Geographic Mobility over the Life Cycle*

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Abstract

When opportunities vary across locations and mobility is frictional, economic outcomes depend on birthplace. Using Spanish micro data and a life-cycle model, we show that location differences mainly reflect variation in (i) skill accumulation, (ii) job stability and opportunities, and (iii) information about alternative locations. For young individuals, information costs are the main barrier to mobility. Consequently, transfers to residents of distressed areas reduce inequality in economic outcomes with little effect on mobility. In contrast, policies that financially incentivize moving to high-opportunity locations increase inequality and do not significantly raise mobility toward those locations.

Keywords: Mobility; local labor markets; search frictions; life cycle.

JEL Classification: E20, E24, E60, J21, J61, J63, J64, J68, R23, R31.

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1 Introduction

Economic activity is not uniformly distributed across different places (see, for instance, Moretti, 2011). These spatial economic differences would not matter to a resident if moving was costless. Yet, moving costs imply that identical people have different labor prospects and opportunities depending on where they start their careers. As a result, there is a renewed interest in place-based policies to overcome those differences in opportunities.[1] In this paper, we show that policies designed to reduce spatial economic disparities need to take into account the specific features that make locations one of high opportunity, the underlying frictions hampering mobility, as well as their heterogeneous effects on mobility over people's life cycles.

To reach these conclusions, we develop a structural dynamic life-cycle model of migration and calibrate it using Spanish micro data on urban areas, a concept similar to Commuting Zones. We find that starting one's career (henceforth, being born) in a high-unemployment urban area in the top tercile of the unemployment rate distribution reduces lifetime consumption in equivalence units by 15.6 percent relative to being born in a low-unemployment urban area in the bottom tercile. Being born in the middle tercile reduces lifetime consumption in equivalence units by 6.4 percent relative to being born in the bottom tercile.

The life-cycle aspect of the model also allows us to understand the specific features that make low-unemployment urban areas those of high opportunity. That is, the model features average productivity across places and also differences in the speed of skill accumulation when individuals work in a particular place. In addition, local labor markets are characterized by frictional labor markets, where the unemployed and employed search for jobs, and the degree of frictions differs across locations. Moreover, both the employed and unemployed, as well as the retired, search for better opportunities across local labor markets, and moving opportunities differ across urban areas.

We find that low-unemployment urban areas are also more productive, provide more skill accumulation to their workers, jobs are more stable, and spatial mobility opportunities arise more frequently. Slower skill accumulation when working in an urban area in the middle tercile of the urban area unemployment distribution is the single most important factor explaining lower lifetime consumption-equivalence units for people born there relative to those born in the bottom tercile. Differently, less stable jobs and lower job-finding rates in urban areas in the top tercile of the unemployment distribution are the single most important factors explaining the lower lifetime consumption of people born in those urban areas. Differences in average productivities between

[1] See, for instance, Austin et al. (2018), Fajgelbaum and Gaubert (2020), or Bilal (2021).

urban areas explain less than 13 percent of lifetime consumption differences. Put differently, despite large average earnings differences between urban areas, simply reallocating a worker from a high- to a low-unemployment urban area is not going to instantaneously raise her earnings. Instead, for young people, moving to a low-unemployment urban area mainly carries with it dynamic gains. Part of these dynamic benefits of residing in a low-unemployment urban area is that it provides more spatial search opportunities to its residents.

To arrive at these conclusions, we discipline the model with Spanish microdata. Four reduced form moments turn out to be key for our findings: First, urban area fixed effects are relatively small in an earnings regression once we control for heterogeneity in skill accumulation across urban areas. Second, earnings growth is particularly fast in low-unemployment urban areas. Third, job destruction rates are increasing in the unemployment rate of an urban area. Fourth, low-unemployment urban areas have a higher turnover rate of their residents.

The model differentiates between two frictions that hinder people from moving to urban areas with high opportunities: (i) non-pecuniary moving costs, and (ii) infrequent migration decisions due to information frictions. Information frictions turn out to be the main impairment to why young people do not move to better opportunities. In contrast, moving costs mainly reduce mobility of the elderly towards cheaper locations. Resulting from the information friction, policies that give pecuniary incentives to move to low-unemployment areas fail to increase young people's mobility significantly. In particular, we simulate reforms that subsidize (i) mobility and (ii) rents in low-unemployment urban areas and show that they have modest effects on migration. Instead, they mostly benefit people who are already born in those areas. In contrast, paying transfers to people living in economically distressed regions is effective in reducing dispersion in consumption-equivalance units and has little negative implications on people's mobility. As the young have a high potential surplus from moving to urban areas with lower unemployment rates, a moderate subsidy for staying in their current urban area does not discourage them from moving.

To tell apart non-pecuniary moving costs from infrequent migration decisions, we rely on life cycle mobility data from the Spanish Census. In particular, we show that (i) geographic mobility over the life cycle decays slowly and remains significant even for people 70 years and older, and that (ii) conditional moving, people's sorting into particular urban areas over the life cycle is slow. That is, though urban areas with good labor markets attract on net young people and poor labor markets attract on net old people, the age gradient is not particularly steep. We show that this slow sorting of people over the life cycle and the high mobility of old people are hard to reconcile with a model where individuals optimally decide each period where to migrate to. Instead, the data better matches a model where people make mobility decisions infrequently and geographic search is random. Consistent with experimental evidence from Bergman et al. (2024) and Wilson (2021), as well as Spain-specific survey evidence, we interpret this friction as an informational friction that hinders the process of evaluating the benefits of moving.

Literature This paper relates to the literature that explains migration decisions by characteristics of different locations such as Kennan and Walker (2011), Bayer and Juessen (2012), and Rivera-Padilla (2025). In that context, similar to us, Coen-Pirani (2010), Lkhagvasuren (2012), and Hansen and Lkhagvasuren (2015) highlight that gross mobility rates are much higher than net mobility rates, i.e., there exists excess reallocation. We add two new stylized facts to this literature: First, we show that this excess reallocation is higher in urban areas with better labor markets. Second, we show that net flows are systematically related to the quality of local labor markets once we condition on people's age.

We also contribute to the literature on spatial mobility where housing creates a congestion cost in local economies such as Nieuwerburgh and Weill (2010), Monte et al. (2018), Bryan and Morten (2019), Favilukis et al. (2023), Giannone et al. (2023), Bilal and Rossi-Hansberg (2021), and Komissarova (2022). Using a life cycle framework, we highlight that the elderly provide a force limiting high rental prices in urban areas with good labor markets. Moreover, we show that most of the average earnings differences across urban areas highlighted by this literature arise from dynamic gains accruing to workers over time, particularly a faster climbing of the job ladder in high-paying urban areas, instead of the same worker earning different wages across urban areas. Here, our findings are different from those in Baum-Snow and Pavan (2012). The principal reason is that we find job stability to be much higher in high-paying urban areas once we study urban areas by unemployment rates instead of size, which is consistent with recent evidence for other countries provided by Bilal (2021) and Kuhn et al. (2021).

The paper also links to Nanos and Schluter (2018), Heise and Porzio (2023), and Schluter and Wilemme (2023), who try to understand why people do not reallocate to labor markets with better labor market prospects. Using models where workers choose optimally in which local labor market to search, they show that job search frictions reduce the reallocation of workers from low to high-productivity locations. Our model explicitly distinguishes job search and spatial search. Job search is related to the fact that workers frequently move to places as unemployed, suggesting that doing so provides them better access to the local labor market than searching from afar. Differently, by taking into account life cycle mobility, we show that spatial search is more consistent with a random rather than directed search process. Moreover, we show that the strength of this spatial search friction depends on the current place of residence. We motivate this search process on experimental micro evidence that shows that exposure to new information increases the percentage of people moving between locations (Bergman et al., 2024; Wilson, 2021). Moreover, we provide a microfoundation consistent with this evidence that provides a mapping between spatial search frictions and people's prior beliefs about location characteristics and information acquisition costs.

These search frictions imply spatial inequality in lifetime income and amenities. This is also the case in Zerecero (2021), who, differently from us, emphasizes the role of a birthplace bias.[2] Moreover, we show that understanding search frictions as being an integral part of mobility frictions changes the effects of place-based policies (Glaeser and Gottlieb, 2008; Albouy, 2009; Gaubert, 2018; Fajgelbaum et al., 2019; Gaubert et al., 2021). This literature points out that subsidizing people to live in economically depressed areas reduces economic efficiency as it reduces efficient people reallocation. We show that a moderate subsidy has negligible effects on mobility and aggregate output because spatial search frictions imply that young people in economically depressed areas have an on average high mobility surplus.

2 Data

We describe patterns of geographical mobility using the *Spanish Censuses of Population and Housing*, complemented with data from the Spanish Labor Force Survey. To the best of our knowledge, this is the first paper to document mobility in the Spanish Census. To characterize labor markets, we employ Social Security registry data, the Continuous Sample of Employment Histories (*Muestra Continua de Vidas Laborales*). We relegate additional information on the data sources and variable constructions to Appendix A.

2.1 Census and the Spanish Labor Force Survey (SLFS)

The Census is a decennial cross-sectional microdata set created by the Spanish statistical agency, *INE*. The structure is similar to its US counterpart described, for example, in Diamond (2016). In each census year (1991, 2001, and 2011), a random set of households representing about 8% of the population is asked to provide information on the current socio-demographic status of all their

[2] Zabek (2024) and Heise and Porzio (2023) also show the presence of a birthplace bias in mobility data. We also find that people are relatively likely to move to their place of birth in the Spanish data. However, we find that, conditional on moving, the share of people moving to their birthplace is almost flat over the life cycle. It is this life-cycle pattern of mobility that is relevant to us in identifying different mobility frictions.

members aged 16 or older.[3]

Our definition of a location is that of an *Urban Area*, whose definition is similar to that of a commuting zone in the U.S. and is meant to represent the local economy where people work and live.[4] In total, we have 86 Urban areas in Spain that account for 69.4 percent of the total population and about 76.0 percent of total employment in Spain. As in other countries, the Spanish population is fairly concentrated in a few urban areas. In particular, Madrid, Barcelona, Valencia, and Seville account together for almost one half of the population of all urban areas.

Each person in the Census reports on her employment status, allowing us to compute the unemployment rate in each urban area. Moreover, the 2001 and 2011 Censuses included a question on the location of residence during the previous Census, i.e., 10 years ago, which allows us to construct inflow and outflow rates for each urban area.

The Census does not allow us to identify the employment status before changing an urban area. To this end, we supplement the data with the SLFS, which is a quarterly representative household survey containing information on 160,000 individuals in Spain. The first available year of the survey is 1999, and we use the editions between 1999 and 2011.[5]

2.2 Muestra Continua de Vidas Laborales (MCVL)

The MCVL is a Spanish administrative data set that provides a 4 percent random sample of individuals who have any relationship with the Social Security Administration for at least one day during the year of reference. This covers all people who either are working, collecting unemployment benefits, or receiving a public retirement benefit. The first reference year available is 2006. A unique ID number allows us to trace individuals in later editions of the MCVL. We employ the 2006–2008 editions as the labor market was severely affected by the Great Recession in the years after 2008.

Importantly, the data provides longitudinal information on the entire working career, including the place of work, for all individuals in the sample. Hence, we can compute individuals' accumulated work experience in different locations. Moreover, the data provides us with uncoded earnings from tax administration records for the years 2006–2008 that we deflate using the 2009 Consumer Price Index. Finally, employers' ID numbers let us identify job-to-job transitions.

[3]We discard individuals who are institutionalized. 1991 is the first year when the data is publicly available, and a major redesign took place in that year.

[4]The Spanish Ministry of Transport, Mobility, and Digital Agenda uses this classification in the Censuses. For more information, see http://atlasau.mitma.gob.es.

[5]The geographical information in the SLFS is not available at the urban area level but only at the provincial level. However, according to the Censuses, 90% of mobility between urban areas entails also mobility between provinces.

Table 1: Reduced-form evidence for labor market characteristics

	AME (pp.)		**Baseline probability** (%)
	T1	**T2**	**T3**
Unemp. to emp. probability (U2E)	5.5*** (0.3)	2.1*** (0.3)	32.6
Emp. to unemp. probability (EU2)	-2.5*** (0.1)	-2.1*** (0.1)	9.8
Job-to-job probability (JTJ)	1.8*** (0.1)	0.5*** (0.1)	14.7
Share job-to-job down (JTJ down)	-3.9*** (0.4)	-2.4*** (0.5)	41.5

Sources: (a) Unemployment: Time-averaged values from the Census; (b) Flow rates: Time-averaged values from the MCVL 2006-2008. The "Employment to unemployment" rate is the share of non-employed workers who find a job in the next year. The "Unemployment to employment" rate is the share of employed workers who are non-employed in the next year. The "job-to-job" rate (J2J) is the share of employed workers who change employer, and "J2J down" reports the share of J2J that experience earnings losses.

3 Patterns of urban areas and mobility

We classify urban areas according to their unemployment rates to understand the different economic attributes of locations in Spain. Section 3.1 shows that low-unemployment areas feature higher job-finding rates, lower job-destruction rates, higher earnings growth, and higher average annual earnings. These areas also have higher average housing prices. We then relate these locational characteristics to people's geographic mobility in Section 3.2. We show that the vast majority of flows across urban areas are gross rather than net flows, i.e., some people move to while other people leave the same urban area. These gross flows are particularly large in low-unemployment urban areas. In contrast to overall flows, once we condition on people's age, we do observe systematic sorting: Young people reallocate on net to low-unemployment urban areas whereas older people reallocate on net to high-unemployment urban areas. We also show that young people are more likely to be geographically mobile, yet, mobility remains a phenomenon throughout people's life cycles. Finally, we show that employed and unemployed people leave urban areas, and they join new urban areas with and without jobs.

3.1 Urban area characteristics

Labor market flows. We group urban areas into three terciles of the urban-area unemployment distribution, with the first tercile representing the urban areas with the lowest unemployment rates. Unemployment rates differ greatly across locations; the average rate is 16.2% in the first tercile and reaches 27.1% in the third tercile. To understand whether these urban areas offer different job finding, job destruction, and job mobility prospects, we estimate the following Probit regression:

$$P(y_{i\ell t} = 1) = \Phi(\tau_t + \alpha_\ell + \beta' \mathbf{X_{ijt}}), \tag{3.1}$$

where $y_{i\ell t}$ refers to a binary labor market outcome of worker i in an urban area of tercile ℓ at time t, τ_t is a time-fixed effect, α_ℓ is an urban area (of unemployment tercile ℓ) fixed effect, and $\mathbf{X_{ijt}}$ is a vector containing a constant, sex, education, country of origin, and age. We report the average marginal effects (AME) of unemployment urban terciles $\ell \in \{1, 2\}$ relative to tercile three. These effects capture differences in job prospects across urban areas after controlling for the self-selection of workers with different observable job-stability-related characteristics into urban areas. Table 1 reports the AMEs of interest and the baseline probability for different labor market outcomes. Consistent with the findings of Bilal (2021) for France and the U.S. and Kuhn et al. (2021) for Germany and the United Kingdom, the flows of going in and out of employment are correlated with the area unemployment rate. We find that low-unemployment urban areas feature higher job-finding rates for both unemployed and employed workers, as well as a lower job-destruction rate and a lower rate of downward job mobility. Table B.2 in Appendix B shows that these results are robust to additionally controlling for worker fixed effects.

Earnings. The bottom of Table 2 shows that average earnings of employed workers are 22.4 and 3.9 percent higher in urban areas in the first and second terciles compared to the third tercile. Higher average earnings in low-unemployment areas may be the result of those areas providing more productive jobs to their workers, faster earnings growth, or they may reflect the ability of people sorting themselves into those areas. To distinguish between individuals' and locations' attributes, we follow De La Roca and Puga (2017) and specify the following reduced-form relationship for log earnings of worker i in an urban area of tercile ℓ at time t:

$$\ln w_{i\ell t} = \varphi_i + \tau_t + \alpha_\ell + \sum_{\ell=1}^{2} \delta_\ell \, e_{i\ell t} + \gamma_1 \, e_{it} + \gamma_2 \, e_{it}^2 + \varepsilon_{i\ell t}, \tag{3.2}$$

where φ_i is a worker-fixed effect, τ_t is a time-fixed effect, and α_ℓ is an urban area (of unemployment tercile ℓ) fixed effect, $e_{i\ell t}$ is the experience accumulated up to period t in an urban area ranked in the unemployment tercile $\ell = 1, 2$, and e_{it} is overall worker experience (i.e., total span of working experience). The coefficient associated with overall experience captures how earnings grow with experience in the third tercile while δ_1 and δ_2 capture the additional growth in the first and second terciles. We measure overall worker experience as the number of days with a full-time equivalent labor contract, and we express the results in years.

Table 2: Reduced-form evidence for earnings

	T1	T2
Urban area fixed effect, α_ℓ (%)	5.60***	1.91***
	(0.21)	(0.22)
Urban area returns to experience, δ_ℓ (%)	1.35***	0.29***
	(0.03)	(0.04)
Overall returns to experience, γ_1 (%)	7.77***	
	(0.07)	
Overall returns to experience^2, γ_2 (%)	-0.22***	
	(0.01)	
Gap in earnings per worker relative to T3 (%)	22.40	3.88
Job/sector controls	No	
City, worker, time FE	Yes	
N	6,359,219	
R^2	0.03	

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

Before discussing the results of the regression, we note that, as Baum-Snow and Pavan (2012) point out, the reduced-form estimates should not be taken causally as they require strong exogeneity assumptions. Still, Table 2 highlights three elements of the regression results that will prove useful for our structural model below.[6] First, urban areas with low unemployment rates pay high average earnings conditional on worker characteristics. The urban area fixed effect of the first tercile, α_1, is 5.6 percent, whereas the urban fixed effect of the second tercile is 1.9 percent. Notably, the urban area fixed effect for the first tercile is substantially smaller than the average earnings difference between the first and third terciles (5.6 vs 22.4), suggesting that workers in low-unemployment urban areas are relatively more productive. Second, workers' earnings grow faster when working in low-unemployment urban areas. In particular, one additional year of experience in an urban area ranked in the first and second tercile of the urban area unemployment distribution is associated with a rise in average annual earnings by 1.4 and 0.3 percent, respectively, relative to accumulating the same year in the third tercile. Third, earnings are increasing, although concave, in overall experience accumulation.

Housing costs. Better job prospects in low-unemployment urban areas may increase population density and housing demand in these areas. Table 3 reports the statistics of the population and housing market across urban areas. We find that low-unemployment urban areas are, on average, larger and more densely populated. Moreover, we find that this translates into an increase of nearly 55.1 percent in average housing costs in low- relative to high-unemployment urban areas.

[6]Table B.3 in Appendix B shows that the following results prevail when controlling for sectoral-specific shocks that might occur right before the Great Recession.

Table 3: Summary statistics of housing markets across urban areas

	T1	T2	T3
Average population	335,572	200,035	164,857
Average population per km^2	1,500	1,153	844
Housing price per m^2	1,948	1,254	1,256

Sources: (a) Census: Unemployment and Population (b) Digital Atlas of Urban Areas (http://atlasau.mitma.gob.es/#c=home): Population Density and Housing Prices. Unemployment and Population are time-averaged values from the Census 1991, 2001, and 2011. The reference year of housing prices is 2021, deflated to 2009 euros. The reference year of population density is 2011.

3.2 Mobility across urban areas

Mobility patterns across urban areas. Next, we asses the extend of geographic mobility in Spain and how the economic characteristics of urban areas interact with people's mobility flows across them. The mean decennial gross inflow rate, IR, across urban areas is 14.5 percent, and the gross outflow rate, OR, is 11.3 percent. Thus, the average urban area experiences substantial inflows and outflows, and gross flows are considerably larger than the net flows required to account for changes in population over time. We specifically quantify this "excess reallocation" as the difference between gross and net flows:

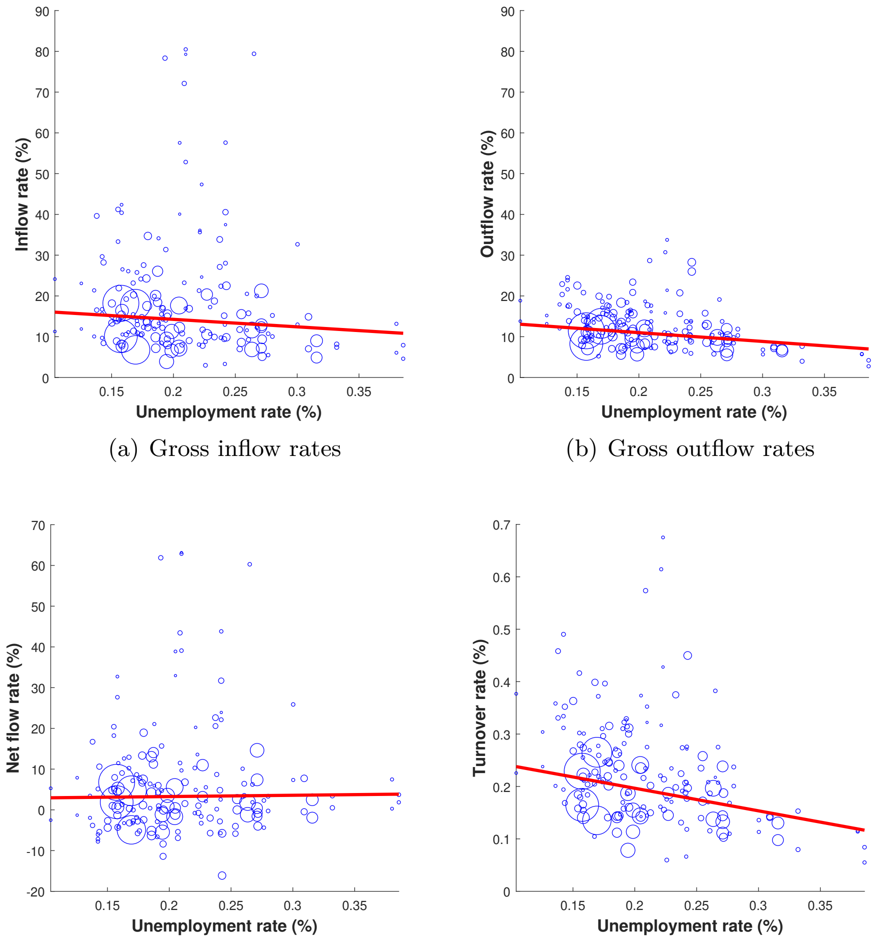
$$ERR_{it} = \underbrace{IR_{it} + OR_{it}}_{\text{Gross reallocation}} - \underbrace{|IR_{it} - OR_{it}|}_{\text{Net reallocation}}.$$

The mean gross reallocation rate is 25.8 percent, out of which 22.6 percent is excess reallocation. In other words, roughly 88 percent of gross reallocation constitutes excess reallocation, which closely aligns with evidence on mobility across US states, where 87 percent of gross mobility is excess reallocation (Coen-Pirani, 2010; Lkhagvasuren, 2012). This regularity highlights that excess reallocation is key to understanding most mobility decisions.

Figure 1 links the flow rates across urban areas to their local labor market conditions. Low-unemployment urban areas have, on average, higher inflow and higher outflow rates than high-unemployment areas. The relative sizes of both flows are such that the net population growth rate shows no systematic relationship with the unemployment rate at the urban area level, as shown in the third panel. As a result, the excess reallocation rate is substantially higher in low-unemployment urban areas. For instance, those areas with an unemployment rate of 17 percent have a predicted excess reallocation rate of 22 percent compared to only 17 percent for urban areas with an unemployment rate of 30 percent.

The lower gross mobility rates in urban areas with higher unemployment may stem from the

Figure 1: Mobility across urban areas.



(a) Gross inflow rates

(b) Gross outflow rates

(c) Net flow rates

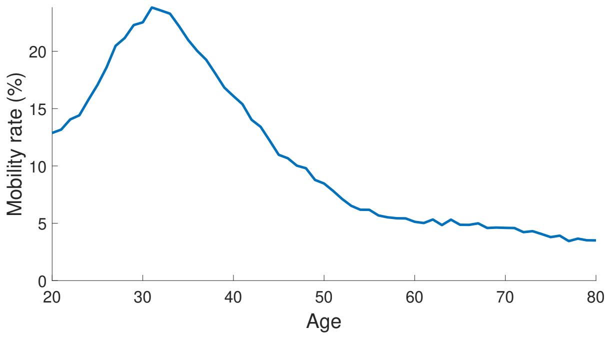
(d) Excess reallocation rates

Note: The unemployment rate is the mean unemployment rate over three Censuses. The lines show size-weighted OLS regression slopes.

characteristics of the people living there rather than those of the urban area itself. However, we find that this is unlikely to be the case. After controlling for observable population characteristics, the negative relationship between the excessive reallocation rate and the unemployment rate becomes yet stronger (see Table B.4 in Appendix B.2).

Mobility patterns across urban areas over the life cycle. Life cycle considerations may drastically shape the incentives on *whether* to migrate. Figure 2 shows the average mobility rate by people's ages. The decennial mobility rate, after initially rising, falls from 24 percent at age 31 to less than 5 percent by age 70. The paper does not speak to the initial rise, which, given the decennial measure, represents mostly mobility decisions of parents. Instead, our focus is on explaining the falling mobility hazard after age 31. One notable aspect of this hazard is that the decay is slow after age 55, and mobility remains somewhat high at all ages. A decreasing

Figure 2: Mean mobility rate by age.



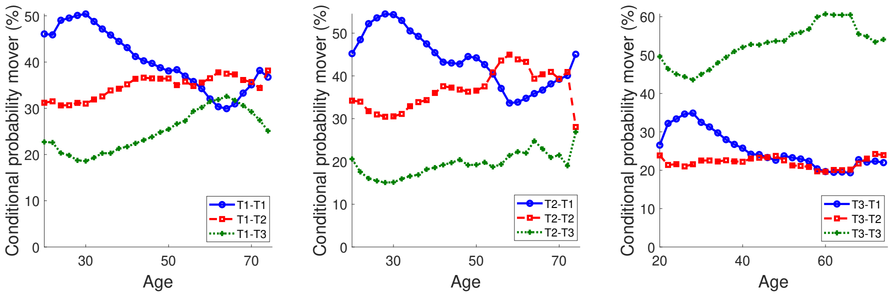
Source: 1991, 2001, and 2011 Censuses.

mobility rate over the life cycle is consistent with the presence of fixed utility moving costs (see, e.g., Kennan and Walker, 2011; Kaplan and Schulhofer-Wohl, 2017; Giannone et al., 2023), which are the common way to model mobility frictions. We note, however, that the shape of the hazard is similar to job quit hazards, documented for example by Topel and Ward (1992), and this literature usually interprets a gradually declining hazard as the result of search frictions. We will combine both types of mobility frictions in our structural model below and discuss how the rate of decay allows us to distinguish the two.

Moreover, life cycle motives may also shape the incentives regarding *where* to move. To illustrate these incentives, Figure 3 plots the probability to move to an urban area within each terciles, conditional on leaving a particular tercile. Regardless of the tercile people are moving away from, most people under 30 years old move towards urban areas with the same or lower unemployment rate, whereas older people move to places with higher unemployment rates. For example, the probability of moving to an urban area in the bottom tercile of the unemployment distribution is highest around age 30. This probability steadily falls over the life cycle. Mirroring these probabilities, the probability of moving to an urban area in the top tercile is the lowest around age 30, and steadily rises over the life cycle. To a lesser extent, the same occurs for the probability of moving to an urban area in the second tercile. To sum up, conditional on moving, the labor market characteristics of the location where people move to vary over the life cycle, regardless of their place of origin. In Appendix B.3, we show that these pattern are not driven by education differences across age cohorts. In fact, and different from age, education plays a second-order role in shaping the sorting of workers across places.

Mobility patterns by job status. Finally, we link individuals' employment status to their mobility decisions. Using SLFS data, we find that 73 percent of movers younger than 65 were

Figure 3: Mobility over the life cycle in the data.



(a) Leaving tercile one (b) Leaving tercile two (c) Leaving tercile three

Source: 1991, 2001, and 2011 Censuses.

employed before moving. Put differently, mobility is not primarily driven by people escaping unemployment. Moreover, 45 percent of those moving are non-employed when arriving at the new urban area. That is, the data suggest that people join local labor markets to search for jobs locally, instead of engaging in a global search.

4 Model

We develop a dynamic structural life-cycle model of migration with heterogeneous individuals and locations to rationalize the empirical patterns discussed above. Locations are ex-ante heterogeneous in productivity, skill accumulation, and employment stability. Ex-ante homogeneous individuals face labor market risk over their life cycle and make decisions regarding consumption of housing and non-housing goods, whether to accept job offers or quit jobs, and whether to migrate. Migration choices depend on income and amenity considerations and are subject to two frictions: (i) a non-pecuniary moving cost, and (ii) a spatial search friction, which involves that only a fraction of people decide whether to migrate to an alternative location due to costly information acquisition.

4.1 Demography, preferences and housing market

The economy is populated by a measure one of people. They live for T periods and are replaced by a newborn whenever they die.[7] There is no population growth, and the probability of dying before age T is zero. People start their lives in the labor force and retire after age $R < T$. During their working life, people are either unemployed or employed. Individuals value consumption of housing and non-housing goods, and they have idiosyncratic tastes for the location they inhabit. Thus, the

[7]We assume that the birthplace of new cohorts is not related to the death place of an existing cohort.

lifetime utility of person i is given by:

$$E_1 \sum_{t=1}^{T} \beta^{t-1} \left[c_{it}^{\theta} h_{it}^{1-\theta} + s_{it} \right], \tag{4.1}$$

where β is the time discount factor, c_{it} is the non-housing consumption at age t, h_{it} denotes housing services, and s_{it} is an idiosyncratic additive utility flow the person extracts from amenities in the particular urban area where she lives. Amenities take value in $S \subset \mathbf{R}_{++}$.

The economy is composed of a unit measure of urban areas that we refer to as *locations*. As in the empirical analysis, we distinguish between three types of locations representing the three terciles of the urban area unemployment distribution, $\ell \in \{1, 2, 3\}$. Each location of type ℓ has a time-invariant productivity type level, A_ℓ. The size of housing in each location of type ℓ, $\overline{H}_\ell$, is exogenously given and can be thought of as land. Finally, each type of location consists of an equal measure of individual locations. As in Nieuwerburgh and Weill (2010), absentee landlords own the housing stock and charge a rental price of housing in location ℓ of r_ℓ.

4.2 Local markets

The unemployed receive unemployment benefits b_U, and retirees receive b_R. The employed produce an output good using a linear production technology in an urban area. They earn their marginal products and, hence, their earnings depend on their location, the type of job they are employed at, and their idiosyncratic productivity. When employed at a location with productivity A_ℓ and a job j with log productivity z_j, a person of age t earns:

$$\ln w_{\ell jt} = \ln A_\ell + z_j + x_t, \tag{4.2}$$

$$x_t = e_t + \psi_1 t + \psi_2 t^2, \tag{4.3}$$

$$e_{t+1} = e_t + \delta_\ell \qquad \text{if employed,} \tag{4.4}$$

$$e_{t+1} = e_t \qquad \text{if non-employed,} \tag{4.5}$$

where x_t is the person's idiosyncratic log productivity that has a deterministic age component given by ψ_1 and ψ_2. Two comments are in order. First, location size correlates with productivity only through cities with higher A_ℓ being endogenously bigger. Beyond that, we abstract from a positive externalities of agglomeration, such as Eeckhout et al. (2014) or De La Roca and Puga (2017). Second, differently from our empirical analysis shown in Equation (3.2), we explicitly model an individual's productivity to depend on her job, z. Similarly to the empirical model, we assume that working in "good" locations gives a static productivity gain, A_ℓ, as well as a steeper profile in productivity gain, given by δ_ℓ. Differently, for computational simplicity, we assume that her productivity increases with age instead of with overall work experience.

The local labor market opens after employed people work and income payments and consumption take place. Then, agents receive random labor opportunities or may be laid off. As we show in Section 3.2, local labor markets differ in their job offer opportunities and the probability that a worker becomes unemployed. Hence, we allow the currently unemployed to receive a job offer with location-specific probability ϕ_ℓ. A job offer is a random draw of job log productivity, z, where we denote the density of this job offer distribution by $f_Z(z)$. We assume that this density is the same across locations. The currently employed exogenously lose their job with location-specific probability λ_ℓ and become unemployed. Otherwise, they may receive an offer from another job with probability Λ.[8] To capture the fact that job-to-job transitions in Spain frequently lead to earnings losses, we allow for two types of job offers. With probability $1 - \lambda_d$, the worker can choose between her current job, the outside offer, and unemployment, i.e., she will only accept the job when the new job pays a higher wage. However, with probability λ_d, the job offer is a reallocation offer whose only alternative is unemployment if it is rejected. Examples of such reallocation offers are that the worker knows that her current job will disappear because of a temporary contract or a plant closure.[9]

4.3 Mobility across locations

Life-cycle models of migration often assume that individuals possess complete information about the fundamentals of all locations in the economy, implying that they reassess and choose their location in every period based on this complete information set. However, two key mobility patterns suggest that people only scan locations infrequently and thus behave *as if* they only consider moving elsewhere occasionally. First, experimental micro evidence shows that exposure to new information increases the fraction of people who move across locations (see, e.g., Bergman et al., 2024; Wilson, 2021).[10] Second, as documented in Figure 2, the mobility hazard decays slowly over the life cycle. This slow decay may be the result of: (i) shocks that change individuals' preferred location over

[8] We assume that the parameters governing on-the-job search are common to all urban areas, as there is little heterogeneity in the targets across urban areas.

[9] Notice that we do not model firms' vacancy creation and, hence, are not interested in how the surplus is split. For simplicity, we assume all surplus goes to the workers.

[10] Wilson (2021) provides evidence that limited knowledge about different local labor markets reduces people's mobility. Moreover, Bergman et al. (2024) find that also other frictions such as the housing search process in the new place play a role in people not considering moving. They find that assisting families to obtain better information about prospective locations increases upward mobility from 15% to around 50%.

the life cycle, such as the labor market risk captured in our model, (ii) age-dependent mobility costs, or (iii) search costs that lead people to acquire information and move infrequently. Evidence from a Spanish administrative survey suggests that the last channel may be significant (Centro de Investigaciones Sociológicas, 2012). According to this survey, only 17 percent of the Spanish population have "*thought about the possibility of living in another place*" during the last 12 months.

In view of this evidence, we introduce two frictions that discourage people from moving to the location that provides the highest consumption or amenity value. First, we include an age-varying *fixed mobility cost* that people pay when they move $\kappa_t = \kappa_0 + \kappa_1 \cdot t \in \mathbf{R}_+$, which reflects the costs of the time and effort required to move and settle in a new location (Kennan and Walker, 2011; Giannone et al., 2023). Second, we model a *spatial search friction* so that people infrequently decide whether to migrate. This may reflect, for instance, that an individual learns by chance about a job offer in a particular location, prompting her to consider relocating there. Specifically, individuals choose whether to migrate to an alternative given location with probability μ_ℓ^J, which we allow to depend on the current location ℓ and the employment status $J \in \{E, U, R\}$. We assume that migration opportunities μ_ℓ^J are uniformly distributed across alternative locations ℓ', so that each occurs with probability one-third. Online Appendix C.1 shows that infrequent mobility decisions can arise in an environment where heterogeneous individuals make optimal information acquisition and migration decisions. This framework delivers a direct mapping between μ and the joint distribution of individuals over prior beliefs about locations' characteristics and information acquisition costs. This micro-foundation makes clear that individuals are not confined to locations; rather, some choose not to acquire information and, therefore, prefer not to move, either because their information costs are too high or because they are sufficiently convinced that they already live in the best location.

Lastly, consistent with evidence on the employment status of movers from Section 3.2, we consider that an opportunity to move to a different location may come with a job offer or as unemployed. The conditional probability of moving with a job offer depends on the labor market conditions in the other location, $\phi_{\ell'}$. In case the offer comes with an employment offer, the offered job type is again a random draw from $f_Z(z)$. A mobility offer entails, in addition to the employment and job offer type, an idiosyncratic location amenity s' with density $f_S(s')$. The amenity value of a location stays constant for the entire period a person lives there.

4.4 Value functions

We conjecture that locations of the same productivity level have the same rental price of housing. In Section 4.5 we show that this is, indeed, the case. Recall that there are three stages within each period: First, people work, collect income payments, and consume. Second, the local labor market opens. Working age people receive local labor market shocks which may change their labor status. At the final stage, a fraction of individuals decides whether to migrate. We describe the individual's problem faced at each stage backward, from the last to the first stage.[11]

4.4.1 Migration stage

This is the final stage within each period. All agents have already consumed at the first stage and working age population already know their employment status and productivity at their current location ℓ. Agents can migrate with probability μ_ℓ^j, where ℓ is the productivity type of their current location and j refers to their employment status: retired, unemployed or employed in their current location.

Retirees Consider a retiree of age $t = R+1, \ldots, T-1$, who lives in a location of type ℓ and amenity value s. The value function V_t^R is the expected utility before the migration opportunity is realized:

$$V_t^R(\ell, s) = \left(1 - \mu_\ell^R\right) \beta W_{t+1}^R(\ell, s) + \mu_\ell^R \sum_{\ell'} \frac{1}{3} \Omega_t^R(\ell, s, \ell') \tag{4.6}$$

$$\Omega_t^R(\ell, s, \ell') = \int_{s'} \max\left\{\beta W_{t+1}^R(\ell, s) \ , \ \beta W_{t+1}^R(\ell', s') - \kappa_t\right\} f_S(s')\, ds'. \tag{4.7}$$

$W_t^R(\ell, s)$ is the value function of a retiree of age t living in ℓ with amenity value s. $\Omega_t^R(\ell, s, \ell')$ comprises all the expected net gains of moving from ℓ to ℓ' type. The realized gains depend on the realization of the amenity value of location ℓ', which is drawn from the density distribution f_S. The current value of either choice (migration or not) is discounted with the factor β. The migration cost, however, is born at the time of migration. The solution to the migration decision is a policy function $g_t^{R,\mu}(\ell, s, \ell', s') \in \{0, 1\}$ that indicates if the agent wants to move to the new location ℓ' with amenity level s'.

Unemployed At the migration stage, an unemployed person's state includes her end-of-period experience level e', her current location, ℓ, and its associated amenity level, s. Unemployment at

[11] For parsimony, we omit the value functions in the last period of working life and the last period of life.

this stage may be the result of two different events: First, being unemployed at the beginning of the period and not becoming employed at home or, second, being laid off at the previous stage. In the first case, the experience level e' at this stage is equal to her experience level at the beginning of the period, e. In the second case, $e' = e + \delta_\ell$, as she has worked at the beginning of the period.

Unemployed agents receive an opportunity to migrate to a location of type ℓ' with probability $\mu_\ell^U/3$, which may come with a job offer with probability $\phi_{\ell'}$. This job offer will have a particular productivity z' attached, drawn from the distribution $f_Z(z')$. $V_t^U(\ell, s, e')$ is the value function at the beginning of the migration stage for an unemployed individual of age $t \leq R-1$ with accumulated experience e'. Thus,

$$\begin{aligned} V_t^U(\ell, s, e') \;=\; & \left(1-\mu_\ell^U\right)\beta\, W_{t+1}^U(\ell, s, e') + \\ & \mu_\ell^U \sum_{\ell'} \frac{1}{3}\Big[(1-\phi_{\ell'})\,\Omega_t^{UU}(\ell, s, e', \ell') \;+\; \phi_{\ell'}\,\Omega_t^{UE}(\ell, s, e', \ell')\Big]. \end{aligned} \tag{4.8}$$

$\Omega_t^{UU}(\ell, s, e', \ell')$ comprises the expected gains of having a moving opportunity from ℓ to ℓ' when the moving opportunity does not come along with a job offer. Thus,

$$\Omega_t^{UU}(\ell, s, e', \ell') \;=\; \int_{s'} \max\left\{\beta\, W_{t+1}^U(\ell, s, e')\,,\; \beta\, W_{t+1}^U(\ell', s', e') \;-\; \kappa_t\right\} f_S(s')\, ds'. \tag{4.9}$$

Likewise, $\Omega_t^{UE}(\ell, s, e', \ell')$ denotes the expected gains of moving with a job offer. This expected gain takes into account that the job offer productivity is a realization drawn from f_Z:

$$\Omega_t^{UE}(\ell, s, e', \ell') = \int_{z'}\int_{s'} \max\left\{\beta\, W_{t+1}^U(\ell, s, e')\,,\; \beta\, W_{t+1}^E(\ell', s', e', z') \;-\; \kappa_t\right\} f_S(s')\, ds'\, f_Z(z')\, dz'. \tag{4.10}$$

As in the case of retirees, unemployed agents have a migration decision policy. We denote as $g_t^{UE,\mu}(\ell, s, e, \ell', s', z')$ the policy when the migration opportunity comes along with a job offer and as $g_t^{UU,\mu}(\ell, s, e, \ell', s')$ when it is an unemployment offer.

Employed Employment at this stage may be the result of two different events: First, being unemployed at the beginning of the period and becoming employed or, second, staying employed. In the first case, the experience level e' at this stage is equal to her experience level at the beginning of the period, e. In the second case, $e' = e + \delta_\ell$, as she has worked at the beginning of the period.

Employed individuals receive a migration opportunity with probability μ_ℓ^E, which may come with a job offer or not. The value function at this stage, $V_t^E(\ell, s, e', z)$, satisfies:

$$V_t^E(\ell, s, e', z) = \left(1 - \mu_\ell^E\right) \beta W_{t+1}^E(\ell, s, e', z) + \\ \mu_\ell^E \sum_{\ell'} \frac{1}{3}\Big[(1 - \phi_{\ell'})\, \Omega_t^{EU}(\ell, s, e', z, \ell') + \phi_{\ell'}\, \Omega_t^{EE}(\ell, s, e', z, \ell')\Big] \tag{4.11}$$

$\Omega_t^{EU}(\ell, s, e', z, \ell')$ comprises the expected net gains of a migration opportunity without a job offer:

$$\Omega_t^{EU}(\ell, s, e', z, \ell') = \int_{s'} \max\left\{\beta W_{t+1}^E(\ell, s, e', z), \beta W_{t+1}^U(\ell', s', e') - \kappa_t\right\} f_S(s')\, ds'. \tag{4.12}$$

Likewise, $\Omega_t^{EE}(\ell, s, e, z, \ell')$ comprises the expected net gains of a migration opportunity with a job offer:

$$\Omega_t^{EE}(\ell, s, e, z, \ell') = \int_{z'}\int_{s'} \max\left\{\beta W_{t+1}^E(\ell, s, e, z), \beta W_{t+1}^E(\ell', s', e, z') - \kappa_t\right\} f_S(s')\, ds'\, f_Z(z')\, dz'. \tag{4.13}$$

The migration policy function is $g_t^{EE,\mu}(\ell, s, e, z, \ell', s', z')$ if the moving opportunity comes with a job offer and $g_t^{EU,\mu}(\ell, s, e, z, \ell', s')$ when it comes without a job offer.

4.4.2 Local labor market shocks and production and consumption stages

Retirees At the beginning of the period the state of a retiree is her age, t, the productivity of her location, ℓ, and the amenity value attached to it, s. Once retired, people receive retirement benefits b_R and stay retired until the end of life. Since they are inactive, their value function depends on current consumption and the expected continuation value of going to the migration stage:

$$\begin{aligned} W_t^R(\ell, s) = \quad & \max_{c,h}\left\{u(c, h, s) + V_t^R(\ell, s)\right\} \\ \text{s.t.} \quad & c + r_\ell\, h \le b_R, \\ & c \ge 0,\ h \ge 0. \end{aligned} \tag{4.14}$$

We define the housing demand policy function as $g_t^{R,h}(\ell, s)$.

Unemployed The individual state of an unemployed person is summarized by her location, ℓ, the amenity attached to it, s, and the work experience accumulated, e. An unemployed person receives a job offer with probability ϕ_ℓ and, conditional on that, the job offer has productivity z

with probability $f_Z(z)$:

$$
\begin{aligned}
W_t^U(\ell, s, e) = \quad & \max_{c,h} \left\{ u(c,h,s) + (1-\phi_\ell)\ V_t^U(\ell,s,e) + \phi_\ell \int_z \Psi_t^{EU}(\ell,s,e,z)\, f_Z(z)\, dz \right\} \\
\text{s.t.} \quad & c + r_\ell\, h \le b_U, \\
& c \ge 0,\ h \ge 0,
\end{aligned}
\tag{4.15}
$$

where the value of receiving an employment offer of productivity z is

$$
\Psi_t^{EU}(\ell,s,e,z) = \max \left\{ V_t^U(\ell,s,e), V_t^E(\ell,s,e,z) \right\} \tag{4.16}
$$

In the event of receiving a local job offer the corresponding policy by $g_t^{U,z}(\ell,s,e,z) \in \{0,1\}$. The housing demand function is $g_t^{U,h}(\ell,s,e,z)$.

Employed Workers have a more convoluted problem as they have to make more choices. Their individual state is described by her location, ℓ, amenity value, s, her work experience, e, and also her productivity in her job at the beginning of the period, z. They become unemployed with probability λ_ℓ. If they do not become unemployed, they may receive a job offer:

$$
\begin{aligned}
W_t^E(\ell,s,e,z) = \quad & \max_{c,h} \left\{ u(c,h,s) + \lambda_\ell\, V_t^U(\ell,s,e') + (1-\lambda_\ell)\ \Psi_t(\ell,s,e',z) \right\} \\
\text{s.t.} \quad & c + r_\ell\, h \le w(\ell,e,z,t), \\
& c \ge 0,\ h \ge 0, \\
& e' = e + \delta_\ell,
\end{aligned}
\tag{4.17}
$$

where

$$
\Psi_t(\ell,s,e',z) = (1-\Lambda)\, \Psi_t^{EU}(\ell,s,e',z) + \Lambda \Big[(1-\lambda_d)\, \Psi_t^{EE}(\ell,s,e',z) + \lambda_d\, \Psi_t^{ER}(\ell,s,e',z) \Big]. \tag{4.18}
$$

The worker may remain at her current job with probability $1-\Lambda$. In that case, she may decide between keeping it or quitting to non-employment as shown in Equation (4.16). With probability Λ she receives a new job offer and with probability $\Lambda\,(1-\lambda_d)$ she has the option to stay with her current job or become unemployed. Hence, her upper envelope of choices reads

$$
\Psi_t^{EE}(\ell,s,e',z) = \int_{z'} \max \left\{ \Psi_t^{EU}(\ell,s,e',z), V_t^E(\ell,s,e',z') \right\} f_Z(z')\, dz', \tag{4.19}
$$

with associate policy function $g_t^{EE,z}(\ell,s,e',z,z') \in \{0,1\}$. Finally, with probability $\Lambda\,\lambda_d$ she receives a reallocation offer, and her only alternatives are moving to a new job or rejecting the offer and becoming unemployed:

$$\Psi_t^{ER}(\ell,s,e',z)=\int\limits_{z'}\Psi_t^{EU}(\ell,s,e',z')\,f_Z(z')\,dz'. \tag{4.20}$$

In this case her policy function is denoted as $g_t^{ER,z}(\ell,s,e',z,z')\in\{0,1\}$. The housing demand function is $g_t^{E,h}(\ell,s,e,z)$.

4.5 Stationary equilibrium

We solve the model in steady state. Thus, the notion of migration in the model corresponds to excess mobility, which, as we document in Section 3.2, accounts for the vast majority of mobility flows observed in the data. We relegate to Appendix C.2 the formal definition of the equilibrium. Here, we show that rental prices are the same across locations within the same type ℓ.

Let y be an individual's income. Then, the Cobb-Douglas preferences imply that consumption expenditures for each good are constant shares of income:

$$c=\theta\,y,\quad h=(1-\theta)\,\frac{y}{r_\ell}.$$

Thus, the aggregate demand for housing in each location type ℓ is given by:

$$H_\ell^D=\frac{(1-\theta)}{r_\ell}\,y_\ell,$$

where y_ℓ is the aggregate level of income in location type ℓ, which is given by:

$$y_\ell=\sum_{t=R+1}^{T}N_t^R(\ell,s)\;b_R\;+\sum_{t=1}^{R}N_t^U(\ell,s,e)\;b_U\;+\sum_{t=1}^{R}\sum_{e\in\mathcal{E}}\int\limits_{Z}N_t^E(\ell,s,e,z)\;w(\ell,e,z,t)\;f_Z(z)\,dz.$$

$N_t^R(\ell,s)$, $N_t^U(\ell,s,e)$, and $N_t^E(\ell,s,e,z)$ denote, respectively, the mass of retirees, unemployed and employed working people of certain characteristics, whereas $g_t^{J,h}$ is the housing demand function of those individuals that also depends on their individual state. Moreover, $\mathcal{E}$ is the set of all possible values of experience, and Z is the set of labor productivity. Using the market clearing condition of the housing rental market, we find that:

$$r_\ell=\frac{(1-\theta)}{\overline{H}_\ell}\,y_\ell. \tag{4.21}$$

Hence, through aggregate demand, the rental price of a location of type ℓ depends on the size of the population and the demographic and productivity composition of the location.

In the description of our economy, we have conjectured that rental prices depend only on the type ℓ, and that locations of the same type have the same rental price. This result is straightforward without mobility costs and a distribution of idiosyncratic amenities, f_S, that is identical across locations. In that case, the more expensive location would not have any comparative advantage in any dimension. However, when agents face moving costs, it could be the case that there were multiple equilibria. Appendix C.2 argues that this is not the case given the following assumptions:

Assumption 1. *The employment distribution of 1-year-old agents is equal to the stationary distribution associated with the employment Markov process of the location type where they are born,* $\phi_\ell / (\phi_\ell + \lambda_\ell)$.

Assumption 2. *The distribution of idiosyncratic amenities draws,* f_S*, is independent and identically distributed across locations.*

Proposition 1. *Assumptions 1 and 2 imply that all locations of the same type,* ℓ*, have the same rental price of housing.*

5 Calibration

In this section, we describe our calibration strategy and evaluate the ability of our model economy to match untargeted moments. Specifically, the rates and patterns of mobility over the life cycle and its aggregate implications; namely, location size and aggregate productivity.

5.1 Calibration

Our overall strategy is calibrating the model to match selected aggregate statistics of the labor market and aggregate statistics pertaining to peoples' mobility. Recall that we characterize urban areas in the data according to their unemployment rate, which is an endogenous object in our model. Instead, in the model, the fundamental differences between location types are in terms of: (i) productivity shifter (A_ℓ), (ii) productivity accumulation (δ_ℓ), (iii) job creation and destruction rates (ϕ_ℓ, λ_ℓ), and (iv) migration opportunities (μ_ℓ^J).

The model period is a year. Households are born at age 20 and live until age 80. We calibrate exogenously the parameters of the utility function, governmental programs, urban area housing stocks, and the initial distribution of people over states. The value of the discount factor, β, is chosen to target a 3 percent annual interest rate. The median household rent expenditure was 520€ in 2009, which is about 24 percent of the median household income in our model. Hence, we set the housing expenditure share to $1 - \theta = 0.24$. The median monthly social security retirement payment in Spain is about 76 percent of the mean wage in the reference period (776€), which we use for our model. The calibration of unemployment benefits is less straightforward. In Spain, a worker who has worked long enough to be eligible for benefits receives an initial replacement rate of about 50 percent. However, not all workers satisfy this criterion, and the young, who are particularly important for mobility, are the least likely to satisfy it. Moreover, our model is about unemployment risk at the yearly frequency, and unemployment benefits are time-limited and drop to zero after some months. In fact, in the MCVL, we find that the average monthly unemployment benefits of those younger than 65 and non-employed is only 10 percent of the mean wage (108€). We decide to take an intermediate replacement rate of 15 percent of the mean wage in our model.

We assume that the job log productivity z follows a normal distribution, $z \sim N(0, \sigma_Z^2)$. Likewise, the log of the amenity value is drawn from $\log s \sim N(0, \sigma_S^2)$. We set the available housing stock in each urban area, $\overline{H}_\ell$, to match the rent price dispersion, as shown in Table 3. Turning to the distribution of people at birth, we calibrate the distribution of newborns across location types to match the population shares of 20–22 years old in the data. Conditional on the urban area type, we additionally calibrate the share of employed people aged 20–22. Finally, we assign the job types and idiosyncratic amenities at birth as random draws from the respective distributions.

We calibrate the remaining parameters inside the model. The labor market parameters are set to match statistics pertaining to individuals in the MCVL who are not switching urban areas. The exogenous job loss probability, λ_ℓ, is set to match the share of EU transitions in the data in each tercile of the distribution of urban areas, as shown in Table 1. To be consistent with the data, we compute these probabilities as average marginal effects after controlling for age. We find a higher job loss rate in low-productivity urban areas. The job offer rate in unemployment, ϕ_ℓ, is set to match the average unemployment rate in each urban area tercile. The resulting calibration implies that high-productivity urban areas exhibit more job opportunities and lower unemployment rates. Hence, in what follows, we will refer either to low-unemployment or high-productivity locations interchangeably. The job-offer probability of those employed, Λ, is set to match the average job-to-job transition rate. We use the probability that a job offer is a reallocation offer, λ_d to match the fact that 41 percent of those moving job-to-job experience an earnings loss.[12] We find that about

[12] To reduce noise, we calculate moments of earnings changes only for the employed with at least 4,500€ of yearly earnings, which is about half of the yearly earnings under the national minimum wage.

Table 4: Calibration

	T1	T2	T3	Target
A: Labor market				
λ_ℓ (%)	7.10	7.30	9.85	EU rate of city stayers
ϕ_ℓ (%)	41.00	33.00	29.00	UA-level unemp.
Λ (%)		19.00		Average 11 % J2J rate
λ_d (%)		48.0		41 % J2J involve wage losses
σ_Z		0.28		Std of wages of job switchers 0.31
B: Productivity				
$\ln A$	7.36	7.32	7.30	Tercile wage fixed effect
δ_ℓ (%)	0.58	0.00	0.00	Tercile experience effect
ψ_1 (%)		9.6		Experience profile
ψ_2 (%)		-0.2		Experience profile
C: Migration				
p_U (%)		4.83		Average mobility rate of 9.6%
p_E (%)		4.00		Ratio of E to U movers: 2.71
p_R (%)		4.83		$p_R = p_U$
ω_ℓ	1.52	1.00	0.67	Relative worker turnover
κ_0		0		Mobility age 45: 10.97%
κ_1%		7.4		Mobility ages 76-80: 3.64%
σ_S		0.33		48% T1 to T1 age 30
D: Preferences				
β		0.97		3% annual discount rate
θ		0.76		Housing median share 24%
E: Transfers				
b_U		0.41		15% of mean wage
b_R		2.08		76% of mean wage
F: Housing				
$\overline{H}_\ell$ (%)	1.02	1.00	0.77	Housing rents
$N_{1\ell}$ (%)	0.47	0.28	0.25	Pop. % of 20-22 years old

Note: The left column states the calibrated parameter. The second to fourth columns display the calibrated values for the three terciles of the urban area unemployment distribution. The rightmost column describes the data target.

half of job-to-job offers actually result from reallocation offers. Together with an average job loss rate of around 5.8 percent, this high reallocation rate implies that jobs are highly unstable in Spain. The risks arising from job loss and the benefits of on-the-job search depend on the dispersion of different job types, σ_Z. We calibrate the dispersion to the standard deviation of log wage changes of job-to-job switchers. To reduce noise in the data statistic, both in the model and in the data, we drop observations in the top and bottom 5 percent of log wage changes.

Next, we calibrate the parameters of the productivity process shown in Equations (4.2) to (4.5) so that an estimation with model data of Equation (3.2) matches the estimates found with the MCVL data. Table 5 shows that this match is close. Consistent with the relatively small urban area fixed effects that we find in the data, urban area productivity differences across areas in the model are

TABLE 5: Model and data estimates of Equation (3.2).

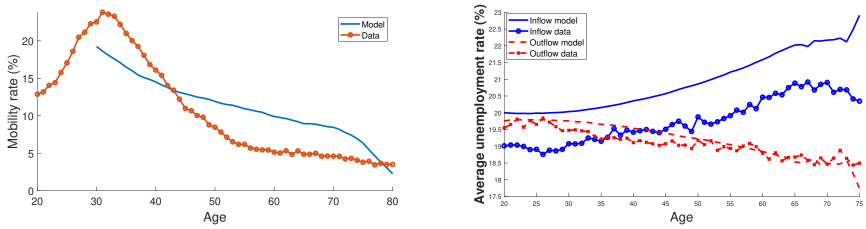
Moment and parameter	Model T1	Model T2	Model T3	Data T1	Data T2	Data T3
Urban area fixed effects (%); α_ℓ	5.83	1.94	0.00	5.60	1.91	0.00
Earnings growth in UA (%); δ_ℓ	1.45	0.44	0.00	1.40	0.29	0.00
Earnings growth (%); γ_1		8.08			7.78	
Earnings growth (%); γ_2		-0.23			-0.22	

Note: We normalize the log productivity of the least productive urban area to one.

small. What is more, the dynamic effect on productivity, δ_ℓ, is virtually the same in types two and three, whereas being in the lowest unemployment urban area provides an additional small gain of nearly 0.58 percent. The model implies substantially less dispersion in experience gains than the reduced-form estimates may suggest because of higher job stability in low-unemployment urban areas. More stable jobs allow workers to have better job ladders with higher match qualities. Differences in job productivities being important to explain average wage differences across Spanish labor markets are consistent with Porcher et al. (2021), who show that more workers are employed at large plants in high-paying urban areas.

Finally, we target moments of mobility across ages and places. We write the spatial search friction as $\mu_\ell^J = \omega_\ell \, p_J$, where p_J measures the search efficiency of different employment states, and ω_ℓ the urban-specific search efficiency. The shape of the mobility hazard over age allows us to distinguish between fixed mobility costs and spatial search frictions. Intuitively, fixed mobility costs imply relatively high mobility at young age as people benefit from the mobility for the rest of their lives. In contrast, search frictions imply a slowly decaying mobility hazard. We restrict the fixed costs of mobility to be non-negative. Our data targets are: (i) the average mobility rate, (ii) the mobility rate at age 45, (iii) the mobility rate at ages 76–80. In addition, we target three additional moments, one pertaining to sorting, one pertaining to the type of people who move, and one pertaining to the turnover rate by urban area: (iv) the share of 45-year aged movers going to urban areas with the lowest unemployment rates, given that they are currently already in the lowest unemployment rate tercile, (v) the share of movers who were previously employed, and (vi) the people turnover rate across different urban areas. To match the relatively high mobility of young people, the calibration requires no fixed costs for the youngest, however, substantial fixed costs for the elderly. The calibration implies that about five percent of people consider moving in any given year, which is lower than the discussed survey evidence. However, one needs to keep in mind that a movement opportunity in the model is a much more concrete choice than the survey question framing. Search efficiency is about one-fifth higher for the non-employed relative to the

Figure 4: Mobility over the life cycle in the model



(a) Mobility rate by age (b) Sorting across locations by age

Note: The left panel shows the mobility rate across urban areas over the life cycle in the model (solid line) and in the data (dotted line). The right panel shows how people sort across urban areas. The blue lines plot the average unemployment rate of the origin urban area in the model (solid line) and in the data (dotted line). The red lines plot the average unemployment rate of the destination urban area in the model (dashed line) and in the data (dash−dot line).

employed. To match the high turnover rates at low-unemployment urban areas, we require large differences in search efficiency across urban areas. We think of this as representing, for example, that people in low-unemployment (densely populated) urban areas have larger networks of people telling them about alternative locations. Moreover, their employers are more likely to operate multi-establishment firms and, hence, provide within-firm job mobility that is associated with moving to different locations. Finally, to match that a a substantial fraction of people moves to higher-unemployment urban areas at prime age, we require substantial dispersion in idiosyncratic amenities. Section 6.1 discusses the importance of each type of friction impeding mobility in our theory compared with the rest of the literature.

5.2 Untargeted moments

In this section, we describe the implications of our model in those dimensions which have not been targeted in our calibration.

5.2.1 Mobility across urban areas in the model

We inspect the mobility patterns over the life cycle implied by our calibrated model. The blue-solid line in Figure 4(a) displays the model mobility rate of people over the life cycle.[13] Comparing this rate with its data counterpart, we see that the model matches the fact that the mobility hazard rate decreases after age 31. Various features of the model are key to delivering the decreasing age-mobility hazard. First, young people have a higher mobility offer acceptance rate because they have a longer horizon to enjoy the benefits of moving. Second, as people sort into more productive locations and jobs and into locations with higher amenities, the probability of receiving a better

[13] The figure displays a 10-year backward-looking mobility hazard and, hence, the model starts at age 30.

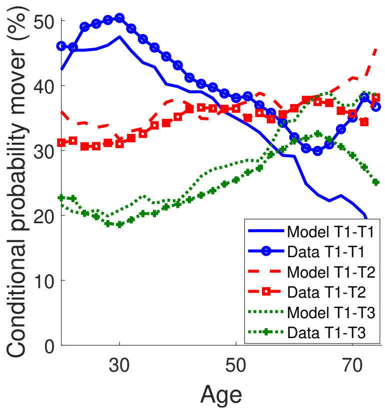
offer from a different urban area decreases with age. The rate in the model, though, despite no fixed costs of mobility for the very young, decays too slowly initially.

Regarding the sorting patterns across individuals' age, Figure 4(b) displays the average unemployment rate of the locations which to individuals come and leave during their life cycle. The model matches many aspects of the sorting pattern in the data. In particular, it matches almost perfectly the average unemployment rate from urban areas that people leave over the life cycle. It also matches the increase in the unemployment rate of urban areas where people arrive over the life cycle; however, it underestimates the level of that unemployment rate. The model rationalizes these life cycle patterns due to the value different people attach to being in a low-unemployment urban area. When young, high wages, high expected experience gains, and good job opportunities are all attributes that make low-unemployment urban areas an attractive destination. In contrast, elderly people, for whom future experience growth is less important, find it optimal to sort into urban areas with lower housing rents. This is particularly true for retirees. Yet, and consistent with the data, workers in their mid-40s already start sorting into higher unemployment urban areas as they look forward to their retirements.

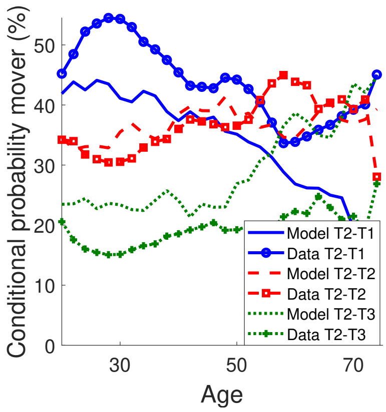
Figure 5 compares the model performance in matching the life cycle flows between different terciles of the urban area unemployment rate distribution. Recall that the only targeted moment is the share of T1–T1 movers at age 45. The model matches closely the movement of people leaving urban areas in the first tercile over the entire life cycle. The only exception is that, in the data, the share of people moving to the first tercile rises again after age 65. The model also matches the flows of people leaving the second tercile, again missing the late in life increase of people moving to the first tercile. Regarding mobility from the highest-unemployment urban areas, the share of people moving from T3-T3 is somewhat low in the model, so people remain more in these areas in the data than in the model. However, the model matches the life cycle movements in these shares.

Finally, the data highlights that employment transitions may play a major role in spatial mobility. Our calibration targets the share of people moving who were previously employed. However, we do not target the share of working-age people moving to a new urban area as non-employed. According to the data, about 46 percent of the movers migrate to urban areas without a job. The model matches this fact well: 52 percent of movers join the new urban area as unemployed. By allowing people to move to other urban areas as non-employed, our model decouples the mobility friction from the job offer friction that, e.g., Baum-Snow and Pavan (2012), Heise and Porzio (2023), and Schluter and Wilemme (2023) study. In doing so, we emphasize again the role of the life cycle. The young move to low-unemployment urban areas even without a concrete job offer, as it allows them

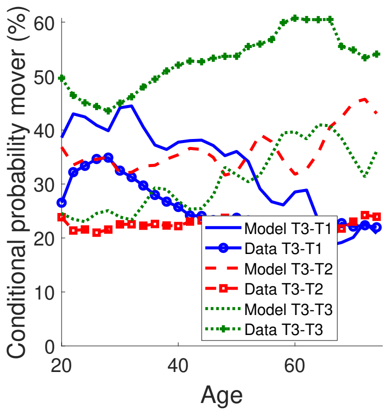
Figure 5: Mobility across location types over the life cycle in the model



(a) Leaving tercile one



(b) Leaving tercile two



(c) Leaving tercile three

Note: The graph displays the share of movers who migrate to each tercile in the model and data, conditional on departing from each tercile.

to search more efficiently for work from within the local job market. Moreover, starting around age 50, workers move to urban areas with higher unemployment rates, as they expect to retire soon.

5.2.2 Characteristics of urban areas in the model

Table 6 shows that our model also captures the observed salient characteristics of urban areas, shown in Section 3.1. The model closely matches the age-averaged population shares, i.e., low-unemployment urban areas are bigger.[14] The table also shows that low-unemployment urban areas have higher average earnings. Notably, the difference between the second and third tercile is relatively small compared to the difference between the first and third tercile. Lastly, the calibration targets the observed unemployment rates across terciles and generates endogenously the

[14]The literature usually estimates heterogeneity in average amenities across urban areas when targeting population sizes. We do not require these as there is a lot of heterogeneity of amenities at the municipality level within the three unemployment terciles.

Table 6: Heterogeneity across urban areas

	Model	Data	Model	Data
	Population		$U2E$ flow rate	
$T1/T3$	1.58	2.13	1.41	1.13
$T2/T3$	1.19	1.27	1.13	1.03
	Earnings per worker			
$T1/T3$	1.20	1.32		
$T2/T3$	1.04	1.04		

Note: The table reports summary statistics in the model and data of the demography and labor market of urban areas ranked in three different unemployment terciles.

unemployment-to-employment flow rates. The model matches that these rates are almost the same in the third relative to the second tercile but that the rate is somewhat higher in the first tercile.

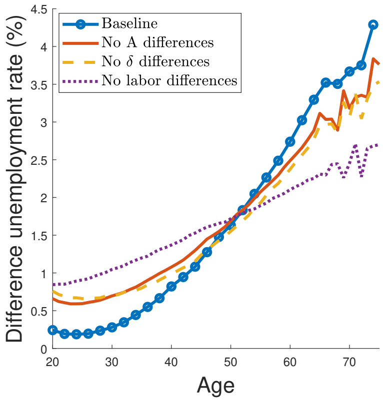
6 Counterfactual simulations

We find that higher dynamic gains, rather than higher permanent productivity levels, in low-unemployment urban areas primarily drive young people to sort into these locations. However, strong spatial search frictions significantly limit their ability to relocate to labor markets with better opportunities, generating substantial inequality in consumption-equivalent terms depending on the urban area in which individuals begin their careers. Policies aimed at increasing mobility fail to reduce this inequality. By contrast, moderate transfers to high-unemployment urban areas effectively reduce consumption-equivalent disparities with almost no effect on mobility.

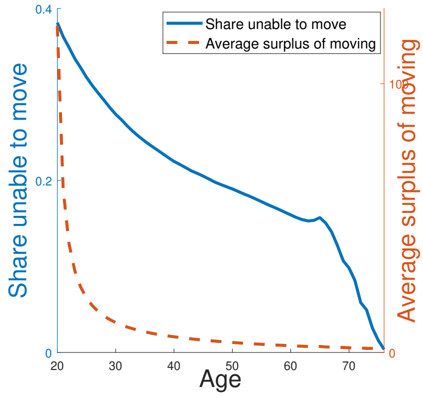
6.1 Understanding mobility

The role of differences in local labor markets. Figure 6(a) eliminates one-by-one differences between local labor markets and shows the resulting sorting patterns over the life cycle. To measure the degree of sorting, we calculate the average difference between the urban area unemployment rate people arrive to and separate from. The solid red and dashed yellow lines show the sorting over the life cycle when all urban areas have the same static and dynamic productivity gains, respectively. In both cases, most of the life cycle sorting patterns remain; that is, productivity differences only partially explain why young people sort into low-unemployment urban areas. Instead, the key element driving the observed spatial sorting over the life cycle is differences in job-finding and job-destruction rates. Without those differences, the life cycle pattern is much flatter (dotted line). Low-unemployment urban areas allow their inhabitants to find jobs quicker, and those jobs are

FIGURE 6: Understanding mobility.



(a) Counterfactuals



(b) Mobility surplus

Panel (a) displays the difference between the average urban area unemployment rate across all individuals arriving and separating from an urban area in the baseline model and three counterfactual simulations: *No A differences* eliminates differences in urban area average productivities; *No δ differences* eliminates differences in urban area skill accumulation; *No labor differences* eliminates differences in urban area job loss and job finding rates. The blue straight line in Panel (c) displays the share of people who would accept a random mobility offer minus the share of people actually moving given a random mobility offer. The red dashed line displays the value of those actually moving at their destination location minus the value at their originating location. This excess value is set relative to the fixed mobility costs, κ_t.

more stable allowing people to sort into more productive jobs over time. As these gains accumulate dynamically over time, the benefit of moving when young is particularly high.

The role of mobility frictions over the life cycle. Figure 6(b) illustrates the role of each mobility friction in explaining the migration rate over the life cycle. The solid blue line (left axis) displays the share of people willing to move given a random mobility offer minus the realized mobility rate, and the red-dashed line (right axis) displays the average value of moving relative to the fixed migration cost in the absence of the spatial search friction. At the beginning of the life cycle, mobility would be over 30 percent higher in the absence of spatial search frictions, and the average value of moving exceeds the fixed mobility costs by a factor of a hundred. As individuals relocate over time to locations and jobs with better idiosyncratic characteristics and the fixed costs of mobility rise, the value of moving falls. Moreover, the value of moving without spatial search frictions is highest when the expected remaining lifespan is long, so the share of people constrained by search frictions decreases with age. In other words, spatial search frictions are the primary barrier to mobility for young individuals, many of whom do not migrate despite large economic disparities across urban areas. In contrast, fixed mobility costs become the dominant deterrent for older individuals, as the average surplus of moving is close to the fixed cost of mobility.

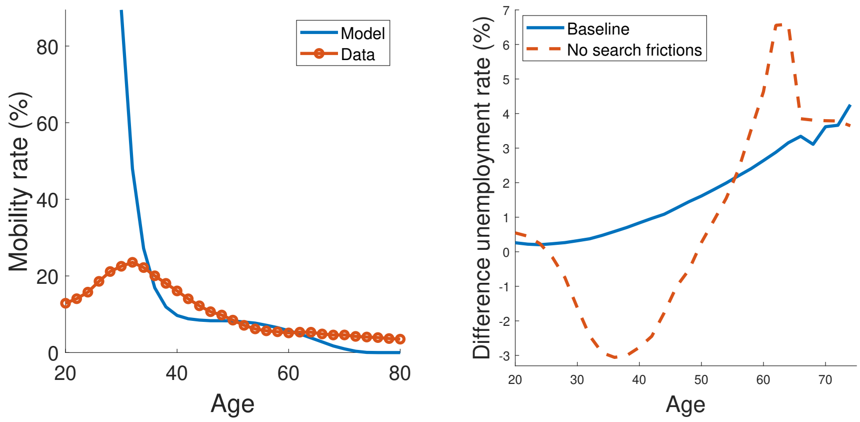
Spatial search frictions versus mobility fixed costs. The spatial search frictions modeled here are different from most of the urban literature in three important aspects: First, people have infrequent moving opportunities; second, those opportunities are random, and third, the frequency that people have those opportunities differs across urban areas. In contrast, the literature typically assumes that people can move each period and, after observing the distribution of amenities, choose optimally across all possible locations given only fixed mobility costs. To better understand our identification strategy of search frictions and mobility fixed costs, we compare our benchmark calibrated model to a re-calibrated model without search frictions where everyone optimally decides across all locations every period. In this alternative model, we calibrate the intercept of the costs of migrating, κ_0, to match the aggregate mobility rate. We then calibrate the age-slope parameter to match the mobility at old age, imposing that mobility costs cannot be negative. This leads to zero non-pecuniary moving costs at age 80. We relegate the description of that model and further calibration details to Appendix C.4.

The red dashed line in Figure 7(a) shows that the model without search frictions implies too high mobility for young people while the elderly almost do not move. If everyone compares all locations and chooses their preferred location every period, they do so as soon as possible (when young) and do not move after retirement because they have done so right at the moment of retirement. Thus, this model cannot rationalize why young people do not quickly leave high-unemployment urban areas while, at the same time, the elderly still find it optimal to move. Search frictions provide a rationale for the flatter hazard. They slow down sorting at young ages, and they reduce the calibrated moving costs, which makes it attractive for the elderly to still move. As the non-pecuniary moving costs are lower, in the baseline model, these costs are equivalent to one times the average yearly income, compared to an "unreasonable high" 2.7 times in the alternative model.[15]

Furthermore, Figure 7(b) shows that the model without search frictions not only implies too much age variation in overall mobility but also too much age variation in the sorting patterns. We summarize the degree of sorting again as the difference between the average unemployment rate at arriving and separating urban areas. To understand the differences in life cycle sorting patterns and the role of search frictions, first note that both models calibrate the dispersion of idiosyncratic amenities to match the share of people in the lowest tercile of the urban area unemployment rate distribution who, when moving at age 45, go to another first tercile urban area. Despite this common calibration of sorting at age 45, the model without search frictions implies too much age-variation

[15] In a model with only fixed costs, Kennan and Walker (2011) estimate for the U.S. a cost of 312,000 dollars. Schluter and Wilemme (2023) also note that spatial search frictions are a possible way to rationalize low mobility.

FIGURE 7: Search frictions and mobility



(a) Mean mobility by age

(b) Unemployment, inflows, and outflows at urban areas

Notes: The left panel displays the decennial mobility rate of people over the life cycle. The right panel displays the average urban area unemployment rate across all individuals flowing to (separating from) an urban area. The blue straight lines show the baseline model and the red dashed lines show a recalibrated model without search frictions for mobility. Source: Model simulations.

in sorting into urban areas with different labor markets. Without spatial search frictions, the incentives to move to low-unemployment urban areas are highest at young ages. Similarly, when old, people are much more likely to move to high-unemployment urban areas. In contrast, the data suggest that this sorting process is rather slow, and people do not necessarily move directly to their preferred urban area but, instead, only move there over time. This outcome is natural when people make mobility decisions infrequently and mobility opportunities are random instead of chosen optimally.

In addition, the model without spatial search frictions also implies that people turnover is 10 percent higher in urban areas in the highest unemployment tercile relative to the lowest tercile. That is, this model implies larger gross migration flows in high-unemployment areas. The reason for this result is that the unemployed have relatively higher mobility acceptance rates. The baseline model overcomes this by modeling low-unemployment areas as search hubs: their inhabitants decide about moving elsewhere more frequently.

To sum up, for a model without search frictions to match the data, we would need three ingredients: The first one would be yet more age-variation in fixed mobility costs, which implies even lower mobility costs at old age relative to young age. We note that already in the current alternative model calibration, non-pecuniary moving costs are highest at young ages, which we find implausible as location attachment should increase with age, not fall. The second ingredient would be age-varying dispersion in amenity shocks to slow down sorting across urban areas at young ages, which we find hard to interpret. The third ingredient would be lower fixed costs of mobility in low-unemployment urban areas, which we find a less intuitive interpretation than lower search fictions at said urban areas.[16] We note that two of the three counterfactual implications of a model without mobility frictions are related to the life cycle dimension of our model economy. It is precisely the interaction of life cycle and differences across urban areas that allows us to calibrate the importance of search frictions and non-pecuniary costs.

6.2 Inequality in consumption-equivalent units across locations

Due to mobility frictions, heterogeneous locations imply that ex-ante identical individuals experience different levels of lifetime income and amenities depending on where they are born. We interpret these frictions arising from fixed mobility costs and, based on our micro-foundation, arising from idiosyncratic beliefs about places or information acquisition costs. Therefore, we remain agnostic and do not interpret this inequality as a welfare loss relative to a first-best allocation but as rational choice given the environment. Regarding how we measure this inequality, an individual's utility depends on three types of goods: non-housing, housing consumption, and the amenity value of location. To provide a summary measure, we express the consumption-equivalent difference between being born in an arbitrary location relative to the lowest unemployment location as the percentage of lifetime consumption (both housing and non-housing) that would equalize the individual's value from being born in both locations. Appendix C.5 formally derives this concept of consumption-equivalent inequality.

The first column of Table 7 displays the lifetime consumption of starting one's career (age 20) in the second and third terciles of the urban area unemployment distribution relative to the first tercile. On average, lifetime consumption is 15.6 and 6.4 percent lower for an individual born in the third and second tercile than for someone born in the first tercile, respectively. These consumption disparities amount to 6.8 and 2.8 times the average fixed moving cost, respectively. Put differently, spatial search frictions are important in explaining spatial inequality. We further decompose this inequality into a component arising from lifetime consumption being higher when born in a low-unemployment urban area and from those people enjoying on average higher amenities over the life cycle. The table shows that both effects are important. Comparing the third to the first tercile of the urban area unemployment distribution, on average, lifetime income is 17.7 percent lower, and lifetime amenities are 4.4 percent lower.

[16]To take an explicit example, the baseline model interprets the many observed flows from Madrid to Barcelona (relative to the flows from a higher unemployment urban area, such as Cadiz, to Barcelona) as resulting from people in Madrid receiving relatively many offers to move. Differently, much of the existing literature that explicitly targets mobility patterns between individual locations, e.g., Caliendo et al. (2019) and Zerecero (2021), relies on pair-wise

TABLE 7: Consumption-equivalent inequality across locations

	Baseline	Same prod. (A)	Same exper. (δ)	Same emp. (ϕ, λ)	Same mob. (ω)
T2 relative to T1					
Consumption-equivalent	93.6	95.3	97.7	94.3	96.8
Income	88.4	91.4	95.1	91.3	87.7
Amenities	97.6	97.4	96.6	96.9	100.2
T3 relative to T1					
Consumption-equivalent	84.4	87.1	88.9	88.5	90.3
Income	82.3	86.2	88.9	89.7	82.1
Amenities	95.6	95.4	94.2	94.3	100.4

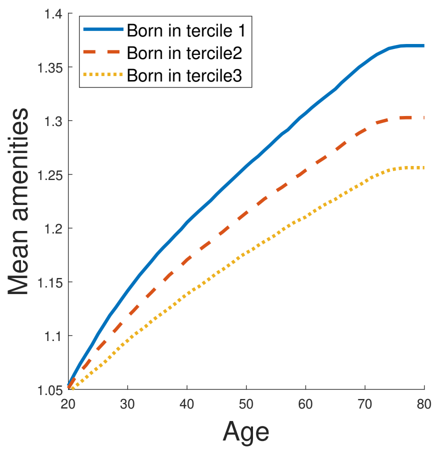
Consumption-equivalent refers to the percentage reduction in lifetime consumption experienced by a person born in the second tercile ($T2/T1$) or third tercile ($T3/T1$) of the urban-area unemployment distribution relative to someone born in the first tercile. *Income*: The relative discounted average lifetime income. *Amenities*: The relative discounted average in amenity values. Baseline: the baseline model. *Same productivity*: all urban areas have the aggregate productivity from the highest unemployment urban area; *Same experience*: all urban areas have the experience accumulation process from the highest unemployment urban area; *Same emp.* ϕ, λ: all urban areas have the mean job finding and job loss rate across urban areas; *Same mob.* ω: all urban areas have the calibrated search efficiency from the highest unemployment urban area. Source: Model simulations.

Table 7 decomposes those urban area differences into differences in average productivity, in returns to experience, in job search opportunities and job stability, and in search opportunities to move to other urban areas. The row entitled "Same productivity" eliminates differences in aggregate productivity, A_ℓ. The lifetime consumption equivalence fall of a person born in the second and third tercile is reduced to 4.7 and 12.9 percent, respectively, relative to a person born in the first tercile. Put differently, urban area productivity differences, a factor often thought to explain differences in desirability across urban areas, explains only about one-fourth of lifetime consumption-equivalent and income inequality across urban areas at birth. Instead, most of these differences across urban areas arise from dynamic benefits that low-unemployment urban areas provide, to which we turn next.

The row entitled "Same experience" shows the effects when experience accumulation is the same in all urban areas, i.e., $\delta_\ell = 0$. The consumption-equivalent difference from being born in the second and third tercile of the urban area unemployment distribution falls to 2.3 and 11.1 percent, respectively. In fact, differences in experience accumulation are the main factor explaining lifetime income differences between urban areas in the first and second tercile of the unemployment distribution. Turning to differences in labor market frictions, the row entitled "Same employment risk (ϕ, λ)" equalizes the job offer rates of unemployed workers and the exogenous job loss rates across urban areas. The reduction in consumption-equivalent units for people born in the second in comparison

specific fixed mobility costs to match the data.

Figure 8: Idiosyncratic amenities for urban areas over the life cycle.



Note: The Figure displays the average amenity level of individuals born in urban areas with different unemployment rates.

to the first tercile is relatively small, highlighting that labor market frictions are similar in both location types. However, the effects for people born in the third tercile are substantial. Specifically, the reduction in consumption-equivalent units from being born in the third tercile falls from 15.6 to 11.5 percent, and the lifetime income drop decreases from 17.7 to 10.3 percent.

To this point, the reductions in consumption-equivalent units arise almost exclusively from reducing income differences across urban areas. Average amenity differences change little. The row entitled "Same mobility search friction (ω)" shows that the consumption-equivalent reduction from lower lifetime amenities arises from differences across urban areas in the search efficiency for mobility opportunities. As highlighted above, low-unemployment urban areas serve as search hubs that allow people to sort into urban areas with relatively high idiosyncratic amenities. Figure 8 highlights this effect over the life cycle. It displays the mean amenities for cohorts being born in different terciles of the urban area unemployment distribution. By assumption, idiosyncratic amenities are equally distributed in the three terciles at birth. However, over time, people born in low-unemployment urban areas receive more mobility offers and, as a result, sort into urban areas with higher idiosyncratic amenities. Eliminating the heterogeneity in search opportunities, hence, reduces the consumption-equivalent reduction from being born in high-unemployment urban areas.

6.3 Public policies

Policymakers often implement policies aimed at reducing spatial inequalities. Examples include programs that encourage people to move to economically successful locations or transfers directed to residents of economically distressed locations. Thus, we now turn to study these policies by studying their steady-state effects. Each policy changes the government's budget, and we use a proportional wage tax to keep the budget at the (deficit) level of the baseline economy. What is more, by changing housing rental prices, the reforms change peoples' housing expenditures. In our model, changes in rents affect the absent landlords and, thereby, policy reforms change the total amount of resources available to the economy. To avoid this, we assume that all changes in housing rent expenditures are taxed by the government and integrate those taxes into the government's budget.

Reducing mobility costs. We start evaluating a simple policy which is giving subsidies to movers. Specifically, we provide a transfer to movers that offsets the utility cost from the non-pecuniary moving cost. The column entitled "Subsidy moving" in Table 8 shows the results in this alternative economy.

We find that the mobility rate increases by more than 56 percent. Maybe surprisingly, however, lifetime consumption-equivalent dispersion at birth increases slightly. The reason is that a reduction the utility moving costs affects people differently depending on their age. For young people, mobility is an investment whose return well exceeds the utility costs of moving, and spatial search frictions are the main source of limited mobility. As a consequence, the increase in mobility also leaves the aggregate output almost unchanged, as Table 8 shows. The reduction in the fixed cost affects, mostly, older workers and retirees who now flock in larger flows to cheaper locations, thus, offsetting the small population loss of young people in those locations. As a result, housing rents are almost unchanged in high-unemployment urban areas. Furthermore, as search is most efficient in low-unemployment urban areas, people born there disproportionally benefit from the increase in mobility that is triggered by moving to higher idiosyncratic amenities.

Place-based policies. We discuss two types of place-based policies that are of particular interest. First, high housing rents in low-unemployment urban areas create the worry that young people will not move to those areas because they cannot afford to pay for housing. As a result, the city of Madrid, one of the low-unemployment urban areas, pays a rent subsidy to those younger than age 35. Second, to increase consumption in high-unemployment urban areas, we consider a policy that pays transfers to high-unemployment urban areas. One type of such policy is the European Regional Development Fund, which pays nearly 50 percent of its overall funds assigned to Spain to its fifth poorest region that accounts for only 25 percent of its population.

We begin by simulating a rent subsidy for young people who live in the lowest unemployment urban area tercile. In 2023, Madrid paid a subsidy of 450€, and, according to the renting portal

Table 8: Policies targeted at mobility

	Baseline	Subsidy moving	Subsidy young T1	Transfer T3 10%	Transfer T3 30%	Transfer T3 50%
T2 relative to T1						
Consumption-equivalent	93.6	92.81	92.47	93.64	93.63	93.62
Housing rents (r_2/r_1)	0.65	0.66	0.61	0.65	0.65	0.65
T3 relative to T1						
Consumption-equivalent	84.4	83.58	83.36	86.25	89.34	92.23
Housing rents (r_3/r_1)	0.64	0.66	0.61	0.69	0.79	0.91
Fixed rents (r)		83.86	82.01	87.48	93.38	98.87
Aggregate variables						
Mobility rate (%)	9.52	14.88	9.61	9.57	9.66	9.76
Output (Y)	1.66	1.65	1.66	1.66	1.65	1.65
Mean amenities ($\ln s$)	6.79	7.07	6.80	6.80	6.82	6.83

The table compares model outcomes from the baseline model to counterfactual simulations. *Subsidy moving*: no fixed mobility costs; *Subsidy young T1*: a subsidy to people younger than age 35 who live in urban areas in the lowest tercile of the urban area unemployment distribution; *Transfer T3*: a transfer to all people living in the highest tercile of the urban area unemployment distribution expressed as a percentage of housing expenditure in T3 without a transfer. $Tx/T1$ the percent of lifetime income a person born in tercile x of the urban area unemployment distribution loses compared to someone born in the first tercile; *Mobility rate*: Decennial mobility rate between urban areas; r_x/r_1 Housing rent in tercile x compared to the first tercile of the unemployment distribution; Y: Aggregate income; *Mean* $\ln s$: Mean log of the peoples' amenities. Source: Model simulations.

Idealista, the median rent was 1,776€, leading to a 25 percent rent subsidy. Column three in Table 8 shows that this policy increases lifetime consumption-equivalent inequality at birth. This is to be expected, as the main beneficiaries are those already born in the lowest unemployment urban area tercile. Maybe surprisingly, at first sight, the policy has little impact on the mobility rate and on the number of under-30-year old living in the lowest unemployment urban areas. The reason is, again, that search frictions make it impractical for them to migrate, despite there being a potentially large gain. One can also see this effect by noting that the policy leaves aggregate output almost unchanged. Instead, the dominant effect of the policy is to increase housing demand by the young who already live in a low-unemployment urban area which increases housing rent dispersion across urban areas. The increase in housing rents in low-unemployment urban areas mitigates somewhat the increase in dispersion in consumption-equivalent units. However, the increase in housing rents leads to elderly people moving out of low-unemployment urban areas and, thereby, the subsidy actually decreases the population in those urban areas. This behavior, in turn, mitigates the rise in housing rent dispersion and, thereby, aggravates the increase in consumption-equivalent dispersion across urban areas at birth.

Next, we simulate a subsidy to people living in urban areas with an unemployment rate in the highest tercile. We start with a subsidy that amounts to 10 percent of the pre-reform average housing expenditures in urban areas with the highest unemployment rate. The transfer reduces the average income gap from the first to the third tercile from 25 to 17 percent. Column four in Table 8 shows that this policy reduces the consumption-equivalent inequality from being born in the highest unemployment urban area tercile by close to two percentage points. Critiques of place-based policies to high unemployment urban areas usually object to those on the grounds that they reduce efficient reallocation of people away from those urban areas. However, we find that the reform has almost no effect on the mobility rate or aggregate output. The reason is, again, the prominent role spatial search frictions play in our framework. That is, as spatial search frictions imply a large share of high-surplus movers at young ages, a moderate subsidy for living in the highest-unemployment urban areas simply does not deter them from moving to low-unemployment urban areas when given the opportunity.

Even higher levels of the subsidy do not change this basic intuition as columns five and six show. Consumption-equivalent inequality from being born in the highest unemployment urban area decline almost linearly in the size of the subsidy. Even a subsidy of 50 percent of the pre-reform average housing expenditures has basically no effects on mobility rates or aggregate output, thus, highlighting again the large average surplus for young people to leave high-unemployment urban areas. These high mobility surpluses also highlight the distributional consequences of the transfer. That is, the policy benefits mostly the elderly, who want to live in a high-unemployment urban areas.

The effects of the transfer are offset by an increase in rental prices in subsidized urban areas. To quantify this, we solve for the effects on consumption-equivalent inequality when housing rents remain as in the baseline economy. That is, when the housing supply is fully elastic. The row "Fixed rents" in Table 8 shows that the effect is large: Across the different transfers, the inequality in consumption-equivalent units in the first instead of the third tercile of the urban area unemployment rate distribution drops by an additional one to six percentage points when housing costs are fixed.

7 Conclusion

This paper studies the economic consequences of people being born in low- and high-unemployment urban areas in Spain using a life cycle model of frictional labor markets and frictional spatial mobility. Being born in a low-unemployment urban area carries with it higher income: lifetime discounted income is 17.7 percent lower for someone being born in the top tercile of the urban area unemployment rate distribution compared to someone being born in the bottom tercile. Workers earning more for the same job across different urban areas explains only one-fourth of those lifetime income differences. Instead, workers accumulate most of the gains of living in low-unemployment urban areas over time. That is, those workers accumulate more valuable work experience and, more importantly, spend less time unemployed and have more stable jobs allowing them to faster climb the job ladder. In addition to higher lifetime income, workers born in low-unemployment urban areas also decide whether to migrate elsewhere more frequently, leading them to find locations with better idiosyncratic amenities. Taken together, being born in the highest rather than the lowest tercile of the urban-area unemployment distribution results in a 15.6 percent reduction in lifetime consumption-equivalent units.

These large economic differences are possible because of strong mobility frictions. We find young people move less mainly due to spatial search frictions, i.e., information frictions. Thus, despite large potential gains, many young people remain in urban areas with poor labor market prospects. In contrast, the elderly, who have an incentive to move to high-unemployment urban areas and economize on housing rent, migrate less due to the fixed non-pecuniary costs of mobility.

Understanding mobility frictions as partly arising from spatial search frictions has major implications on the design of policies that wish to address spatial inequality due to the birthplace. That is, a moderate transfer to people living in high-unemployment urban areas reduces inequality and has almost no adverse effect on the outward mobility of young people toward low-unemployment urban areas or aggregate output. Moreover, policies that encourage people to move to low-unemployment urban areas mostly increase consumption for those already born in those locations and fail to meaningfully increase mobility towards these more successful locations. Ultimately, to increase mobility towards successful urban areas, the government would need to address the spatial search friction. We are not aware of governmental programs that specifically target to overcome this friction within a country, e.g., provide information to individuals about moving opportunities. However, there exist cross-country programs to facilitate mobility such as the *EURES Targeted Mobility Scheme* that may carry valuable lessons.

We have ignored asset accumulation which would greatly complicate our model as the state space is already big. We believe that it is a reasonable abstraction when addressing decennial mobility, however, borrowing constraints may carry important insights for the mobility of young people. We also have ignored intergenerational altruism. Clearly, migration is also an opportunity to invest in our children's human capital. Compounding the consumption of future generations in our measurement would increase consumption-equivalent differences across locations and, therefore, the gains from moving for younger people. We leave these issues for further research.

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