_j}\right)\right]^{\frac{\gamma}{1-\gamma}}}{\sum_j \left[\gamma\left(W_j - \frac{\underline{W}}{Q_j}\right)\right]^{\frac{\gamma}{1-\gamma}}} \overline{L}. \tag{31}$$

Thus, in this economy, for each location $j \in \{1, \ldots, J\}$, an *equilibrium* given $\{\mathcal{Z}_j, \mathcal{A}_j, \mathcal{P}_j\}$ is a set equilibrium outcomes $\{\theta_j, z_j^c, S_j(z), p_j^r, p_j^h, \ell_j(z), W_j; L_j, K_j, C_j\}$ satisfying the following conditions: (i) $\theta_j, z_j^c, S_j(z)$ solve (22)-(24); (ii) p_j^r and p_j^h are given by (29); (iii) $\ell_j(z)$ solves (18); (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 (31); (vi) K_j solves (15); and (vii) C_j is given by (13).

4.3 Inspecting the Mechanism

Section 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 5). Equations (25) and (26) imply the following elasticities for separation and finding rates out of fundamental productivity differences $\mathcal{Z}_j$:[21]

$$\boldsymbol{\varepsilon_{s_j,\mathcal{Z}_j}} = -\frac{1-s_j}{s_j}\varepsilon_{1-F(z_j^c),z_j^c}\boldsymbol{\varepsilon_{z_j^c,\mathcal{Z}_j}}, \tag{32}$$

$$\boldsymbol{\varepsilon_{f_j,\mathcal{Z}_j}} = (1-\mu)\boldsymbol{\varepsilon_{\theta_j,\mathcal{Z}_j}} + \varepsilon_{1-F(z_j^c),z_j^c}\boldsymbol{\varepsilon_{z_j^c,\mathcal{Z}_j}}; \tag{33}$$

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 (32) and (33) 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 5.[22] 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 B.4.

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

$$\boldsymbol{\varepsilon_{z_j^c,\mathcal{Z}_j}} = -\underbrace{1}_{\substack{\text{Direct}\\ \text{effect}}} - \underbrace{\frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(\frac{\mu}{p(\theta_j)}-\eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j}}_{\text{Indirect effect}} + \underbrace{\frac{1-\alpha}{\alpha}\varepsilon_{W_j,\mathcal{Z}_j}}_{\text{GE effect}}. \tag{34}$$

The elasticity of the separation threshold level to location-specific productivity, $\varepsilon_{z_j^c,\mathcal{Z}_j}$, consists 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 $\mu/p(\theta_j) > \eta$.[23]

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

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

[23] Under an empirically plausible calibration $\mu/p(\theta_j) > \eta$ is satisfied as μ is estimate by Ottonello (2021) around

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 η 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:

$$\boldsymbol{\varepsilon_{\theta_j, \mathcal{Z}_j}} = \underbrace{\Upsilon_j \frac{\mathbb{E}\pi_j(z')}{\mathbb{E}\pi_j(z') - c}}_{\substack{\text{Standard} \\ \text{search-and-matching} \\ \text{amplification}}} \left[\underbrace{1}_{\substack{\text{Direct} \\ \text{effect}}} + \underbrace{\Omega_j \varepsilon_{z_j^r, \mathcal{Z}_j}}_{\substack{\text{Endogenous} \\ \text{separation} \\ \text{effect}}} - \underbrace{\frac{1-\alpha}{\alpha} \varepsilon_{W_j, \mathcal{Z}_j}}_{\text{GE effect}} \right], \tag{35}$$

where Υ_j and Ω_j take the following form:

$$\Upsilon_j \equiv \frac{(1-\delta)\beta(1-d)(1-F(z_j^c))\eta p(\theta_j) + (1-(1-\delta)\beta(1-d)(1-F(z_j^c)))}{(1-\delta)\beta(1-d)(1-F(z_j^c))\eta p(\theta_j) + (1-(1-\delta)\beta(1-d)(1-F(z_j^c)))\mu}, \tag{36}$$

$$\Omega_j \equiv \varepsilon_{\mathbb{E}z', z_j^c} + \frac{\mathbb{E}\pi_j(z') - c}{\mathbb{E}\pi_j(z')} \left(1 + \frac{\kappa(1-\eta p(\theta_j))}{q(\theta_j)(1-\eta)(\mathbb{E}\pi_j(z') - c)}\right) \varepsilon_{1-F(z_j^c), z_j^c}. \tag{37}$$

Equation (35) 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 Υ_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 (35) extends the concept of the fundamental surplus, from Hagedorn and Manovskii (2008) and Ljungqvist and 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 Ω_j is positive. Conversely, if Ω_j is negative, the indirect effect from endogenous separations acts as an amplifying force.

0.70 and $p(\theta_j)$ is on average 0.40, with $\eta \in (0, 1)$.

While it is not possible to determine the sign of Ω_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 Υ_j and the inverse fundamental surplus, $\frac{\mathbb{E}\pi_j(z')}{\mathbb{E}\pi_j(z')-c}$, must be relatively small. Υ_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: μ and c.

In conclusion, equations (34) and (35) 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.

4.4 Efficiency

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

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

subject to the following constraints:

$$C_j = \left[\frac{1}{1-F(z_j^r)}\int_{z\geq z_j^c}\left[(\mathcal{Z}_j z)^\alpha \ell_j(z)^{1-\alpha} - c\right] f(z)dz\right] K_j^e$$

$$+ (1-\delta)K_j - \left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1}{\phi}} - (L_j)^{\frac{1}{\gamma}} - \kappa E_j^k - K_j', \tag{39}$$

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

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

$$L_j = \int_{z\geq z_j^c} \ell_j(z)dzK_j^e, \tag{42}$$

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

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 (39), the law of motion for capital employment (40), the definition of capital market tightness (41), the location-specific labor market clearing condition (42), and the aggregate population constraint (43).

Online Appendix B.5 provides detailed derivations of the social planner's problem. The decentralized equilibrium is efficient if and only if

$$\mu = \eta, \tag{44}$$

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 is useful to realize that at the core of the local capital market structure are firms making investment decisions, which are characterized by their costly effort in searching for capital. In this setting, two inefficiencies arise in this investment process. First, since the firm is the sole decision-maker in the investment, it must fully capture the returns. However, under Nash bargaining, the firm appropriates only a $1-\eta$ share of the surplus generated from the matching. This effectively acts as a "tax" on the firm's return on investment, resulting in an inefficiently low level of costly search effort and, consequently, excessively low firms in equilibrium.

Second, a firm's decision generates externalities that affect both other firms and capital owners. However, since firms are the sole decision-makers in this setting, the key externality to consider is the one imposed on other firms. This externality is given by the total amount of search effort multiplied by the change in the matching probability for each of the other firms, as expressed by:

$$E_j^k \times \frac{\partial}{\partial E_j^k}\left(\frac{M\left((1-\delta)K_j^u + X_j, E_j^k\right)}{E_j^k}\right)$$

$$= M_2\left((1-\delta)K_j^u + X_j, E_j^k\right) - \frac{M\left((1-\delta)K_j^u + X_j, E_j^k\right)}{E_j^k} \tag{45}$$

$$= -\mu q(\theta_j) \tag{46}$$

The first term on the right-hand side of equation (45), $M_2\left((1-\delta)K_j^u + X_j, E_j^k\right)$, represents the number of matches generated by the marginal search effort. Instead, the second term, $M\left((1-\delta)K_j^u + X_j, E_j^k\right)/E_j^k$, reflects the firm's private perception of the likelihood of forming a new match when searching for capital. The difference between these two terms constitutes the externality. In other words, the externality arises from the gap between the marginal increase in the number of matches and the average number of matches per unit of search effort. Since this externality is negative, it leads to excessive search effort and, consequently, an inefficiently high level of firm entry in the market equilibrium.

The overall effect is determined by the balance of these two inefficiencies, which act in opposite directions. When the Hosios (1990) condition holds, the tax imposed on firm investment exactly offsets the excessive search incentive caused by the externality, leading to an efficient equilibrium. However, if $\mu > \eta$, the second inefficiency dominates, leading to excessive firm entry in equilibrium, which results in too little unemployed capital and a higher effective cost of searching. Conversely, if $\mu < \eta$, the first inefficiency prevails, leading to insufficient firm entry and, as a result, 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 B.6:[24]

$$\tau_j = \frac{\mu - \eta}{1 - \eta} \left(\mathbb{E}\pi_j(z) - c + (1 - \delta)\kappa\theta_j \right) \tag{47}$$

Equation (47) 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.

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 3.2.

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 β is set at 0.96. We set the depreciation rate to 2 percent, as in the empirical analysis. The capital share α is set to 0.35, a number in line with the literature. The matching function elasticity μ is set to 0.70, which is the lower bound estimate from the micro-data in Ottonello (2021).[25] This must be interpreted as a conservative choice, as a high value of this elasticity will increase the role of the separation

[24]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.

[25]This value is close to those in macro-labor, such as empirical estimates reported by Petrongolo and Pissarides (2001) and the parameterization in Shimer (2005).

rate in explaining spatial capital unemployment gaps, as explained in Section 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. (2021), assuming that λ_1 and λ_2 are both equal to 1, implying a uniform probability distribution.[26] 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 ϕ to 0.5, reflecting a high degree of decreasing returns, as is typical in service sectors. We set γ 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, $\mathcal{Z}_{median}$, so that average unconditional profits form equation (18) in that location equal 1.[27] Finally, we normalize total population in the economy $\overline{L}$ and the workers outside option $\underline{\mathcal{W}}$ to 1.

Fitted parameters. Thus, $3J + 3$ parameters remain to be calibrated: the matching efficiency m; the capital vacancy posting cost κ; the fixed operating cost c; the capital owners bargaining power η; the location-specific fundamental productivity levels, $\{\mathcal{Z}_j\}_{j=1}^J \setminus \{\mathcal{Z}_{median}\}$; 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 η using the median observed capital unemployment rates which is 9 percent. The bargaining power of capitalists, η, is an important parameter in the model governing the efficiency of the equilibrium and is inversely related to capital vacancy creation in all locations, 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

[26] We adopt this functional form for the distribution of z to remain consistent with the literature. However, Kuhn et al. (2021) demonstrate that this assumption is quantitatively inconsequential for this class of models.

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

Table 3: Parameters

Parameter	Description	Value
Fixed		
β	Discount factor	0.96
δ	Depreciation rate	0.02
α	Capital share in production	0.35
μ	Matching function elasticity	0.70
d	Exogenous separation rate	0.01
λ_1, λ_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
ϕ	Real estate sector returns to scale	0.50
γ	Housing sector returns to scale	0.20
$\mathcal{Z}_{median}$	Median productivity	0.93
$\overline{L}$	Total population	1
$\underline{W}$	Workers' outside option	1
Fitted		
m	Matching efficiency	0.112
κ	Capital vacancy posting cost	0.002
c	Fixed operating cost	0.850
η	Capitalists bargaining power	0.455
$\{\mathcal{Z}_j\}_{j=1}^J \setminus \{\mathcal{Z}_{median}\}$	Location-specific fundamental productivity levels	Figure C.8a
$\{\mathcal{A}_j\}_{j=1}^J$	Location-specific amenities	Figure C.8b
$\{\mathcal{P}_j\}_{j=1}^J$	Location-specific real estate sector productivity	Figure C.8c

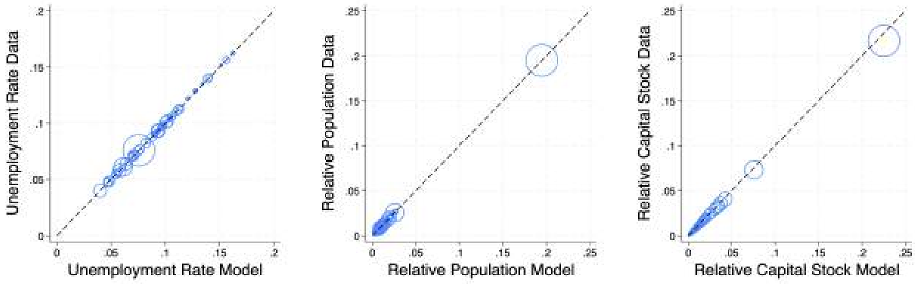
a firm, thus affecting the level of matches that can be sustained in equilibrium and, as a consequence, the separation threshold level. Another important parameter is the fixed operating cost c, which determines the size of the fundamental surplus and thus the relative importance of the finding versus 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, $\{\mathcal{Z}_j\}_{j=1}^J \setminus \{\mathcal{Z}_{median}\}$, 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.

Table 4: Moments

Moment	Data	Model
Separation rate	0.03	0.03
Finding Rate	0.40	0.40
Fixed cost share of total costs	0.30	0.30
Capital unemployment rates	Figure 6a	
Population	Figure 6b	
Capital stock	Figure 6c	

Note. The table presents parameter values and target moments from both the model and the data.

Figure 6: Capital Unemployment Rate and Capital Stock



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

Note: Figure 6 compares capital unemployment rates, population and total capital between the model and UK data. In Figures 6a–6c, blue circles represent model values plotted against data, with a dashed black 45-degree line for reference. Specifically, Figure 6a shows unemployment rates, Figure 6b total population, and Figure 6c total capital. 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 are presented in Table 3. Table 4 shows the fit of the model on several identifying moments. Even though the model is nonlinear, it fits the target moments satisfactorily. Unfortunately, as local capital markets have been relatively understudies 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 η 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 η are postponed to Section 6.2, where we delve into the normative implications of the model. While η 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.

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 3.2.

5.2.1 Model Validation.

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

Decomposition of output per capita differences. Section 3.1 shows that output per capita differences can be decomposed in the role of differences in the stock of capital, differences in the unemployment rate of capital, and differences in other determinants. Here we compare how the model performs quantitatively in explaining these regularities.

Table 5: 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
Others (%)	75	65

Table 5 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.

Table 5 reports the fraction of variation in local output per capita explained by differences across locations in capital unemployment rates, total capital, and other factors. In the model, these factors include productivity, while in the data, they also encompass labor force participation. Without calibrating any shares, we find that the model matches satisfactorely 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.

Relative GDP by location. To validate the performance of our calibration strategy, we look at the local GDP predicted by the model and compare it with the data. Online Appendix C.2 plots the local GDP in the model against the one in the data. The model matches the GDP in the data satisfactorily, as shown visually and by a weighted correlation of 0.77 between the GDP of the model and that in the data.

Investment rates. The model also replicates the investment patterns observed in the empirical analysis. Online Appendix C.3 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.

Rental rates. Table 1 in Section 3 reports a regression coefficient of -0.067 between the log rental rate and capital unemployment rates, while the model produces a correlation of -0.074. Furthermore, in Section 6.2, we analyze the elasticity between the capital unemployment rate and the rental rate of capital, showing a close fit between the model and the data. Overall, the model's qualitative and quantitative predictions on capital rental rates align well with the data.

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,[28] 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 C.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.

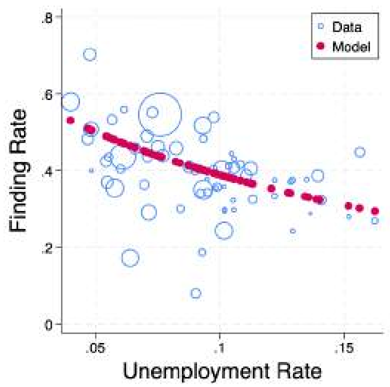
5.2.2 Spatial Capital Unemployment Gaps Decomposition. Having demonstrated the estimated model's ability to capture both targeted and non-targeted moments—such as GDP, net investment rates, rental rates, and amenities—we now turn to the main positive results. Specifically, we assess the model's ability to quantitatively explain the key features of local capital markets documented in Section 3.2.

Figure 7 displays the finding (Figure 7a) and separation rates (Figure 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 quantita-

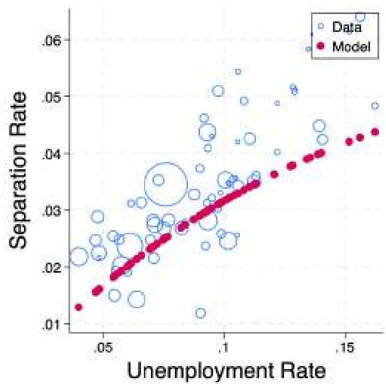
[28] PMA's amenity scores are based on the presence of key anchor stores, national and regional fashion, non-fashion, and food & beverage multiples within each retail location. The scores reflect both the size and quality of key anchor stores, variety stores, and fashion multiples. A high score indicates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

tively. 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.

Figure 7: Finding and Separation Rate across Local Capital Markets: Model vs. Data



(a) Finding Rate



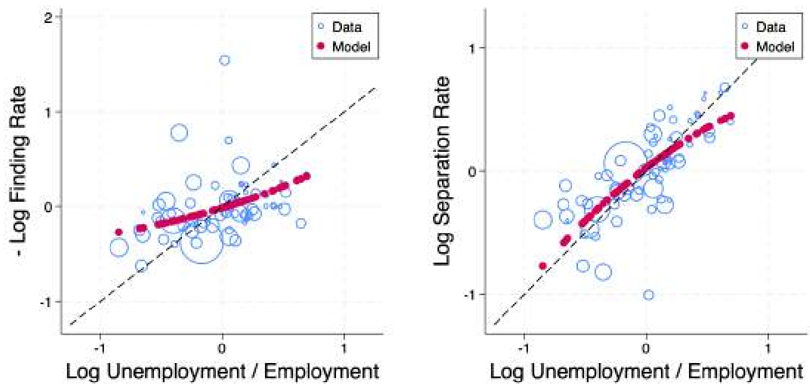
(b) Separation Rate

Note: Figure 7 shows finding rates and separation rates from the model (red) and the data (blue) across UK locations. Figure 7a shows finding rates. Figure 7b shows separation rates. The size of the circles is proportional to the size of the location.

A close alignment with the observed patterns of finding and separation rates across space 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 8, which presents the decomposition of the local capital unemployment rate differences between its different capital-flows, i.e., finding rate (Figure 8a) and separation rate (Figure 8b), from the model (red) and the data (blue) from Figure 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 3.2 assuming δ close to zero. Online Appendix C.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 find-

Figure 8: Decomposition of Spatial Capital Unemployment Gaps: Model vs. Data



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

Note: Figure 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 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 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.

ing rate and the large contribution of the separation rate to local capital unemployment rate differences, it is helpful to refer to Section 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 Ω, meaning that the indirect effect from endogenous separations acts as a dampening force, and a sufficiently large fundamental surplus, which weakens the amplification 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 (34), 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.

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.

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 6: Variance Decomposition of Local Output per Capita: Model vs. Data

		Change	
	Baseline	**1.5×m**	**2×m**
Avg. capital unemployment rate	9.20	-1.45 p.p.	-3.44 p.p.
Avg. finding rate	40.74	+19.66 p.p.	+38.96 p.p.
Avg. separation rate	2.86	+1.03 p.p.	+1.55 p.p.
Avg. rental rate	14.03	-0.23 p.p.	-0.35 p.p.
Total output	1.88	+2.38 %	+4.85 %
Total consumption	1.86	+2.41 %	+4.90 %

Table 6 presents the macroeconomic implication of easing search frictions, obtained by increasing m by a factor of 1.5 and 2.

Table 6 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 a increase in market tightness and wages, which, in turn, rises the effective cost of searching for firms and lowers 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 5 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 6 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.

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 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 (21) to derive the unit-free rental rate elasticity of the capital unemployment rate in a given location, which is given by:

$$\varepsilon_{r_j,k_j^u} = -\eta \frac{\kappa\theta_j}{\mathbb{E}r_j(z)}, \tag{48}$$

which shows that the capital unemployment rate is unambiguously negatively associated with the rental rate, with the strength of this relationship mediated by η, 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 7 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 unemploy-

Table 7: Rental Rate Elasticity of Capital Unemployment Rate: Model vs. Data

Dependent Variable	Rental Rate			
	Data (OLS) (1)	Data (TSLS) (2)	Data (TSLS) (3)	Model (4)
Capital unemployment rate	-0.11** (0.05)	-0.54** (0.23)	-0.29*** (0.07)	-0.46
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 as an instrument. Finally, column (4) reports the theoretical elasticity (48) derived from the model.

We find a statistically significant negative rental rate elasticity of the capital unemployment 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.

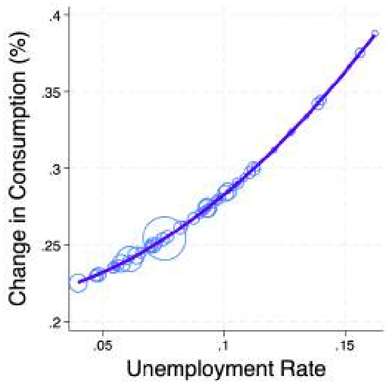
Social planner allocation and quantification of place-based policies. This section provides a quantitative exploration of the implications of place-based policies that implement the social planner allocation described in Section 4.4.

Table 8: 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 8 presents the macroeconomic implications of achieving the social planner allocation, i.e., introducing place-based policies.

Figure 9: Local Welfare Gains in the Social Planner Allocation



Note: Figure 9 illustrates the change in consumption following the implementation of the social planner's allocation. adsfsdEach circle represents a city, with its size proportional to the capital stock. The thick blue line represents the quadratic best-fit curve.

Table 8 presents the results. When $\mu > \eta$, as recovered by our calibration, congestion externalities dominate, resulting in 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 a tax on firms, as capital owners in the planner's equilibrium have a higher outside option.

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 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.

Next, we examine the distribution of welfare gains across locations and their implications for inequality. Figure 9 illustrates these gains, which range from 0.225 to 0.388 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 C.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 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. (2021) 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.

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.

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Employed and Unemployed Capital in Space

Andrea Chiavari and Charles Cheng Zhang

Online Appendix

A Data Appendix

A.1 Data Cleaning and Summary Statistics

We leverage a comprehensive dataset sourced from PMA encompassing office, industrial, and logistic buildings at the city level from 1981 to 2022.[29] To get a comprehensive picture of spatial capital allocations, we combine all commercial real estate within each city.

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.

Additionally, we define the investment rate as investment over the capital stock and calculate investment based on equation (7). We derive the finding rate and separation rate according to equations (8) and (9). 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.

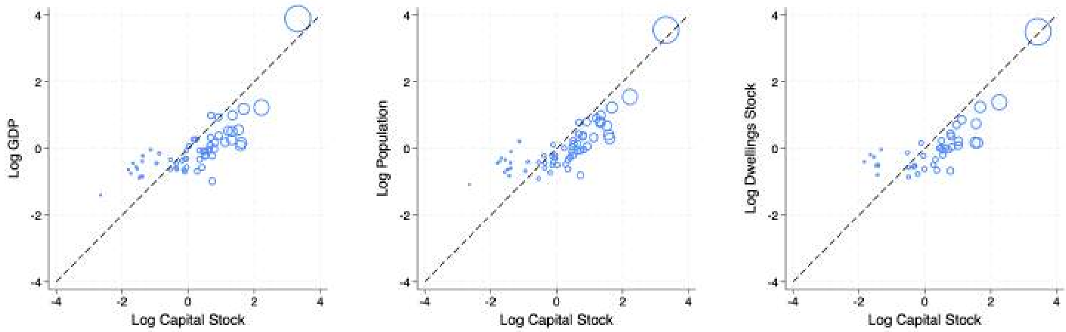
A.2 Data Validation

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.

[29]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.

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 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 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.

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).[30] 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 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).

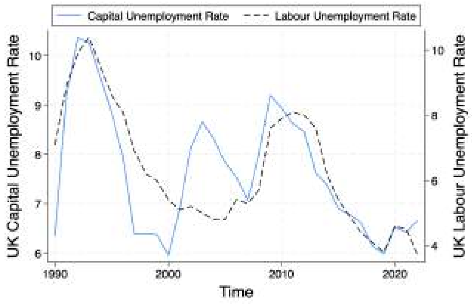
A.3 More on The Distribution and Spatial Persistence of Capital Unemployment Rates

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

A.3.1 More on The Capital Unemployment Rate and Its Correlates. Since the paper focuses on long-run, steady-state forces, in this section of the appendix we reproduce the correlations presented in Table 1, omitting city-fixed effects to capture all long-run variation in the data. The results are presented in Table A.2. Although the correlations are sometimes estimated with less precision, they remain often significant and in the same direction as those in the main text, thereby supporting our primary findings.

[30] See: ONS definitions.

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.

Table A.2: Capital Unemployment Rate and Its Correlates—Robustness

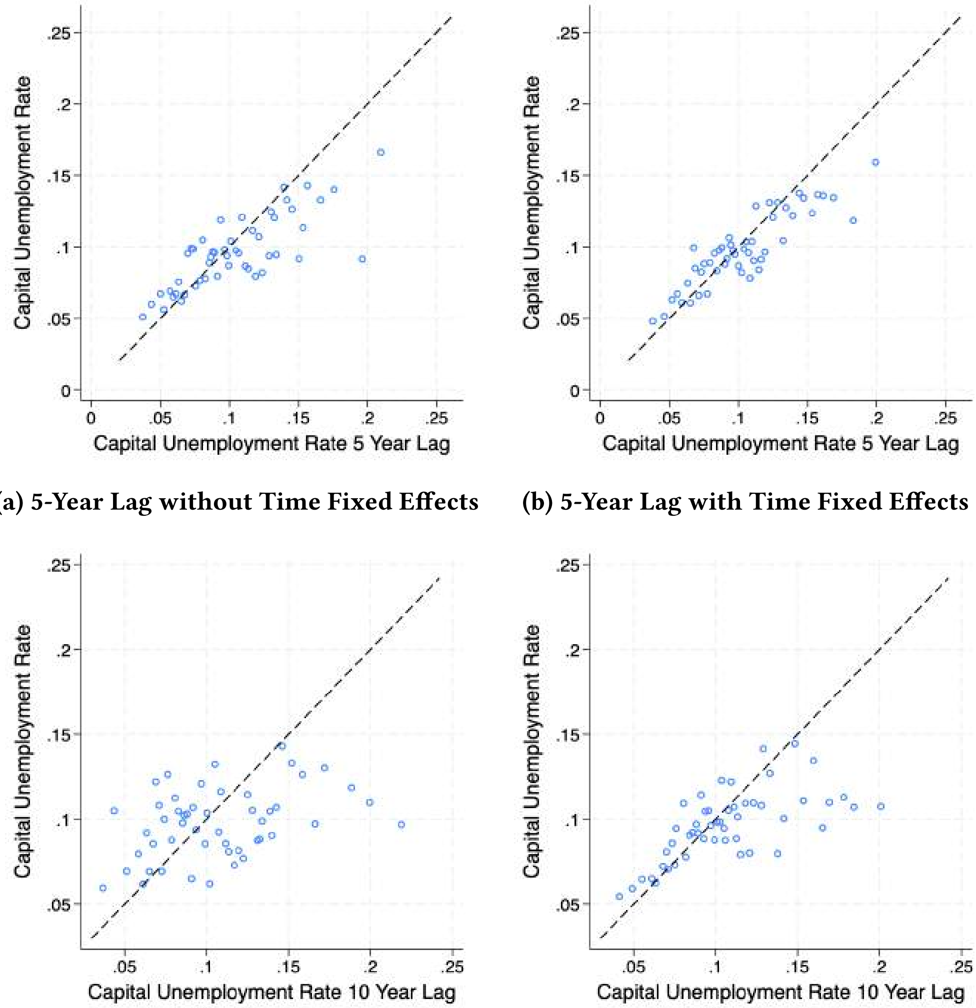
Dependent Variable	Capital Unemployment Rate								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor Productivity	-0.107^{+}								
	(0.070)								
Capital Productivity		-0.086^{+}							
		(0.056)							
Density			-0.189*						
			(0.107)						
Rental rate				-0.024					
				(0.020)					
House price					-0.049^{+}				
					(0.030)				
Household income						-0.146			
						(0.132)			
Labor Unemployment Rate							0.742*		
							(0.396)		
Capital Mix									
Industrial Property Share								-0.064*	
								(0.036)	
Logistics Facilities Share								-0.068	
								(0.055)	
Net Investment Rate									0.059
									(0.081)
Fixed Effects									
City	✗	✗	✗	✗	✗	✗	✗	✗	✗
Time	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls									
City-specific Time Trend	✓	✓	✓	✓	✓	✓	✓	✓	✓
Others	✓	✓	✓	✓	✓	✓	✓	✗	✗
Observations	828	855	856	744	812	874	887	987	558

Note: Labor productivity, capital productivity, density, rental rate, house price, household income and rent are in logs, the other independent variables are ratios. City-specific time trends are linear. Other controls include the capital mix. Standard errors are clustered at the city level and reported in parentheses. $^{+}$, *, **, and *** denote 15, 10, 5, and 1% statistical significance respectively.

A.3.2 Additional Specifications. 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.

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**

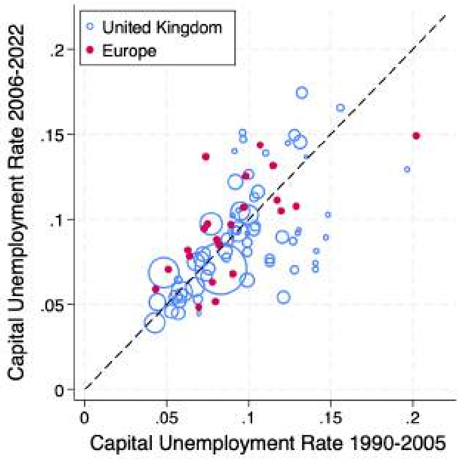
Note: Figure A.3 displays binscatters of the capital unemployment rate against itself with 5- and 10-year lags, both with and without time fixed effects. Light blue circles represent group averages. The dashed black line represents the 45-degree line.

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.[31]

A.3.3 Evidence from Europe. In Section 2.2, we showed 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.

[31] Controlling for location-specific exposure to economy-wide industry cycles, as explained in Appendix A.3.4, yields very similar results, which are available upon request.

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.

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.

A.3.4 Accounting for Persistent Shocks. This section of the Appendix explores the potential role of persistent shocks in the documented persistence of capital unemployment rate gaps. These shocks may create a mismatch between the existing local supply of capital and the changing demand due to evolving local sectoral composition, driven by the deindustrialization process experienced by the UK.

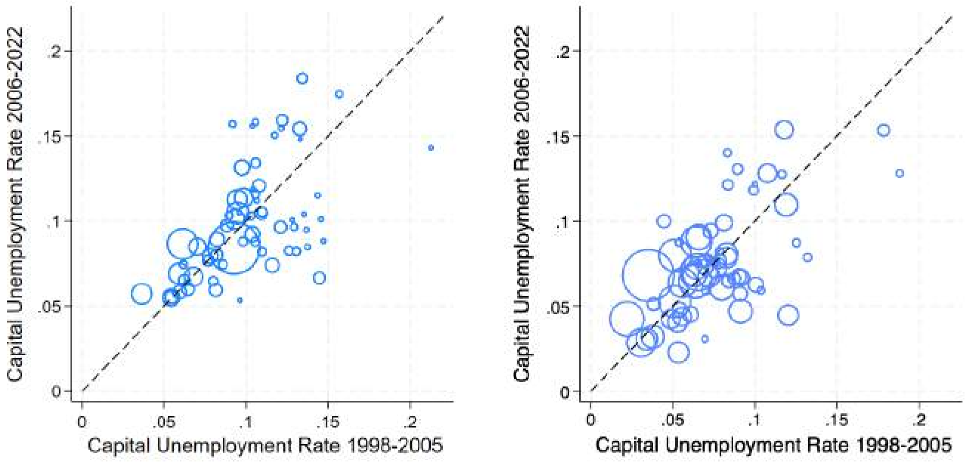
To do so, we construct a location-specific exposure measure to economy-wide industry cycles. In particular, we define exposure as follows:

$$E_{jt-1990} = \sum_i \omega_{ij1990} \times \Delta_{t-1990} \log Y_{it}, \tag{49}$$

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) and time fixed effects and industry cycles simultaneously (Figure A.5b). The blue circles represent cities in the UK, and the size of each

Figure A.5: Spatial Persistence Accounting for Persistent Shocks



(a) Without Time Fixed Effects

(b) Without Time Fixed Effects and Industry Cycles

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) and time fixed effects and industry cycles simultaneously (Figure A.5b). 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.

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 and industry cycles does not significantly affect the persistent patterns documented in the main text. However, Figure A.5b is slightly less neat because controlling for industry cycles results in some loss of observations, as the PMA data define locations at a more granular level than the ONS. Thus, we conclude that while the UK economy has witnessed a slow-moving deindustrialization process, our data suggest that this is unlikely to be the main driver of the observed persistence in capital unemployment rates.

To reinforce this conclusion, we follow the approach used in Table 1 of the main text. Specifically, we regress the location-specific exposure measure to economy-wide industry cycles, as defined in equation (49), against the capital unemployment rate gaps. The results are presented in Table A.3.

Overall, we find that the location-specific exposure measure to economy-wide industry cycles has minimal and insignificant predictive power for capital unemployment rate gaps, often moving in the opposite direction of what would be expected if deindustrialization dynamics were the primary driver of these differences across locations. This result confirms our previous findings from Figure A.5b and supports our conclusion that the UK deindustrialization process is unlikely to explain the capital unemployment rate gaps observed in the data.

A.3.5 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.

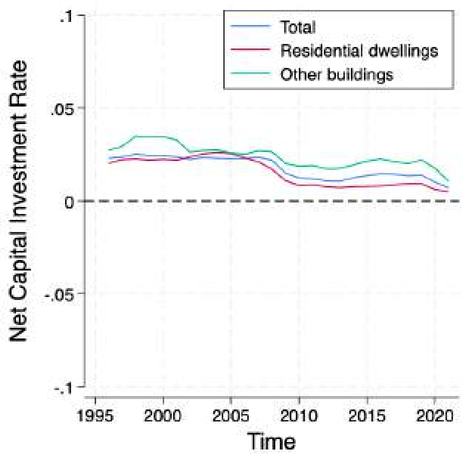
Figure A.6 displays the evolution of net capital investment rates in the UK from 1996 to 2021. Overall, we find that these rates are minimal and not far from zero, averaging around 2

Table A.3: Regression Results with Cumulative Weighted Changes

Dependent Variable	**Capital Unemployment Rate**		
	(1)	(2)	(3)
$E_{jt-1990}$	0.006	-0.038	-0.132
	(0.016)	(0.081)	(0.126)
Fixed Effects			
City	✗	✓	✓
Time	✗	✓	✓
Controls			
City-specific Time Trend	✗	✗	✓
Observations	839	838	838

Note. Standard errors are reported in parentheses. $^{+}$,*, **, and *** denote 15, 10, 5, and 1% statistical significance respectively.

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.

percent. This finding is consistent with our results presented in the main text.[32]

A.4 More on The Spatial Ins and Outs of Unemployed Capital

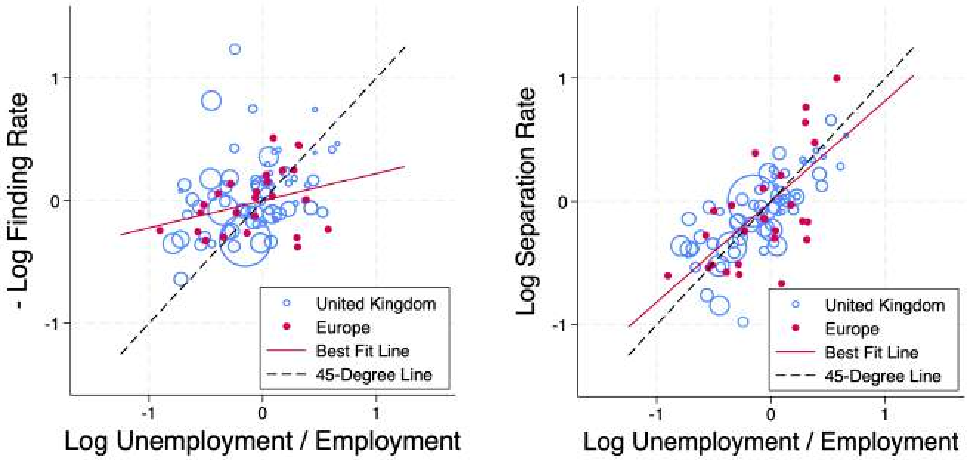
Here, we present additional evidence on the central role of separation rates in explaining capital unemployment rate gaps in our data.

A.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

[32]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.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.

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 explaining 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.4.2 Expanded Decompositions. In Section 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 δ, assessing its impact on our empirical findings.

In particular, we can generalize equation (10) in the main text to the case with $\delta \neq 0$ yielding the following decomposition of the log of the unemployment-employment capital rate:

$$\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right) = \log(s_j) - \log(f_j) + \log\left(\left(\frac{s_j(1-\delta) + (1-f_j)\delta/\boldsymbol{k}_j^e}{\delta + f_j(1-\delta)}\right)\frac{f_j}{s_j}\right). \tag{50}$$

The first two terms in equation (50) mirror those in equation (10), 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 (50), we arrive at a spatial decomposition of the variance of the log of the unemployment-employment capital rate ratio, given by:

$$\begin{aligned} \text{Var}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right)\right) &= \text{Cov}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), \log(s_j)\right) + \text{Cov}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), -\log(f_j)\right) \\ &+ \text{Cov}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), \log\left(\left(\frac{s_j(1-\delta)+(1-f_j)\delta/\boldsymbol{k}_j^e}{\delta+f_j(1-\delta)}\right)\frac{f_j}{s_j}\right)\right) \\ &+ \text{Cov}\left(\log\left(\frac{\boldsymbol{k}_j^u}{\boldsymbol{k}_j^e}\right), \varepsilon_j\right), \end{aligned} \tag{51}$$

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 (51) to inspect if our empirical findings from Section 3.2 are robust to allow for the extensive margin. Table A.4 presents the results from this expanded decomposition for the UK and Europe and compares them with the results from the decomposition outline by equation (11) in the main text.

Table A.4: 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 (11), while columns 3 and 5 show the variance decomposition in equation (51). 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, suggesting 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.

B Model Appendix

B.1 Intermediation in the Commercial Real Estate Market

This section presents anecdotal evidence highlighting the prevailing role played by intermediaries in the UK's commercial real estate market. Although not legally required, the vast majority of land transactions in the UK are handled by professional conveyancers, such as solicitors. According to HM Land Registry, professional assistance is overwhelmingly preferred. The typical conveyancing fee ranges from 0.25 % to 1.25% of the transaction value, as reported online by comparemymove.

B.2 Household Euler Equation Derivation

Here we derive the household's Euler equation (15). The household solves the following problem:

$$\mathcal{W}(K_j, K_j^e) = \max_{\{K_j'\}} \mathcal{A}_j \log\left(W_j L_j + \int_{z \geq z_j^c} r_j(z) dF(z) K_j^e + (1-\delta)K_j + \Pi_j - p_j^r K_j - p_j^h L_j - K_j'\right)$$
$$+ \beta \mathcal{W}\left(K_j', (1-s_j)(1-\delta)K_j^e + f_j(K_j' - (1-\delta)K_j^e)\right). \tag{52}$$

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

$$\frac{\partial \mathcal{W}_j}{\partial K_j'} = -\frac{\mathcal{A}_j}{C_j} + \beta\left(\frac{\partial \mathcal{W}_j'}{\partial K_j'} + f_j \frac{\partial \mathcal{W}_j'}{\partial K_j^{e'}}\right) = 0. \tag{53}$$

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:

$$\frac{\mathcal{A}_j}{C_j} = \beta\left[(1-\delta-p_j^{r'})\frac{\mathcal{A}_j}{C_j'} + f_j \frac{\partial \mathcal{W}_j'}{\partial K_j^{e'}}\right]. \tag{54}$$

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:

$$Q_j = \beta\left[Q_j'(1-\delta-p_j^{r'}) + f_j \eta \mathbb{E} S_j\right], \tag{55}$$

which corresponds to equation (15).

B.3 Rental Rate of Capital Derivation

Here we derive the rental rate of capital in equation (21). Nash bargaining implies

$$\eta V_j^p(z) = (1-\eta)(V_j^e(z) - V_j^u), \tag{56}$$

while the free entry condition on (20) implies

$$Q_j \frac{\kappa}{q(\theta_j)} = \beta(1-d)\mathbb{E}[V_j^p(z')]^+. \tag{57}$$

Combining these two equation together with equations (16)-(19) yields the following expressions:

$$V_j^e(z) - V_j^u = Q_j r_j(z) + (1-\delta)(1-p(\theta_j))\beta(1-d)\mathbb{E}[V_j^e(z') - V_j^u]^+ \tag{58}$$

$$= Q_j r_j(z) + (1-\delta)(1-p(\theta_j))\beta(1-d)\frac{\eta}{1-\eta}\mathbb{E}[V_j^{p'}]^+, \tag{59}$$

$$= Q_j \left[r_j(z) + (1-\delta)(1-p(\theta_j))\frac{\eta}{1-\eta}\frac{\kappa}{q(\theta_j)} \right]; \tag{60}$$

and

$$V_j^p(z) = Q_j \left(\pi_j(z) - c - r_j(z) + (1-\delta)\frac{\kappa}{q(\theta_j)} \right). \tag{61}$$

Substituting these values back in the Nash bargaining equation gives

$$Q_j \eta \left(\pi_j(z) - c - r_j(z) + (1-\delta)\frac{\kappa}{q(\theta_j)} \right) = Q_j(1-\eta) \left[r_j(z) + (1-\delta)(1-p(\theta_j))\frac{\eta}{1-\eta}\frac{\kappa}{q(\theta_j)} \right], \tag{62}$$

which simplifies to

$$r_j(z) = \eta\left(\pi_j(z) - c + (1-\delta)\kappa\theta_j\right). \tag{63}$$

B.4 Tightness and Separation Cutoff Elasticities Derivations

B.4.1 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:

$$\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j \mathbb{E} r_j + \left[(1-s_j)(1-\delta) - f_j(1-\delta)\right]\beta \frac{\partial \mathcal{W}_j'}{\partial K_j^{e'}}. \tag{64}$$

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

$$\frac{\partial \mathcal{W}_j'}{\partial K_j^{e'}} = \frac{\eta}{1-\eta}\frac{1}{\beta(1-d)(1-F(z_j^c))} Q_j \frac{\kappa}{q(\theta_j)}, \tag{65}$$

Combining equations (64) and (65), 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:

$$\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j \left(\mathbb{E} r_j + \frac{\eta}{1-\eta}(1-\delta)(1-p(\theta_j))\frac{\kappa}{q(\theta_j)} \right), \tag{66}$$

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

$$Q_j \frac{\kappa}{q(\theta_j)} = \beta Q_j'(1-d)(1-F(z_j^c))(1-\eta)\left(\mathbb{E}\pi_j(z') - c + (1-\delta)\frac{1-\eta p(\theta_j')}{1-\eta}\frac{\kappa}{q(\theta_j')}\right). \tag{67}$$

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:

$$\eta\mathbb{A}(1-F(z_j^c))\theta_j + \frac{1-\mathbb{A}(1-F(z_j^c))}{q(\theta_j)} = \frac{1}{1-\delta}\frac{1-\eta}{\kappa}\mathbb{A}(1-F(z_j^c))(\mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\mathbb{E}z' - c). \tag{68}$$

After implicit differentiating the LHS of equation (68) with respect to $\mathcal{Z}_j$ the following is obtained:

$$\left(\eta\mathbb{A}(1-F(z_j^c)) + \frac{(1-\mathbb{A}(1-F(z_j^c))\varepsilon_{q,\theta}}{\theta_j q(\theta_j)}\right)\frac{\partial\theta_j}{\partial\mathcal{Z}_j} + \mathbb{A}\left(\eta\theta_j - \frac{1}{q(\theta_j)}\right)\frac{\partial(1-F(z_j^c))}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j}. \tag{69}$$

While implicitly differentiating the RHS of equation (68) with respect to $\mathcal{Z}_j$ the following is obtained:

$$\frac{(1-\eta)(1-F(z_j^c))\mathbb{A}\mathbb{B}}{(1-\delta)\kappa}\left(W_j^{-\frac{1-\alpha}{\alpha}}\mathbb{E}z' + W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\frac{\partial\mathbb{E}z_j'}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j} - \frac{1-\alpha}{\alpha}W_j^{-\frac{1}{\alpha}}\frac{\partial W_j}{\partial z_j^c}\mathcal{Z}_j\mathbb{E}z' + \frac{1}{\mathbb{B}}\frac{\mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\mathbb{E}z' - c}{1-F(z_j^c)}\frac{\partial(1-F(z_j^c))}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j}\right). \tag{70}$$

Equating (69) and (70) and rearranging we obtain the following:

$$\begin{aligned}\frac{\partial\theta_j}{\partial\mathcal{Z}_j} &= \frac{\theta_j q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta_j q(\theta_j) + (1-\mathbb{A}(1-F(z_j^c))\varepsilon_{q,\theta}}\frac{(1-\eta)(1-F(z_j^c))\mathbb{A}}{(1-\delta)\kappa} \\ &\times\left(\mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathbb{E}z' + \mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\frac{\partial\mathbb{E}z'}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j} - \mathbb{B}\frac{1-\alpha}{\alpha}W_j^{-\frac{1}{\alpha}}\frac{\partial W_j}{\partial\mathcal{Z}_j}\mathcal{Z}_j\mathbb{E}z' + \frac{\mathbb{B}W_j^{-\frac{1-\alpha}{\alpha}}\mathcal{Z}_j\mathbb{E}z' - c}{1-F(z_j^c)}\frac{\partial(1-F(z_j^c))}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j}\right) \\ &- \frac{\theta_j q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta_j q(\theta_j) + (1-\mathbb{A}(1-F(z_j^c))\varepsilon_{q,\theta}}\mathbb{A}\left(\eta\theta_j - \frac{1}{q(\theta_j)}\right)\frac{\partial(1-F(z_j^c))}{\partial z_j^c}\frac{\partial z_j^c}{\partial\mathcal{Z}_j}.\end{aligned} \tag{71}$$

We can simplify this expression using the following steps. Rearranging (68),

$$\frac{(1-\eta)\mathbb{A}(1-F(z_j^c))}{(1-\delta)\kappa} = \left[\eta\mathbb{A}(1-F(z_j^c))\theta_j + \frac{1-\mathbb{A}(1-F(z_j^c))}{q(\theta_j)}\right]\frac{1}{\mathbb{E}\pi_j(z') - c}, \tag{72}$$

and therefore,

$$\frac{\theta q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta q(\theta_j)+(1-\mathbb{A}(1-F(z_j^c)))\varepsilon_{q,\theta}}\frac{(1-\eta)(1-F(z_j^c))\mathbb{A}}{(1-\delta)\kappa}$$

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

$$=\frac{\left[\eta\mathbb{A}(1-F(z_j^c))q(\theta)\theta_j+1-\mathbb{A}(1-F(z_j^c))\right]}{\eta\mathbb{A}(1-F(\mathcal{Z}))\theta q(\theta)+(1-\mathbb{A}(1-F(\mathcal{Z})))\varepsilon_{q,\theta}}\frac{\theta}{\mathbb{E}\pi_j(z')-c},$$

$$=\Upsilon\frac{\theta}{\mathbb{E}\pi_j(z')-c}. \tag{73}$$

where

$$\Upsilon\equiv\frac{\left[\eta\mathbb{A}(1-F(z_j^c))q(\theta)\theta_j+1-\mathbb{A}(1-F(z_j^c))\right]}{\eta\mathbb{A}(1-F(z_j^c))\theta q(\theta)+(1-\mathbb{A}(1-F(z_j^c)))\varepsilon_{q,\theta}},$$
$$\equiv\frac{(1-\delta)\beta(1-d)(1-F(z_j^c))\eta p(\theta_j)+(1-(1-\delta)\beta(1-d)(1-F(z_j^c)))}{(1-\delta)\beta(1-d)(1-F(z_j^c))\eta p(\theta_j)+(1-(1-\delta)\beta(1-d)(1-F(z_j^c)))\mu}. \tag{74}$$

Moreover, we get

$$\frac{\theta q(\theta_j)}{\eta\mathbb{A}(1-F(z_j^c))\theta q(\theta_j)+(1-\mathbb{A}(1-F(z_j^c)))\varepsilon_{q,\theta}}=\Upsilon\frac{\theta_j}{\mathbb{E}\pi_j(z')-c}\times\frac{\kappa}{(1-\eta)(1-F(z_j^c))\mathbb{A}}. \tag{75}$$

Substituting everything back (71), and expressing in terms of elasticity,

$$\varepsilon_{\theta_j,Z_j}=\Upsilon\frac{1}{\mathbb{E}\pi_j(z')-c}\times\left(\mathbb{E}\pi_j(z')+\mathbb{E}\pi_j(z')\varepsilon_{\mathbb{E}z',z_j^c}\varepsilon_{z_j^c,\mathcal{Z}_j}-\frac{1-\alpha}{\alpha}\mathbb{E}\pi(z_j')\varepsilon_{W_j,\mathcal{Z}_j}+(\mathbb{E}\pi(z_j')-c)\varepsilon_{1-F(z_j^c),z_j^c}\varepsilon_{z_j^c,\mathcal{Z}_j}\right)$$
$$+\Upsilon\frac{1}{\mathbb{E}\pi_j(z')-c}\times\frac{\kappa(1-\eta p(\theta_j))}{(1-\eta)q(\theta_j)}\varepsilon_{1-F(z_j^c),z_j^c}\varepsilon_{z_j^c,\mathcal{Z}_j}. \tag{76}$$

Collecting terms, we get

$$\varepsilon_{\theta_j,\mathcal{Z}_j}=\Upsilon_j\frac{\mathbb{E}\pi_j(z')}{\mathbb{E}\pi_j(z')-c}\left[1+\Omega_j\varepsilon_{z_j^c,\mathcal{Z}_j}-\frac{1-\alpha}{\alpha}\varepsilon_{W_j,\mathcal{Z}_j}\right], \tag{77}$$

where Ω_j take the following form:

$$\Omega_j\equiv\varepsilon_{\mathbb{E}z',z_j^c}+\frac{\mathbb{E}\pi_j(z')-c}{\mathbb{E}\pi_j(z')}\left(1+\frac{\kappa(1-\eta p(\theta_j))}{q(\theta_j)(1-\eta)(\mathbb{E}\pi_j(z')-c)}\right)\varepsilon_{1-F(z_j^c),z_j^c}. \tag{78}$$

B.4.2 Derivation of Separation Threshold. Firm's profit maximization problem, (18), states that

$$\pi_j(z)=\max_{\ell_j(z)}\,(\mathcal{Z}_j z)^\alpha\ell_j(z)^{1-\alpha}-W_j\ell_j(z). \tag{79}$$

The first-order condition solves:

$$(1-\alpha)(\mathcal{Z}_j z)^{\alpha}\ell_j(z)^{-\alpha} = W_j, \tag{80}$$

which implies:

$$\pi_j(z) = \frac{\alpha}{1-\alpha}(1-\alpha)^{\frac{1}{\alpha}} W_j^{-\frac{1-\alpha}{\alpha}} \mathcal{Z}_j z. \tag{81}$$

Hence, the cut-off threshold from (24) can be expressed as

$$0 = \frac{\alpha}{1-\alpha}(1-\alpha)^{\frac{1}{\alpha}} W_j^{-\frac{1-\alpha}{\alpha}} \mathcal{Z}_j z_j^c - c + (1-\delta)\frac{1-\eta p(\theta)}{1-\eta}\frac{\kappa}{q(\theta_j)}. \tag{82}$$

Rearranging,

$$z_j^c = \frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}}\frac{1}{\mathcal{Z}_j} W_j^{\frac{1-\alpha}{\alpha}}\left(c + \frac{(1-\delta)\eta}{1-\eta}\kappa\theta - \frac{\kappa}{1-\eta}\frac{1}{q(\theta)}\right). \tag{83}$$

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

$$\begin{aligned}
\frac{\partial z_j^c}{\partial \mathcal{Z}_j} &= -\frac{1}{\mathcal{Z}_j} z_j^c + \frac{1-\alpha}{\alpha W_j} z_j^c \frac{\partial W_j}{\partial \mathcal{Z}_j} + \frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}}\frac{1}{\mathcal{Z}_j} W_j^{\frac{1-\alpha}{\alpha}}\left(\frac{\eta}{1-\eta} + \frac{1}{1-\eta}\frac{1}{q(\theta)^2}q'(\theta)\right)\kappa(1-\delta)\frac{\partial\theta}{\partial \mathcal{Z}_j}, \\
&= -\frac{1}{\mathcal{Z}_j}\left(\frac{\kappa(1-\delta)}{1-\eta}\frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}} W_j^{\frac{1-\alpha}{\alpha}}\left(-\frac{q'(\theta)}{q(\theta)^2} - \eta\right)\frac{\partial\theta_j}{\partial \mathcal{Z}_j} + z_j^c - \frac{1-\alpha}{\alpha W_j} z_j^c \frac{\partial W_j}{\partial \mathcal{Z}_j}\mathcal{Z}_j\right), \\
&= -\frac{1}{\mathcal{Z}_j}\left(\frac{\kappa(1-\delta)}{1-\eta}\left(-\frac{q'(\theta)}{q(\theta)^2} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j}\theta_j\left(\frac{1-\alpha}{\alpha}(1-\alpha)^{-\frac{1}{\alpha}} W_j^{\frac{1-\alpha}{\alpha}}\mathcal{Z}_j^{-1}\right) + z_j^c - \frac{1-\alpha}{\alpha} z_j^c \varepsilon_{W_j,\mathcal{Z}_j}\right), \\
&= -\frac{1}{\mathcal{Z}_j}\left(\frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(-\frac{q'(\theta)}{q(\theta)^2} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j} z_j^c + z_j^c - \frac{1-\alpha}{\alpha} z_j^c \varepsilon_{W_j,\mathcal{Z}_j}\right), \\
&= -\frac{1}{\mathcal{Z}_j}\left(\frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(\frac{\mu}{p(\theta_j)} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j} z_j^c + z_j^c - \frac{1-\alpha}{\alpha} z_j^c \varepsilon_{W_j,\mathcal{Z}_j}\right),
\end{aligned} \tag{84}$$

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

$$\begin{aligned}
\varepsilon_{z_j^c,\mathcal{Z}_j} &= -\frac{1}{\mathcal{Z}}\left(\frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(\frac{\mu}{p(\theta_j)} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j} z_j^c + z_j^c - \frac{1-\alpha}{\alpha} z_j^c \varepsilon_{W_j,\mathcal{Z}_j}\right)\frac{\mathcal{Z}_j}{z_j^c} \\
&= -1 - \frac{\kappa\theta_j(1-\delta)}{(1-\eta)\pi_j(z_j^c)}\left(\frac{\mu}{p(\theta_j)} - \eta\right)\varepsilon_{\theta_j,\mathcal{Z}_j} + \frac{1-\alpha}{\alpha}\varepsilon_{W_j,\mathcal{Z}_j}.
\end{aligned} \tag{85}$$

B.5 Social Planner Derivations

This section solves the social planner's problem discussed in Section 4.4. The social planner solves the following optimization problem:

$$\mathcal{W}^{SP}(K_j, K_j^e, z_j^c) = \max_{\{K_j', E_j^k, z_j^{c'}, \ell_j(z), L_j\}} \mathcal{A}_j \log(C_j) + \beta \mathcal{W}^{SP}(K_j', K_j^{e'}, z_j^{c'}), \tag{86}$$

subject to the following constraints:

$$C_j = \left[\frac{1}{1-F(z_j^r)} \int_{z \geq z_j^c} \left[\left((\mathcal{Z}_j z)^\alpha \ell_j(z)^{1-\alpha} - W_j \ell_j(z)\right) - c\right] f(z) dz\right] K_j^e$$

$$+ (1-\delta)K_j + W_j L_j - \left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1}{\phi}} - (L_j)^{\frac{1}{\gamma}} - \kappa E_j^k - K_j', \tag{87}$$

$$K_j^{e'} = (1-d)(1-F(z_j^{c'}))(1-\delta)K_j^e + p(\theta_j)(1-d)(1-F(z_j^{c'}))(K_j' - (1-\delta)K_j^e), \tag{88}$$

$$\theta_j = \frac{E_j^k}{K_j' - (1-\delta)K_j^e}, \tag{89}$$

$$\sum_j L_j = \overline{L} \tag{90}$$

First order conditions are as follows:

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j'} = -Q_j + \beta \left[\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j'} + \frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} \frac{\partial K_j^{e'}}{\partial K_j'}\right] = 0, \tag{91}$$

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial E_j^k} = -Q_j \kappa + \beta \left[\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} \frac{\partial K_j^{e'}}{\partial E_j^k}\right] = 0, \tag{92}$$

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial z_j^{c'}} = \beta \left(\frac{\partial \mathcal{W}^{S\mathcal{P}'}{}_j}{\partial K_j^{e'}} \frac{\partial K_j^{e'}}{\partial z_j^{c'}} + \frac{\partial \mathcal{W}_j^{SP'}}{\partial z_j^{c'}}\right) = 0, \tag{93}$$

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial \ell_j(z)} = Q_j K_j^e \frac{1}{1-F(z_j^r)} \left((1-\alpha)(\ell_j(z))^{-\alpha}(Z_j \mathbb{E}z)^\alpha - W_j\right) = 0, \tag{94}$$

$$\frac{\partial W_j}{\partial L_j} = Q_j \left(W_j - \frac{1}{\gamma}(L_j)^{\frac{1-\gamma}{\gamma}}\right) - \mathbb{L} = 0. \tag{95}$$

B.5.1 Derivation of Euler Equation and Capital Creation Equation.

Take the first two FOCs, we have

$$Q_j = \beta \left[\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j'} + \frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} \frac{\partial K_j^{e'}}{\partial K_j'}\right], \tag{96}$$

$$Q_j\kappa = \beta\left[\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}}\frac{\partial K_j^{e'}}{\partial E_j^k}\right]. \tag{97}$$

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

$$\frac{\partial K_j^{e'}}{\partial K_j'} = (1-d)(1-F(z_j^{c'}))\varepsilon_{q,\theta}p(\theta_j), \tag{98}$$

and

$$\frac{\partial K_j^{e'}}{\partial E_j^k} = (1-d)(1-F(z_j^{c'}))(1-\varepsilon_{q,\theta})q(\theta_j). \tag{99}$$

and,

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j} = Q_j\left(1-\delta-\frac{1}{\phi\mathcal{P}_j}\left(\frac{K_j}{\mathcal{P}_j}\right)^{\frac{1-\phi}{\phi}}\right), \tag{100}$$

and

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j^e} = Q_j\left(\mathbb{E}\pi_i - c\right) + \beta\left[(1-d)(1-F(z_j^{c'}))(1-\delta)\left[1-\varepsilon_{q,\theta}p(\theta_j)\right]\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}}\right]. \tag{101}$$

Taking stock,

$$Q_j = \beta\left[Q_j'\left(1-\delta-\frac{1}{\phi\mathcal{P}_j}\left(\frac{K_j'}{\mathcal{P}_j}\right)^{\frac{1-\phi}{\phi}}\right) + (1-d)(1-F(z_j^{c'}))\varepsilon_{q,\theta}p(\theta_j)\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}}\right], \tag{102}$$

and

$$Q_j\kappa = \beta\left[(1-d)(1-F(z_j^{c'}))(1-\varepsilon_{q,\theta})q(\theta_j)\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}}\right], \tag{103}$$

and

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j^e} = Q_j\left(\mathbb{E}\pi_i - c\right) + \beta\left[(1-d)(1-F(z_j^{c'}))(1-\delta)\left[1-\varepsilon_{q,\theta}p(\theta_j)\right]\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}}\right]. \tag{104}$$

We first examine (102), using the fact that $f_j \equiv (1-d)(1-F(z_j^{c'}))p(\theta_j)$, A, as well as $p_j^{r'} = \frac{1}{\phi\mathcal{P}_j}\left(\frac{K_j'}{\mathcal{P}_j}\right)^{\frac{1-\phi}{\phi}}$, (102) can be expressed as

$$Q_j = \beta\left[Q_j'(1-\delta-p_j^{r'}) + f_j\varepsilon_{q,\theta}\mathbb{E}S_j\right]. \tag{105}$$

This expression is identical to 15 if $\varepsilon_{q,\theta} = \eta$.

We move on to construct the capital creation equation. Substituting (103) into (104),

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial K_j^e} = Q_j\left(\mathbb{E}\pi_j - c + (1-\delta)\frac{1-\varepsilon_{q,\theta}p(\theta_j)}{1-\varepsilon_{q,\theta}}\frac{\kappa}{q(\theta_j)}\right), \tag{106}$$

rolling one period forward,

$$\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} = Q_j' \left(\mathbb{E}\pi_j' - c + (1-\delta) \frac{1-\varepsilon_{q,\theta} p(\theta_j')}{1-\varepsilon_{q,\theta}} \frac{\kappa}{q(\theta_j')} \right). \tag{107}$$

Finally, substituting (107) back into (103)

$$Q_j \frac{\kappa}{q(\theta_j)} = \beta Q_j' (1-d)(1-F(z_j^{c'}))(1-\varepsilon_{q,\theta}) \left(\mathbb{E}\pi_j' - c + (1-\delta) \frac{1-\varepsilon_{q,\theta} p(\theta_j')}{1-\varepsilon_{q,\theta}} \frac{\kappa}{q(\theta_j')} \right), \tag{108}$$

which is capital creation equation in the decentralized equilibrium (67) if $\varepsilon_{q,\theta} = \eta$.

B.5.2 Derivation of Separation Threshold. The first order condition with respect to the separation threshold is written as

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial z_j^{c'}} = \beta \left(\frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} \frac{\partial K_j^{e'}}{\partial z_j^{c'}} + \frac{\partial \mathcal{W}_j^{SP'}}{\partial z_j^{c'}} \right) = 0. \tag{109}$$

As before, we will derive each component of the expression above individually. First, it can be shown that

$$\frac{\partial K_j^{e'}}{\partial z_j^{c'}} = \frac{\partial (1-F(z_j^{c'})}{\partial z_j^{c'}} \frac{1}{1-F(z_j^{c'})} K_j^{e'}. \tag{110}$$

Moreover,

$$\begin{aligned} \frac{\partial \mathcal{W}_j^{SP'}}{\partial z_j^{c'}} &= Q_j' K_j^{e'} \frac{\partial}{\partial z_j^{c'}} \left[\frac{1}{1-F(z_j^{c'})} \int_{z_j^{c'}}^{z^{\max}} \left[\left((\mathcal{Z}_j z')^\alpha \ell_j(z')^{1-\alpha} - W_j \ell_j(z') \right) - c \right] f(z') dz' \right], \\ &= Q_j' K_j^{e'} \left[- \frac{1}{(1-F(z_j^{c'}))^2} \frac{\partial (1-F(z_j^{c'}))}{\partial z_j^{c'}} \int_{z_j^{c'}}^{z^{\max}} \left[\left((\mathcal{Z}_j z')^\alpha \ell_j(z')^{1-\alpha} - W_j \ell_j(z') \right) - c \right] f(z') dz' \right] \\ &+ Q_j' K_j^{e'} \left[\frac{1}{1-F(z_j^{c'})} \frac{\partial}{\partial z_j'^{c}} \int_{z_j^{c'}}^{z^{\max}} \left[\left((\mathcal{Z}_j z')^\alpha \ell_j(z')^{1-\alpha} - W_j \ell_j(z') \right) - c \right] f(z') dz' \right]. \end{aligned} \tag{111}$$

Using the Leibniz integral rule,

$$\frac{\partial}{\partial z_j^{c'}} \int_{z_j^{c'}}^{z^{\max}} \left[\left((\mathcal{Z}_j z')^\alpha \ell_j(z')^{1-\alpha} - W_j \ell_j(z') \right) - c \right] = \frac{\partial (1-F(z_j^{c'})}{\partial z_j^{c'}} \left(\pi_j^{c'} - c \right). \tag{112}$$

Hence,

$$\begin{aligned} \frac{\partial \mathcal{W}_j^{SP'}}{\partial z_j^{c'}} &= Q_j' K_j^{e'} \left[- \frac{1}{(1-F(z_j^{c'}))} \frac{\partial (1-F(z_j^{c'}))}{\partial z_j^{c'}} (\mathbb{E}\pi_j' - c) + \frac{1}{(1-F(z_j^{c'}))} \frac{\partial (1-F(z_j^{c'}))}{\partial z_j^{c'}} (\pi_j^{c'} - c) \right] \\ &= Q_j' K_j^{e'} \frac{1}{1-F(z_j^{c})} \frac{\partial (1-F(z_j^{c'}))}{\partial z_j^{c'}} (\pi_j^{c'} - \mathbb{E}\pi_j'). \end{aligned} \tag{113}$$

Finally, substituting (110), (113) as well as the previously derived (107) into (109),

$$0 = \frac{\partial(1-F(z_j^{c'})}{\partial z_j^{c'}} \frac{1}{1-F(z_j^{c'})} K_j^{e'} \frac{\partial \mathcal{W}_j^{SP'}}{\partial K_j^{e'}} + Q_j' K_j^{e'} \frac{1}{1-F(z_j^c)} \frac{\partial(1-F(z_j^{c'}))}{\partial z_j^{c'}} (\pi_j^{c'} - \mathbb{E}\pi_j')$$
$$= Q_j' \left(\mathbb{E}\pi_j' - c + (1-\delta) \frac{1-\varepsilon_{q,\theta'} p(\theta_j)}{1-\varepsilon_{q,\theta}} \frac{\kappa}{q(\theta_j')} + (\pi_j^{c'} - \mathbb{E}\pi_j') \right),$$
$$= \pi_j^{c'} - c + (1-\delta) \frac{1-\varepsilon_{q,\theta'} p(\theta_j)}{1-\varepsilon_{q,\theta}} \frac{\kappa}{q(\theta_j')}. \tag{114}$$

This expression would be the same as 24 if $\varepsilon_{q,\theta'} = \eta$.

B.5.3 Derivation of Labor Wage. The first order condition of firm-level labor demand yields

$$0 = K_j^e \left((1-\alpha)(\ell_j(z))^{-\alpha} (\mathcal{Z}_j \mathbb{E}z)^\alpha - W_j \right), \tag{115}$$

rearranging,

$$\ell_j(z) = \left(\frac{1-\alpha}{W_j} \right)^{\frac{1}{\alpha}} \mathcal{Z}_j \mathbb{E}z, \tag{116}$$

which is identical to the firm-level demand in the decentralized equilibrium as shown in (80).

B.5.4 Derivation of Spatial Equilibrium. The first order condition of aggregate labor demand yields

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial L_j} = Q_j \left(W_j - \frac{1}{\gamma} (L_j)^{\frac{1-\gamma}{\gamma}} \right) = \mathbb{L} \tag{117}$$

for all locations, where $\mathbb{L}$ is the Lagrangian multiplier. Recall that from (29) $p_j^h = \frac{1}{\gamma} L_j^{\frac{1-\gamma}{\gamma}}$, the above can be written as

$$\frac{\partial \mathcal{W}_j^{SP}}{\partial L_j} = Q_j \left(W_j - p_j^h \right) = \mathbb{L} \tag{118}$$

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.

B.6 Optimal Taxation

We derive equation (47) in this section. Suppose we give a placed-based subsidy to the unemployed capitalists , which is isomorphic to taxing employed capitalists or producers, so that $\theta_j^{SP} = \theta_j^{DE}$. The representative family solves the following problem:

$$\mathcal{W}(K_j K_j^e) = \max_{\{K_j'\}} \mathcal{A}_j \log \left(W_j L_j + \int_{z \geq z_j^c} r_j(z) dF(z) K_j^e + (1-\delta) K_j + \Pi_j - p_j^r K_j - p_j^h L_j - K_j' - \tau_j K_j^e \right)$$
$$+ \beta W \left(K_j', (1-s_j)(1-\delta) K_j^e + f_j(K_j' - (1-\delta) K_j^e) \right). \tag{119}$$

and therefore, repeating the same steps for the derivation of (??),

$$\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j \left(\mathbb{E} r_j - \tau_j + \frac{\eta}{1-\eta}(1-\delta)(1-p(\theta_j))\frac{\kappa}{q(\theta_j)} \right). \tag{120}$$

Moreover, household's value functions are now

$$V_j^u = -Q_j p_j^k + (1-\delta)\beta \left\{ V_j^u + p(\theta_j)(1-d)\mathbb{E}[V_j^e(z') - V_j^u]^+ \right\}, \tag{121}$$

$$V_j^e(z) = Q_j(r_j(z) - p_j^k - \tau_j) + (1-\delta)\beta \left\{ V_j^u + (1-d)\mathbb{E}[V_j^e(z') - V_j^u]^+ \right\}; \tag{122}$$

and therefore, the rental rate becomes

$$\mathbb{E} r_j(z) = \eta(\mathbb{E}\pi_j(z) - c + (1-\delta)\kappa\theta_j) + (1-\eta)\tau_j. \tag{123}$$

Substituting the rental rate into the expression of $\frac{\partial \mathcal{W}_j}{\partial K_j^e}$,

$$\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j \eta \left(\mathbb{E}\pi_j(z) - c - \tau_j + (1-\delta)\frac{1-\eta p(\theta_j)}{1-\eta}\frac{\kappa}{q(\theta_j)} \right). \tag{124}$$

Therefore, the total surplus becomes

$$S_j^{DE}(z) = \frac{1}{\eta}\frac{\partial \mathcal{W}_j}{\partial K_j^e} = Q_j \left(\mathbb{E}\pi_j(z) - c - \tau_j + (1-\delta)\frac{1-\eta p(\theta_j)}{1-\eta}\frac{\kappa}{q(\theta_j)} \right). \tag{125}$$

The total surplus under social planner's problem is derived in (106), which is restated below,

$$S_j^{SP}(z) = \frac{\partial \mathcal{W}_j^{SP}}{\partial K_j^e} = Q_j \left(\mathbb{E}\pi_j - c + (1-\delta)\frac{1-\varepsilon_{q,\theta} p(\theta_j)}{1-\varepsilon_{q,\theta}}\frac{\kappa}{q(\theta_j)} \right), \tag{126}$$

Taking stock, we have the following expressions for the surplus

$$\begin{aligned} DE: \quad & S_j^{DE}(z) = Q_j \left(\mathbb{E}\pi_j(z) - c - \tau_j + (1-\delta)\frac{1-\eta p(\theta_j)}{1-\eta}\frac{\kappa}{q(\theta_j)} \right), \\ SP: \quad & S_j^{SP}(z) = Q_j \left(\mathbb{E}\pi_j(z) - c + (1-\delta)\frac{1-\varepsilon_{q,\theta} p(\theta_j)}{1-\varepsilon_{q,\theta}}\frac{\kappa}{q(\theta_j)} \right). \end{aligned} \tag{127}$$

Therefore for $S_j^{DE} = S_j^{SP}$,

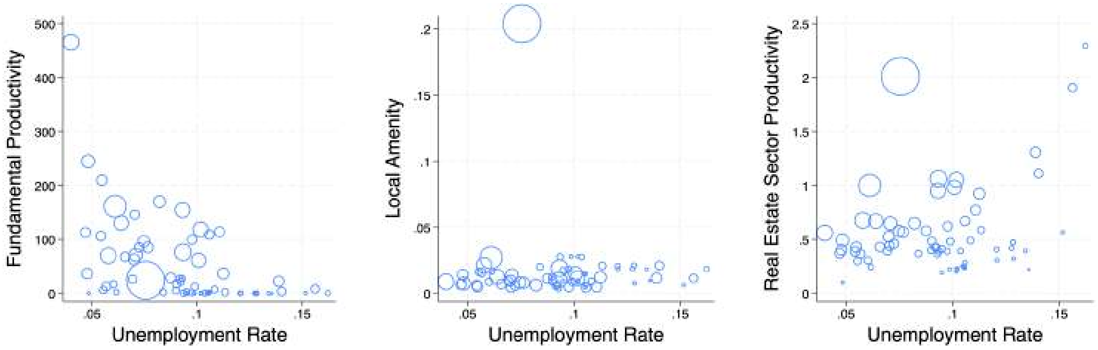
$$\begin{aligned} \tau_j &= \frac{\varepsilon_{q,\theta} - \eta}{1-\eta}\left(\mathbb{E}\pi_j(z) - c + (1-\delta)\kappa\theta_j \right), \\ &= \frac{\mu - \eta}{1-\eta}\left(\mathbb{E}\pi_j(z) - c + (1-\delta)\kappa\theta_j \right). \end{aligned} \tag{128}$$

C Quantitative Appendix

C.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 3. In particular Figure C.8 plots capital unemployment against local productivity, amenity, and real estate sector productivity.

Figure C.8: Capital Unemployment Rate and Capital Stock



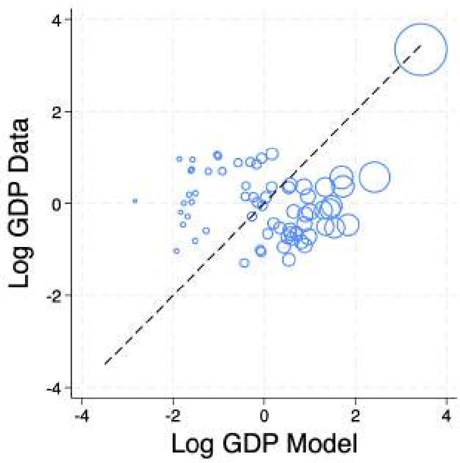
(a) Local Productivity **(b) Amenity** **(c) Real Estate Productivity**

Note: Figure C.8 shows the correlations between capital unemployment rate with local fundamental productivity, amenity, and real estate sector productivity.

C.2 GDP

Here, we validate the GDP implied by the model with that in the data. Figure C.9 shows the scatterplot of GDP rates from the data against those from the model. Overall we find a satisfactory fit between the two.

Figure C.9: Output: Model vs. Data

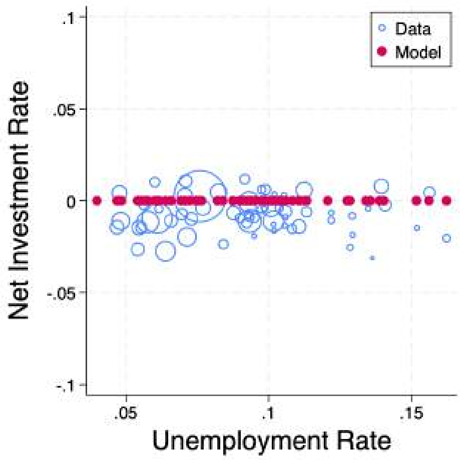


Note: Figure C.9 scatterplots log GDP across cities in the UK from the model and data, with cross-sectional means removed. The dotted line represents the 45-degree line.

C.3 Investment Rates

Here, we validate the investment behavior implied by the model with the findings in the data. Figure C.10 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 C.10: Net Investment Rate: Model vs. Data



Note: Figure C.10 scatterplots net investment rate across cities in the UK against capital unemployment rate from the model and data.

C.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 C.5 shows the results. Overall, a higher amenity is positively associated with higher estimated amenities.

C.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.

Figure C.11 presents our results related to the extensive margin. Figure C.11a 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 C.11b 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 (51) in Appendix A.4.2.

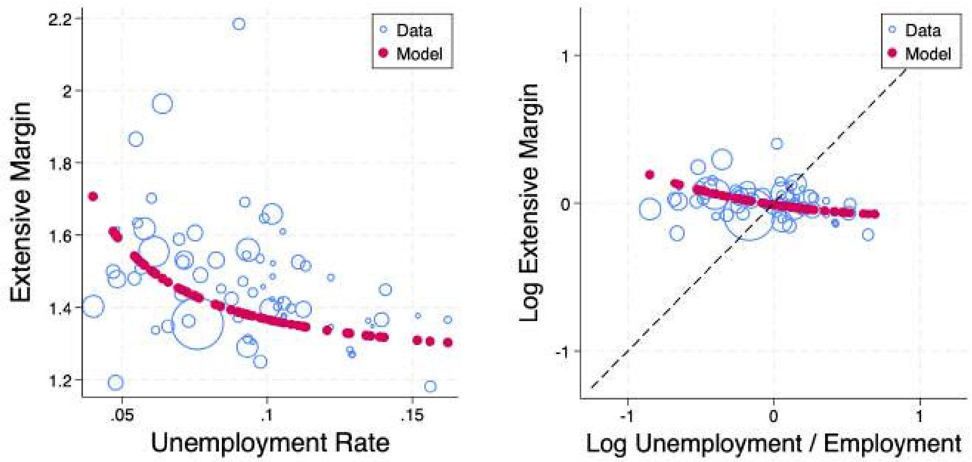
Table C.6 compares the variance decomposition of log unemployment-employment capital ratio between data and model. Columns 1 and 3 show the variance decomposition in equation (11) in the model and the data as discussed in the main text, while columns 2 and 4 show the variance decomposition in equation (51) without measurement error in the model

Table C.5: 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 C.11: Extensive Margin and Capital Unemployment Gap Differences



(a) Raw Data **(b) Contribution to Decomposition** (51)

Note: Figure C.11 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 C.11a, the extensive margin is plotted against the local unemployment rate, along with the dashed black 45-degree line. Figure C.11b 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.

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.

Table C.6: Variance Decomposition of Local Unemployment-Employment Capital Ratio

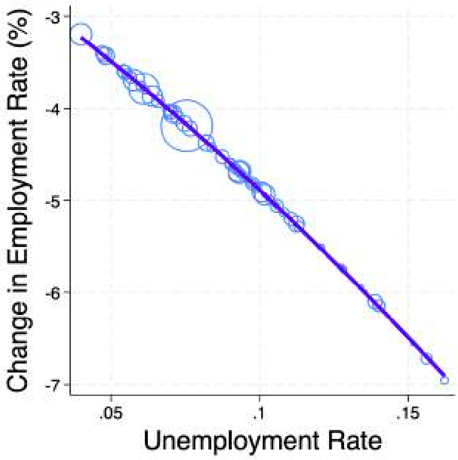
	Data		Model	
Direct flows: separation and finding rates (%)	100	112	100	117
Separation rate (%)	69	78	68	79
Finding rate (%)	31	34	32	38
Extensive margin due to investment (%)	–	-12	–	-17

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 (11), while columns 2 and 4 show the variance decomposition in equation (51) without measurement error. Direct flows represent the contributions of separation and finding rates. All numbers are reported in percent.

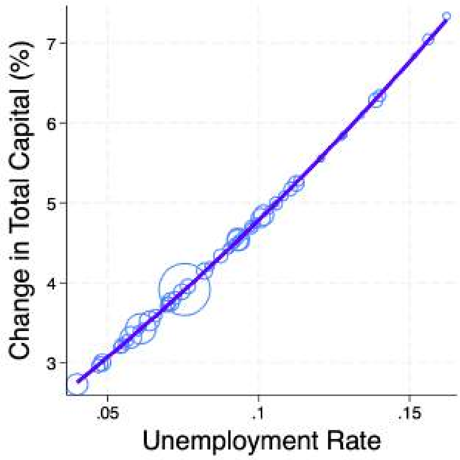
C.6 Social Planner Solution

Figure C.12 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.

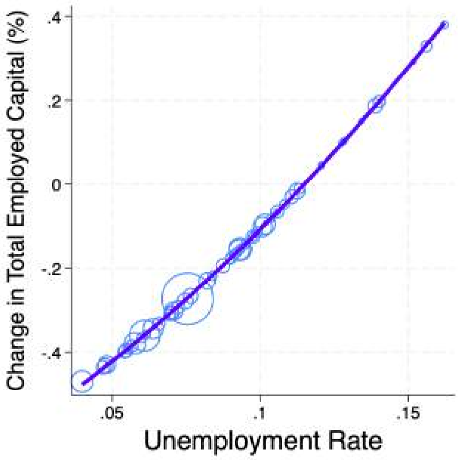
Figure C.12: Changes in Capital Employment Rate, Total Capital, Total Employed Capital and Wage in Social Planner Solution



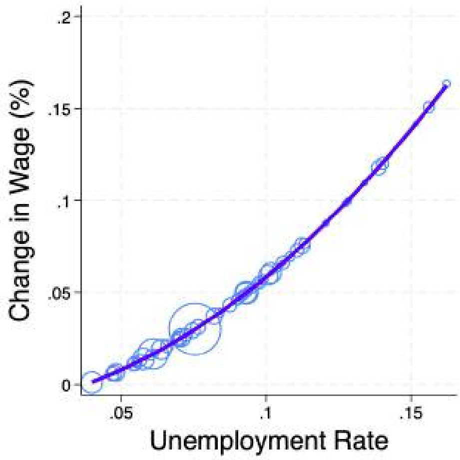
(a) Employment rate



(b) Total Capital



(c) Total Employed Capital



(d) Wage

Notes: Figure C.12 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.