# Geographic Mobility over the Life-Cycle*

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June 14, 2023, Current version

**Abstract**

When mobility between locations is frictional, a person's economic well-being is partially determined by her place of birth. Using a life cycle model of mobility, we find that search frictions are the main impairment to the mobility of young people in Spain, and these frictions are particularly strong in economically distressed locations. As a result, being born in a high-unemployment urban area carries with it a large welfare penalty. Less stable jobs, slower skill accumulation, lower average wages, and fewer possibilities for geographic mobility all contribute to these welfare losses. Paying transfers to people in distressed economic locations decreases these welfare losses without large adverse effects on mobility. In contrast, several policies that encourage people to move to low-unemployment urban areas increase these welfare losses and fail to meaningfully increase mobility towards these more successful locations.

**Keywords:** Mobility; local labor markets; search frictions; life cycle; dynamic spatial models.
**JEL Classification: E20, E24, E60, J21, J61, J63, J64, J68, R23, R31.**

*We thank conference attendants at the SaM Conference in University of Bristol, Bank of Spain, and the Spanish Macroeconomic Network, as well as seminar participants at Goethe University, Universidad Carlos III de Madrid, Complutense de Madrid, Universidad País Vasco, Universidad Autónoma de Barcelona, and Universidad de Barcelona. Antonia Díaz thanks the Ministerio de Ciencia e Innovación, Project PID2019-107161GB-C1, the Ministerio de Economía y Competitividad for María de Maeztu grant (MDM 2014-0431) and the Consejería de Educación, Juventud y Deportes de la Comunidad de Madrid for MadEco-CM grant (S2015/HUM-3444). Moreover, she thanks the European University Institute for its hospitality and the Fernand Braudel Senior Fellowships program for its support while working on this project. Álvaro Jáñez gratefully acknowledges support from the Ministerio de Ciencia e Innovación through research grant PRE2019-088620, and the financial support from the AEI (Spain) through PID2019-110779GB-I00. Felix Wellschmied gratefully acknowledges support from MICIN/AEI/10.13039/501100011033, grant PID2020-117354GB-I00, and the Comunidad de Madrid through research grants EPUC3M11 (V PRICIT) and H2019/HUM-589.

# 1 Introduction

Economic activity is not uniformly distributed across different places, i.e., there is spatial dispersion (see, for instance Moretti, 2011). These differences would not matter to a resident if she could move at will. Yet, costly mobility implies that identical people have different labor prospects and opportunities depending on where they start their careers. Lately, 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 those differences need to take into account the underlying frictions impeding mobility as well as their heterogeneous effects on mobility over peoples' life cycles.

Using Spanish data on mobility between urban areas (a concept akin to a Commuting Zone in the U.S.) together with a structural life-cycle model, we show that spatial search frictions are a major impairment to the mobility of young people, and these frictions are particularly high in high-unemployment urban areas. As a consequence, starting one's career in such an urban area carries with it large welfare losses. Paying transfers to people in distressed economic locations decreases these welfare losses without large adverse effects on mobility. In contrast, several policies that encourage people to move to low-unemployment urban areas increase these welfare losses and fail to meaningfully increase mobility towards these more successful locations.

To arrive at these conclusions, we first link spatial mobility patterns across the life cycle to employment outcomes and labor market conditions. Consistent with the findings of Coen-Pirani (2010) and Lkhagvasuren (2012) pertaining to U.S. states, net people flows across urban areas are much smaller than gross flows, that is, 80% of all flows represent excess flows. Moreover, this excess reallocation is systematically related to the local labor market conditions: Low-unemployment urban areas have a relatively high excess reallocation rate. Next, we show that part of the excess reallocation results from people sorting across urban areas based on their age. Low-unemployment urban areas attract younger people and lose older people (on net) whereas high-unemployment areas lose younger and attract older people. People's mobility hazard is highest at age 30 and declines monotonically but its decay slows down after age 55 with even those 70 years old showing substantial mobility. Finally, we show that of those moving before age 65, 73% were employed prior, i.e., spatial mobility is not only linked to escaping unemployment, and 45% arrive as unemployed, i.e., there are benefits to search from within a local labor market.

To understand what makes low-unemployment urban areas particularly attractive to young

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

people, we incorporate three labor market characteristics into a structural life-cycle model with endogenous migration flows across locations and a fixed housing supply. First, low-unemployment areas pay higher earnings to workers with similar characteristics. Second, workers experience more rapid earnings growth when working in low-unemployment urban areas. Third, low-unemployment areas have lower job loss and higher job-finding rates. Each location has a local frictional labor market where the unemployed and employed search for jobs. Unemployed, employed, and retired people may migrate to other locations given idiosyncratic tastes across locations but mobility fixed costs and spatial search frictions prevent people to move to their preferred urban area. Spatial search frictions differ from migration fixed costs. The latter are costs associated with migration whereas the former comprise all sorts of informational frictions that hinder the process of evaluating the benefits of moving.

We find that search frictions are the main impairment to the mobility of young people, and these frictions are particularly strong in economically distressed locations. In contrast, mobility fixed costs are the main impairment to the mobility of the elderly. Young people move on net to low-unemployment urban areas because these offer more favorable employment opportunities and better search opportunities for spatial mobility. We note that most of the benefits of low-unemployment urban areas accrue to their inhabitants only over time. That is, for young people, moving to a low-unemployment urban area carries with it an asset component, as in Bilal and Rossi-Hansberg (2021). In contrast, the elderly, in particular the retired, benefit less from good labor markets and are more likely to move to cheaper high-unemployment urban areas. Put differently, differences in labor markets create demand for relatively expensive urban areas, while retirement creates demand for relatively cheap urban areas.

Large benefits from being in a low-unemployment urban area when young together with strong search frictions which hinder mobility away from high-unemployment urban areas imply that the welfare loss from being born in a high-unemployment urban area is substantial. A person born in the third or second tercile of the urban area unemployment distribution is willing to pay 17.0 and 9.8 percent of lifetime income, respectively, to be born instead in the first tercile. Higher urban area productivity, higher productivity growth on the job, better job opportunities, and more mobility opportunities all contribute to those large losses. For people born in the second tercile of the urban area unemployment distribution, slower productivity growth on the job relative to the first tercile is the single most important factor for the welfare loss. For people born in the third tercile, differences in job finding and job loss rates are the single most important factor. Notably, static productivity differences across urban areas explain only a small fraction of these welfare losses.

One way to reduce the welfare losses from being born in a high-unemployment urban area is to pay transfers to people living there. We find that a moderate yearly transfer, 15% of average housing expenditures, reduces the welfare losses in urban areas with the highest unemployment rates by 0.9 percentage points of lifetime income. Importantly, the transfer has almost no effect on the mobility rates of young people towards low-unemployment urban areas and, thus, almost no effect on aggregate output. The reason is the spatial search friction: Young people in high-unemployment urban areas have a high surplus of leaving and receiving a moderate transfer does not discourage them to move when given the opportunity. By the same logic, 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 (i) subsidize mobility and (ii) subsidize living in low-unemployment urban areas. As these policies leave spatial search frictions unaltered, they fail to increase the opportunities to move to low-unemployment urban areas. Hence, these reforms mostly benefit those people already born in those areas. The latter does so by subsidizing their living costs. The former does so by increasing the mobility of people who are already in low-unemployment urban areas as they face relatively weak spatial search frictions.

Finally, we simulate a reform of the labor market that increases job stability by reducing job loss rates. This policy raises the return to employment as its duration increases. As a result, the differential returns of working in a low-unemployment area increase, and the welfare losses of being born in a high-unemployment area rise. This surprising effect arises because the main benefit of working in a low-unemployment area is the higher speed at which productivity increases over the individual's life cycle. As a result, this reform widens the welfare differences across locations at birth.

**Literature** This paper relates to the literature that explains migration decisions by characteristics of different locations such as Kennan and Walker (2011) and Bayer and Juessen (2012). 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 good 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. (2019), Giannone et al. (2020), Bilal and Rossi-Hansberg (2021), and Komissarova (2022). Adding a life cycle and modeling in detail local labor markets provides us with four additional insights. First, we show that spatial mobility is best thought of as arising from individuals making mobility decisions infrequently and specific mobility opportunities arising randomly.[2] Second, these spatial search frictions are weaker in urban areas with good labor markets. Third, the elderly provide a force limiting high rental prices in urban areas with good labor markets, as they are more responsive to housing prices. Fourth, young people, in part, move to good labor markets because these promise high future returns even when current earnings might be low.

Nanos and Schluter (2018) and Heise and Porzio (2023) emphasize the role of labor market frictions for limited mobility. Using models where workers choose optimally in which 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 spatial search and job search. Regarding the latter, we show 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. Regarding the former, as noted above, by introducing data on life cycle mobility, we show that search across locations cannot be very directed, i.e., mobility is best thought of as an outcome of a random search process.[3] Moreover, we show that the strength of this spatial search friction depends on the current place of residence.

Adding spatial mobility frictions implies that migration costs are significantly lower than those estimated in Kennan and Walker (2011) and Bayer and Juessen (2012). We think of these mobility frictions as encompassing not only informational frictions about labor markets in different locations but also local housing markets and, in a broad sense, barriers to mobility as those documented by Bergman et al. (2019a). These search frictions imply large welfare losses from being born in a high-unemployment urban area. This is also the case in Zerecero (2021), who, differently from us, emphasizes the role of a birthplace bias in explaining why people do not leave economically distressed areas.[4]

Finally, we connect to the literature that studies the effects of place-based policies on the macro economy (Glaeser and Gottlieb, 2008; Albouy, 2009; Gaubert, 2018; Fajgelbaum et al., 2019;

[2] Porcher (2020) also builds a model with information frictions. In his case, people have restricted information on productivity at different places while in our case. In our case, search frictions lead people not to consider mobility at all.

[3] Jáñez (2022) also employs a random search framework to study the effect of welfare programs on mobility in the U.S.

[4] Zabek (2019) 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 for us in order to distinguish different mobility frictions.

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.

The rest of the paper is organized in the following way. After a description of the related literature, Section 2 describes the data. Section 3 discusses the mobility patterns and differences in local labor markets. We outline our model economy in Section 4. Section 5 discusses the calibration of our benchmark economy and Section 6 presents the results. Finally, Section 7 concludes.

# 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 (SLFS). 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, MCVL*). 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 micro data 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 are asked to provide information on the current socio-demographic status of all their members aged 16 or older.[5] The CENSUS provides information on approximately 8% of the Spanish population.[6]

The Census reports the residence at the municipality level whenever a municipality has more than 20,000 inhabitants. We aggregate the data to *Urban Areas*, whose definition is similar to that of a commuting zone in the US and it is meant to represent the local economy where people work

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

[6]The data provides 3,888,692 individual observations for the 1991 Census, 2,039,274 for the 2001 Census, and 4,107,465 for the 2011 Census.

and live.[7] Therefore, an urban area can consist of multiple municipalities that are close by. In total, we have 86 Urban areas in Spain that account for 69.42% of the total population and about 76% of total employment in Spain.[8] As in other countries, the Spanish population is fairly concentrated in a few urban areas. Four urban areas have a population exceeding one million people (Madrid, Barcelona, Valencia, and Seville) and those four together account for 40% 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. This question allows us to construct inflow and outflow rates to each urban area.

The Census does not allow us to identify the employment status prior to 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. 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.

## 2.2 Muestra Continua de Vidas Laborales (MCVL)

The *Muestra Continua de Vidas Laborales* is a Spanish administrative data set that provides a 4% random sample of individuals who have any relationship with the Social Security Administration (SSA) for at least one day during the year of reference. This covers all people who either are working, collecting unemployment benefits, or receiving a pension. The first reference year available is 2006. A unique ID number allows us to link individuals to later editions of the MCVL where we employ the 2006–2008 editions.[9] Importantly, the data provides longitudinal information on the entire working career, including the place of work, for all individuals in the sample.

We construct both monthly and yearly data sets. As the data provides the entire work history of individuals, we can compute individuals' accumulated work experience in different locations. To that end, we compute for each individual the number of days with a contract in a full-time equivalent

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

[8]About 75% of the non-covered people live in rural areas that we cannot assign to municipalities because the Census does not provide that information for municipalities with fewer than 20,000 inhabitants.

[9]We decide not to use years after 2008 because the Great Recession had a large impact on the Spanish labor market.

job. For interpretive purposes, we express this value in years. 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, we identify job-to-job transitions using changes in the employer ID number.

# 3 Patterns of mobility

To organize the evidence of geographical labor mobility we rank urban areas according to their unemployment rate in the Census. We document four stylized facts about mobility patterns. First, gross mobility flows across urban areas exceed net flows by a factor of five. These "excess" flows are particularly large in low-unemployment urban areas. Second, young people reallocate on net to low-unemployment urban areas whereas older people reallocate on net to high-unemployment urban areas.[10] Third, peoples' mobility hazards are decreasing over the life cycle but decay slowly after prime age. Fourth, both employed and unemployed chose to move to other urban areas and arrive there, both, as employed and as unemployed.

## 3.1 Urban area characteristics

Table 1 highlights some summary statistics for urban areas with different unemployment rates. To that end, we group urban areas into three unemployment terciles, $\ell \in \{1, 2, 3\}$. The first panel shows that there is a large heterogeneity in unemployment rates across urban areas in Spain. The average unemployment rate in the first tercile is 16.2%, whereas the average unemployment rate in the third tercile is 27.1%. The literature on structural urban economics usually ranks locations by size, population density, or earnings. The second and third panels show that these statistics systematically vary with the unemployment rate. Low-unemployment urban areas are on average larger and more densely populated, and the employed have higher average earnings. Moreover, the table shows that the average housing costs are higher in low-unemployment urban areas.

## 3.2 Mobility across urban areas

In Spain, the size-weighted mean gross inflow rate across urban areas is 14.5%, and the size-weighted gross outflow rate is 11.3%. The same urban area may have significant inflows and outflows, i.e.,

[10] Appendix B shows that a different sorting of workers across urban areas based on education cannot explain different mobility patterns across urban areas, i.e., different education groups have very similar mobility patterns.

Table 1: Summary statistics of urban areas

| | Unemp. tercile | | |
|---|---|---|---|
| | **T1** | **T2** | **T3** |
| Average unemployment rate (%) | 16.2 | 20.1 | 27.1 |
| Average population | 335,572 | 200,035 | 164,857 |
| Population per km$^2$ | 1,500 | 1,153 | 844 |
| Average annual earnings per worker | 24,472 | 19,241 | 18,493 |
| Average housing price per m$^2$ | 1,948 | 1,254 | 1,256 |

Note: the table reports summary statistics of the demography and labor market of urban areas ranked in three different unemployment terciles (the first tercile stands for the set of urban areas with the lowest unemployment rate). Unemployment and Population are time-averaged values from the Census 1991, 2001, and 2011. Housing prices are deflated to 2009 euros. The reference year of population density is 2011. Sources: (a) Census: Unemployment and Population (b) MCVL: Earnings (c) Digital Atlas of Urban Areas (http://atlasau.mitma.gob.es/#c=home): Population Density and Housing Prices.

more gross flows than the net flows needed to account for its population variation over time. We measure "excess reallocation" as the difference between peoples' gross flows and net flows:

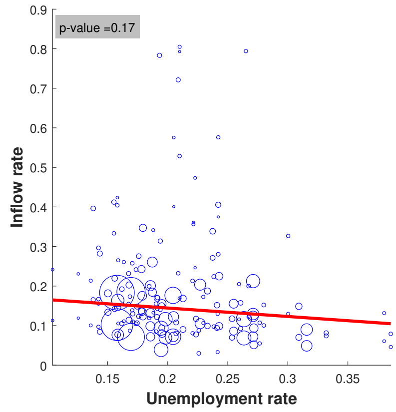
$$ERR_{it} = IR_{it} + OR_{it} - abs(IR_{it} - OR_{it}). \tag{3.1}$$

The size-weighted mean excess reallocation rate is 20.1%. Put differently, 80% of gross reallocation is excess reallocation. Similarly, Coen-Pirani (2010) find that 87% of gross people flows represent excess people reallocation across U.S. states. Our results show that this stylized fact extends to people flows between urban areas in Spain, a smaller geographic unit than a U.S. state.

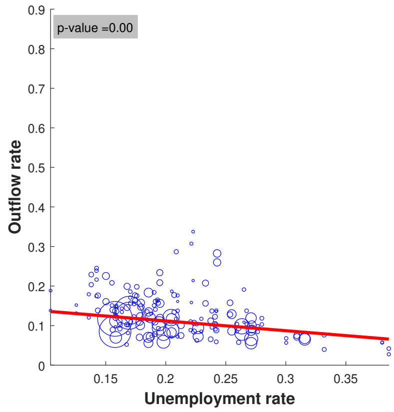
Figure 1 shows flow rates across urban areas ranked according to their unemployment rate. Low-unemployment urban areas have, on average, higher inflow and higher outflow rates than high-unemployment areas. The relative sizes of both flows are such that the net population growth rate shows no systematic relationship with the unemployment rate at the urban area level, as shown in the third panel. Instead, the excess reallocation rate is substantially higher at low-unemployment urban areas. Those with an unemployment rate of 0.17 have a predicted excess reallocation rate of 22% compared to only 17% for urban areas with an unemployment rate of 0.30.

Different from unconditional net mobility, once we condition on peoples' age, we observe systematic sorting across urban areas, as Figure 2(a) shows. The average urban area people flow into at age 25 has an average unemployment rate of 0.19, whereas the urban areas where they depart from have an average unemployment rate of 0.2. This difference disappears when they are about 38 years old, the age from which onward the average unemployment rate is higher at places people flow into relative to places they leave from. By age 65, the average urban area that people are

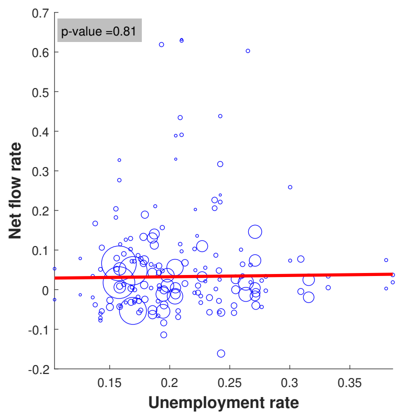
Figure 1: Mobility across urban areas.



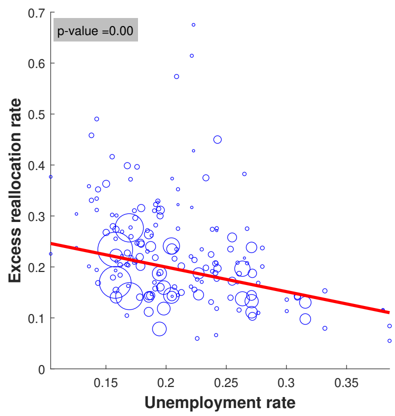

(a)




(b)




(c)




(d)

Notes: The figures display the relationship between people flow rates and the unemployment rate at the urban area level in Spain. We calculate the unemployment rate as the mean unemployment rate over three Censuses. The lines show size-weighted OLS regression slopes. The *net flow rate* is defined as the difference between the inflow and outflow rates. The *excess reallocation rate* is defined as the sum of inflow and outflow rates minus the net flow rate. Source: 1991, 2001, 2011 Censuses moving to has an unemployment rate that is almost 3 percentage points higher than the average unemployment rate of urban areas that people are leaving from. Appendix C displays the underlying flow rates at the level of the individual urban areas, as in Figure 1. It shows that the age sorting patterns that Figure 2(a) highlights are, indeed, statistically significant.

Instead of showing averages, Figure 2(b) provides details on the distribution of inflow rates across urban areas and age. To that end, we again group urban areas into three terciles based on their unemployment rate. The panel displays the age-specific inflow rates of the second and third tercile relative to the first tercile. When young, the inflow rate at the highest unemployment tercile is almost 50% lower than in the lowest tercile. This pattern reverses around age 50, and at age 65, the inflow rate is twice as high in the highest unemployment tercile relative to the lowest tercile.

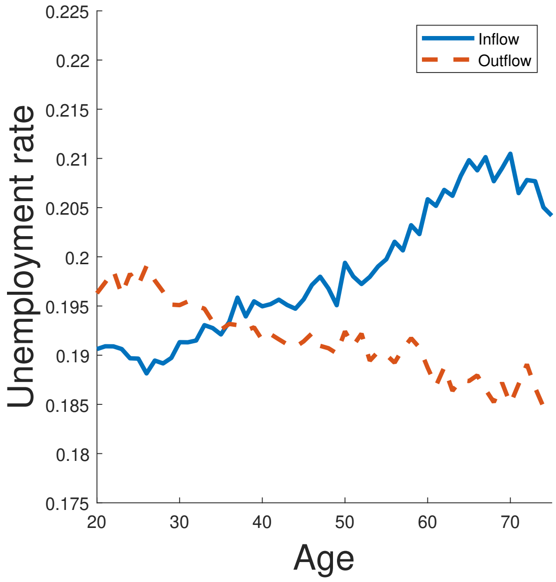
Figure 2(c) shows the average mobility rate lying behind those age-varying flows. The decennial mobility rate falls from 24% at age 31 to less than 5% by age 70. We note that the migration hazard decays slowly after age 55 and remains meaningfully positive at all ages. The shape of the hazard is similar to job quit hazards, documented for example by Topel and Ward (1992). The labor literature usually interprets a gradually declining hazard as the result of search frictions, and we will use this insight to think about mobility between urban areas.

Besides age, given our focus on the labor market, we are also interested in the role employment opportunities play in shaping mobility patterns. Conditioning the population to those younger than 65, we find that 73% of movers were 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, i.e., the data suggest that people join local labor markets to search from within instead from afar.

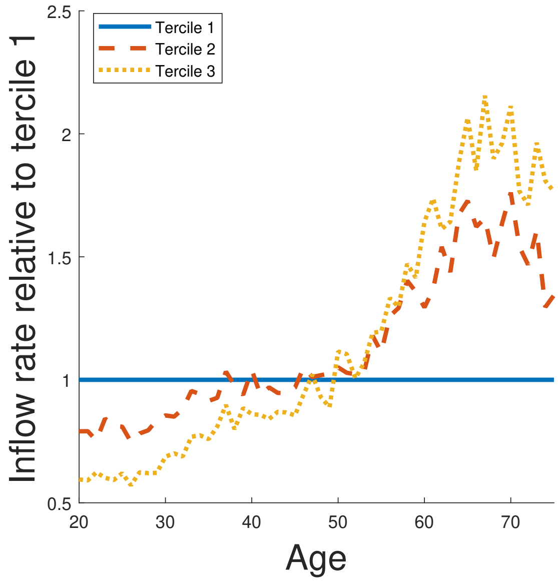
## 4 A benchmark economy with urban areas

The model economy is a dynamic version of the Roback (1982)-Rosen (1979) model in stationary equilibrium. People value consumption and housing and make mobility decisions over their life cycles facing two types of mobility frictions: fixed costs and spatial search frictions. People also face a frictional labor market in the urban area where they are currently living. For reference, Table 2 summarizes all model parameters.

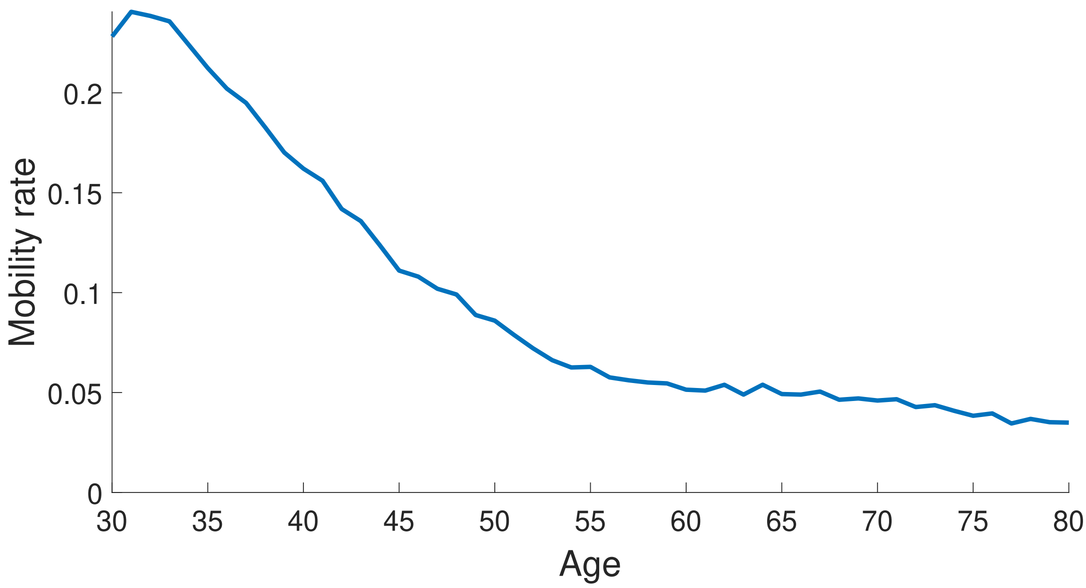
Figure 2: Mobility over the life cycle in the data.




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




(b) Inflow rate by age




(c) Mean mobility rate by age

Notes: The top left panel displays the average urban area unemployment rate across all individuals flowing in (flowing out from) an urban area. The top right panel displays the inflow rate of people in an urban area depending on its tercile in the urban area unemployment distribution relative to the inflow rate in the lowest tercile. The bottom panel shows the mean decennial mobility rate of individuals over age. Source: 1991, 2001, and 2011 Censuses.

Table 2: Model parameters

| Parameter | Description | Parameter | Description |
|---|---|---|---|
| $\overline{H}_\ell$ | Housing stock in urban areas | Income | |
| | | $\ln \mathcal{A}_\ell$ | Earnings fixed effects |
| | | $\tilde{\delta}_\ell$ | Tercile earnings growth |
| Preferences | | $\psi_1$ | Earnings growth linear effect |
| $\beta$ | Discount factor | $\psi_2$ | Earnings growth concavity |
| $\theta$ | Utility of housing | $b_u$ | Unemployment income |
| $\sigma_S$ | Std. idiosyncratic amenities | $b_R$ | Retirement income |
| Labor markets | | UA mobility; $\mu_\ell^J = \omega_\ell \, p^J$ | |
| $\lambda_\ell$ | Exogenous job loss rate | $p^U$ | Search efficiency unemployed |
| $\phi_\ell$ | Job offer rate unemployed | $p^U$ | Search efficiency unemployed |
| $\Lambda$ | Job offer rate employed | $p^R$ | Search efficiency retired |
| $\lambda_d$ | Reallocation rate | $\omega_\ell$ | Search efficiency of urban area |
| $\sigma_Z$ | Std. job quality | $\kappa$ | Fixed mobility costs |

Notes: The table summarizes the model parameters. $\ell$ refers to the urban area (UA) type and $J$ to the employment status.

### 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. There is no population growth, and the probability of dying before age $T$ is zero. Persons start their life in the labor force and retire after age $R$. During working life, people are either unemployed or employed.

People value the consumption of a non-housing good, $c$, and the services of housing, $h$. The lifetime utility of person $i$ is

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

where $\beta$ is the time discount factor, $c_{it}$ is the non-housing consumption at age $t$, $h_{it}$ denotes housing services, and $s_{it}$ is utility flow that the person extracts from amenities in the particular urban area where she lives. The valuation of amenities is idiosyncratic and takes 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. Each location of type $\ell$ has a time-invariant productivity type level, $A_\ell \in \{\mathcal{A}_1, \mathcal{A}_2, \mathcal{A}_3\}$. The size of housing in each location of type $\ell$, $\overline{H}_\ell$, 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), land in any location is managed by competing property funds that are perfectly competitive, risk-neutral, and reside outside the economy. These funds manage 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 $b_U$ whereas 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 $\mathcal{A}_\ell$ and a job $j$ with log productivity $z_j$, a person of age $t$ earns:

$$\ln w_{\ell jt} = \ln \mathcal{A}_\ell + z_j + a_t \tag{4.2}$$

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

$$e_{t+1} = e_t + \tilde{\delta}_\ell \quad \text{if employed} \tag{4.4}$$

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

where $a_t$ is the person's idiosyncratic log ability. Idiosyncratic log productivity has a deterministic age component given by $\psi_1$ and $\psi_2$. De La Roca and Puga (2017) show that, in Spain, productivity gains from working are higher in larger urban areas, and we show the same result when grouping urban areas by their unemployment rates in Appendix D.[11] To allow for this possibility, idiosyncratic log ability changes have an additional location-specific component $\tilde{\delta}_\ell$.[12]

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 Appendix D, 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 $\phi_\ell$. A job offer is a random draw of job log productivity, $z \sim N(0, \sigma_z^2)$, where we denote the density of this job offer distribution by $f_Z(z)$. Similarly, the currently employed exogenously lose their job with location-specific probability $\lambda_\ell$ and become unemployed. Otherwise, they may receive an offer from another job with probability $\Lambda$.[13] To reflect the fact that

[11] We take a slightly different view on the main driver of the urban area earnings premium compared to De La Roca and Puga (2017). In their view, it is the size of the urban area, i.e., agglomeration. Differently, we take a labor market view and rank urban areas by the unemployment rate. Therefore, size is an endogenous object in our analysis.

[12] We note that we have simplified the process relative to the data in order to reduce the state space. Idiosyncratic productivity is quadratic in age instead of the overall experience.

[13] We assume that the parameters governing on-the-job search are common to all urban areas, as there is little

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 $\lambda_d$, 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.[14]

### 4.3 Mobility across locations

After local labor market shocks, people may have the opportunity to change locations. As discussed above, the shape of the mobility hazard over age documented in Figure 2(c) supports the view that people make mobility decisions infrequently. Besides this indirect evidence, administrative survey evidence from the Centro de Investigaciones Sociológicas (2012) also supports this idea. According to that survey, only 17 percent of the Spanish population have "*thought about the possibility of living in another place*" during the last 12 months. That is, even using a very broad definition of searching, the vast majority of people do not search to move to a better place.

Hence, similarly to the labor market, we take the view that migration opportunities are the outcome of a random search process. The fundamentals behind these frictions are likely search costs. In the abstract, it may sound easy to regularly scan all locations in a country for a better match, however, this is unlikely true in reality. Moving entails learning about the quality of life in a different location and a detailed search of the local housing market, and a good match to a household's unique circumstances may arise infrequently. Moreover, a person requires detailed information on each urban area labor market to understand her job opportunities. Accumulating all this information is costly. Consistent with this idea, Bergman et al. (2019b) find that providing information about living opportunities has large positive effects on migration in the US. Hence, we think that moving opportunities rather arise by chance. One example of this idea is that specific job opportunities from other locations arrive stochastically. Another example is a person who hears by chance from friends or the media about a new, affordable housing development or the quality of schools and other living conditions at a particular location. We allow the frequency of such mobility possibilities to depend on the current location and on the employment state $\mu_\ell^J$ with $J \in \{E, U, R\}$.

An opportunity to move to a different location may come with a job offer or as unemployed.

heterogeneity in the targets across urban areas.

[14]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.

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 $s' \sim N(0, \sigma_s^2)$ with density $f_S(s')$. If a person decides to move, she pays a utility cost $\kappa \in \mathbf{R}_+$ that can be thought of as the time and effort required to move and settle in a new location.

## 4.4 Value functions

We are going to 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, they receive local labor market shocks which may change their labor status. At the final stage, individuals may receive migration opportunities and decide whether to migrate or not. We describe the individual's problem faced at each stage backward, from the last to the first stage.[15]

### 4.4.1 Migration stage

Agents receive migration opportunities with probability $\mu_\ell^J$ which depends on the type of their current location, $\ell$, and employment status, $J$. These migration opportunities are uniformly distributed over the types of alternative places, $\ell'$, i.e., each occurs with a probability of one-third. If she receives a migration offer, she decides whether to accept it, in which case she pays the utility cost $\kappa$. The current value of either choice (migration or not) is discounted with the factor $\beta \in (0, 1)$ as the rest of the economic decisions are taken next period. The migration cost, however, is born at the time of migration.

**Retirees** Let us think of a retiree of age $t = R + 1, \ldots, T - 1$, who lives in a location of type $\ell$ and amenity value $s$.

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

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

[15]For parsimony, we also omit the value functions in the last period of working life and the last period of life which have different continuation values.

$W_t^R(\ell, s)$ is the value function of a retiree of age $t$ living in $\ell$ with amenity value $s$. $\Omega_t^R(\ell, s, \ell')$ comprises all the expected net gains of moving from $\ell$ to $\ell'$ type. The realized gains depend on the realization of the amenity value of location $\ell'$, which is drawn from the aforementioned density distribution $f_S$. 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 $\ell'$ 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, $\ell$, and amenity level, $s$. Unemployment at this stage may be the result of two different events: First, being unemployed at the beginning of the period and not becoming employed or, second, it may be the result of 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, $e' = e + \tilde{\delta}_\ell$, as she has worked at the beginning of the period.

Unemployed agents receive a migration opportunity to a location of type $\ell'$ 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 $z'$ 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,

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

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

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

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 $f_Z$:

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

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, $e' = e + \tilde{\delta}_\ell$, as she has worked at the beginning of the period.

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

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

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

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

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

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

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 consumption stages

We now turn to describe the value functions at the beginning of the period.

**Retirees** Once retired, people receive retirement benefits $b_R$ and stay retired until the end of life:

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

it will be useful later to define the housing demand policy function as $g_t^{R,h}(\ell, s)$.

**Unemployed** The unemployed receive a job offer with probability $\phi(\ell)$ and, conditional on that, the job offer has productivity $z$ with probability $f_Z(z)$:

$$\begin{aligned} W_t^U(\ell, s, e) = \quad & \max_{c,h} \Big\{ u(c, h, s) + (1 - \phi_\ell)\; V_t^U(\ell, s, e) + \phi_\ell \sum_z \Psi_t^{EU}(\ell, s, e, z)\, f_Z(z) \\ \text{s. t} \quad & c + r_\ell\, h \leq b_U, \\ & c \geq 0,\; h \geq 0, \end{aligned} \tag{4.15}$$

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

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

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. They become unemployed with probability $\lambda_\ell$. If they do not become unemployed, they may receive a job offer:

$$\begin{aligned} W_t^E(\ell, s, e, z) = \quad & \max_{c,h} \Big\{ u(c, h, s) + \lambda_\ell\, V_t^U(\ell, s, e') + (1 - \lambda_\ell)\; \Psi_t(\ell, s, e', z) \Big\} \\ \text{s. t} \quad & c + r_\ell\, h \leq w(\ell, e, z, t), \\ & c \geq 0,\; h \geq 0, \\ & e' = e + \tilde{\delta}_\ell, \end{aligned} \tag{4.17}$$

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 $\Lambda$ 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

$$\Psi_t^{EE}(\ell, s, e', z) = \sum_{z'} \max \Big\{ \Psi_t^{EU}(\ell, s, e', z), V_t^E(\ell, s, e', z') \Big\}\, f_Z(z), \tag{4.19}$$

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:

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

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

Here, we highlight some properties of the stationary equilibrium and leave a more formal definition to Appendix E. To define the equilibrium we need to keep track of the population size of each location type. Formally, we define the population at the beginning of the period as a measure of people of different characteristics. Let $L$ denote the set of all possible location types and let $S$ denote the set of amenity values. Let $X^R \equiv L \times S$ be the set of state variables for the retirees. Let $N_t^R : \mathcal{X}^R \to [0, 1]$ denote the density of retirees of age $t$ where $\mathcal{X}^R$ is the Borel $\sigma$-algebra on $X^R$. Likewise, $\mathbb{E}$ is the set of all possible values of experience and $Z$ is the set of labor productivities. Let us define $X^U \equiv \mathbb{E} \times S$ as the set of state variables for the unemployed. Likewise, $X^E \equiv Z \times X^U$. Likewise, we can define $\mathcal{X}^U$, $\mathcal{X}^E$, $N_t^U$ and $N_t^E$. Hence, the population at a location of type $\ell$ is

$$N(\ell) = \sum_{t=R+1}^{T} \sum_{S} N_t^R(\ell, s) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}} N_t^U(\ell, s, e) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}\times Z} N_t^E(\ell, s, e, z)\,. \tag{4.21}$$

Finally, we can also denote the housing demand at a location of type $\ell$ as $H_\ell^D$ and is given by

$$\begin{aligned} H_\ell^D = & \sum_{t=R+1}^{T} \sum_{S} N_t^R(\ell, s)\; g_t^{R,h}(\ell, s) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}} N_t^U(\ell, s, e)\; g_t^{U,h}(\ell, s, e) + \\ & \sum_{t=1}^{R} \sum_{S\times\mathbb{E}\times Z} N_t^E(\ell, s, e, z)\; g_t^{E,h}(\ell, s, e, z) \end{aligned} \tag{4.22}$$

To derive the housing demand in each location, let $y$ be an individual's income. We have that consumption expenditures are constant shares of income:

$$c = \theta\, y, \quad h = (1-\theta)\,\frac{y}{r_\ell}, \tag{4.23}$$

and, hence, the indirect felicity function becomes

$$u(c,h,s) = \theta^{\theta}\,(1-\theta)^{1-\theta}\,\frac{y}{r_{\ell}^{1-\theta}} + s \tag{4.24}$$

Using the market clearing condition of the housing rental market, we find that the rental price of a location of type $\ell$ not only depends on the size of the population but also on its demographic composition:

$$r_{\ell} = \frac{(1-\theta)}{\overline{H}_{\ell}}\left[\sum_{t=R+1}^{T}\sum_{S} N_t^R\,(\ell,s)\; b_R + \sum_{t=1}^{R}\sum_{S\times\mathbb{E}} N_t^U\,(\ell,s,e)\; b_U + \right.$$
$$\left.\sum_{t=1}^{R}\sum_{S\times\mathbb{E}\times Z} N_t^E\,(\ell,s,e,z)\; w\,(\ell,e,z,t)\right]. \tag{4.25}$$

In the description of our economy, we have conjectured that rental prices depend only on the type $\ell$, and locations of the same type have the same rental price. This result is straightforward without mobility costs and a distribution of idiosyncratic amenities draws, $f_S$, that is identical across locations. In that case, the more expensive location would not have any comparative advantage in any dimension. However, when agents cannot move at will, it could be the case that there were multiple equilibria. Appendix E 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,* $\phi_{\ell}/\left(\phi_{\ell}+\lambda_{\ell}\right)$.

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

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

# 5 The quantitative model

## 5.1 Calibration

Table 3 summarizes the calibration. The model period is a year. Households are born at age 20 and live until age 80. We calibrate exogenously parameters of the utility function, governmental programs, urban area housing stocks, and the initial distribution of people over states. We target

Table 3: Calibration

| Parameter | Unemp. tercile T1 | T2 | T3 | Target |
|---|---|---|---|---|
| Exogenously calibrated | | | | |
| $\beta$ | | 0.97 | | 3% annual discount rate |
| $\theta$ | | 0.76 | | Share spend on housing 24% |
| $b_u$ | | 0.59 | | 15% of mean wage |
| $b_R$ | | 2.98 | | Monthly benefits of 776€ |
| $\overline{H}_\ell$ | 1.64 | 1 | 0.8 | Housing stock in urban areas |
| $N_1(\ell)$ (%) | 0.48 | 0.27 | 0.25 | Pop. % of 20-22 years old |
| Equation (D.1) | | | | |
| $\ln \mathcal{A}_\ell$ | 1.04 | 1 | 1 | Tercile earnings fixed effects |
| $\tilde{\delta}_\ell$ (%) | 0.57 | 0.00 | 0.00 | Tercile earnings growth |
| $\psi_1$ (%) | | 10.16 | | Earnings growth |
| $\psi_2$ (%) | | -0.20 | | Earnings growth |
| Labor markets | | | | |
| $\lambda_\ell$ (%) | 4.70 | 5.30 | 8.40 | EU rate of city stayers |
| $\phi_\ell$ (%) | 45.0 | 38.5 | 28.5 | Urban area-level unemployment |
| $\Lambda$ (%) | | 19.50 | | 11 % Job-to-Job rate |
| $\lambda_d$ (%) | | 51.0 | | 41 % Job-to-Job share losses |
| $\sigma_Z$ | | 0.46 | | Std of job switchers 0.55 |
| Mobility; $\mu_\ell^J = \omega_\ell \, p^J$ | | | | |
| $p^U$(%) | | 5.50 | | Mobility rate of 0.95% |
| $p^E$(%) | | 5.00 | | Ratio of E to U movers: 2.7 |
| $p^R$(%) | | 5.50 | | $p_R = p_U$ |
| $\omega_\ell$ | 2.08 | 1.00 | 0.68 | Relative people turnover |
| $\kappa$ | | 5.80 | | Mobility ages 76–80 = 3.62 |
| $\sigma_S$ | | 0.44 | | Share T1 to T1 prime-age 55% |

Notes: The table displays the model calibration. 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 right column describes the data target. Table 9 compares the resulting model moments to the data.

with the discount factor, $\beta$, a 3% yearly interest rate. Median household rent expenditure was 520€ in 2009 which is about 24% 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 payment in Spain is 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%. However, not all workers satisfy this criterion, and the young, who are particularly important for mobility, are least likely to satisfy it. Moreover, our model is about persistent unemployment risk, 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 108€. We decide to take an intermediate replacement rate of 15% of the mean wage in our model.

We set the available housing stock in each urban area, $\overline{H}_\ell$, to the total square meters of housing from the Census. 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.[16] 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, and Appendix F shows that the model provides a close data fit. Regarding the earnings process, we normalize the log productivity of the highest unemployed urban area to one. Next, we estimate a regression of workers' log earnings on worker fixed effects, urban area fixed effects, a polynomial in experience, and experience at different urban area terciles. We adjust the parameters of the experience profile and the urban area fixed effects such that this model regression replicates the results from the data that we show in Appendix D. We find that urban area productivity differences are substantially smaller than the urban area earnings fixed effects we find in the data. The reason is that we explicitly differentiate between urban area productivity and job effects. Low-unemployment urban areas have better labor markets implying workers are on average in better jobs which increases their earnings.[17] For the same reason, we find that urban area heterogeneity in productivity accumulation is smaller than the urban area differences in the earnings-experience profiles found in the data.

We calibrate the labor market search efficiency parameters to match statistics pertaining to individuals tracked in the MCVL who are not switching urban areas. The exogenous job loss probability, $\lambda_\ell$, is set to match the share of EU transitions in the data. We find a higher job loss rate in low-productivity urban areas. The job offer rate in unemployment, $\phi_\ell$, is set to match the average unemployment rate in each urban area tercile. The resulting calibration implies that job search is more efficient in high-productivity urban areas. The job offer probability of those employed, $\Lambda$, is set to match the average job-to-job transition rate. We use the probability that a job offer is a reallocation offer, $\lambda_d$ to match the fact that 42% of those moving job-to-job experience

[16] In a typical overlapping generations model, newborns replace the deceased at the same location. This would be distorting in this model economy as it would link the location of residence of the elderly with birthplaces. In reality, people have children when they are young where they reside.

[17] Baum-Snow and Pavan (2012) find that differences in job quality play only a minor role in explaining the city-size wage premium in the U.S. Instead, different experience accumulation on the job and city fixed effects explain most of the wage differences. We note two major differences. First, we estimate for Spain only relatively small urban area fixed effects even in the raw wage data. Second, by focusing on unemployment differences between urban areas, instead of size differences, we select urban areas based on differences in search frictions. Reflecting this, we find more systematic differences in job loss rates and job finding rates between different urban areas than they report in Table 2. As discussed, these systematic differences are consistent with other papers that sort locations based on their unemployment rates. Consistent with our findings that job effects are important to understand wage differences, Porcher et al. (2021) show that more workers are employed at large plants in high-paying urban areas in Spain.

an earnings loss.[18] We find that about half of job-to-job offers actually result from reallocation offers. Together with an average job loss rate of around 5.8%, this 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, $\sigma_Z$. We calibrate the dispersion such that the standard deviation of log wage changes of job-to-job switchers is 0.55.

Finally, we target moments of mobility across ages and places. We write the migration possibility probability as $\mu_\ell^J = \omega_\ell p_J$, where $p_J$ measures the search efficiency of different employment states, and $\omega_\ell$ the urban-specific search efficiency. The shape of the mobility hazard over age allows us to distinguish between fixed mobility costs and search frictions, where the latter implies a slowly decaying hazard. Our data targets are (i) the average mobility rate, (ii) the mobility rate at ages 76–80, (iii) the share of movers who were previously employed, and (iv) the share of prime-age movers going to urban areas with the lowest unemployment rates, given that they are currently already in the lowest unemployment rate tercile, i.e., the strength of sorting at prime-age. The calibration implies that less than 10% of people consider moving in any given year, which we think is broadly in line with the discussed survey evidence given that a movement opportunity in the model is a much more concrete choice than the survey question framing. Nevertheless, fixed costs are substantial, representing about 1.5 times the average annual earnings. Search efficiency is about 10% higher for the non-employed relative to the employed. To match the high excess reallocation rates at low-unemployment urban areas, we require those to have a search efficiency about twice as high as other 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 substantial fraction of people moving to higher unemployment urban areas at prime age, we require substantial dispersion in idiosyncratic amenities.[19]

## 5.2 Untargeted moments

Before turning to the analysis of the model, we briefly show that it captures the previously discussed salient characteristics of urban areas and peoples' mobility. Table 4 displays cross-sectional

[18] To reduce noise, we calculate moments of earnings changes only for the employed with at least 4,500€ of yearly earnings.

[19] Translating idiosyncratic amenities to the well-known labor search framework, one may think about these as representing idiosyncratic compensating differentials as in Vejlin and Veramendi (2020). Similarly to such a job-ladder model, a migration model without idiosyncratic amenities would imply more sorting on earnings than we observe in the data.

Table 4: Heterogeneity across urban areas

| | Model | Data |
|---|---|---|
| **Population Shares** | | |
| $T2/T3$ | 1.20 | 1.27 |
| $T1/T3$ | 1.93 | 2.13 |
| **Annual earnings per worker** | | |
| $T2/T3$ | 1.09 | 1.04 |
| $T1/T3$ | 1.21 | 1.32 |
| $P75/P25$ **of earnings distribution** | | |
| $T2/T3$ | 0.94 | 0.91 |
| $T1/T3$ | 0.96 | 0.90 |
| **Housing price** | | |
| $T2/T3$ | 1.07 | 1.00 |
| $T1/T3$ | 1.21 | 1.55 |

Note: the table reports summary statistics of the demography and labor market of urban areas ranked in three different unemployment terciles (the first tercile stands for the set of urban areas with the lowest unemployment rate). All statistics are normalized by the value in the thrid tercile, $T3$. Census 1991, 2001, and 2011: Unemployment and population; MCVL: Earnings; Digital Atlas of Urban Areas: Housing prices.

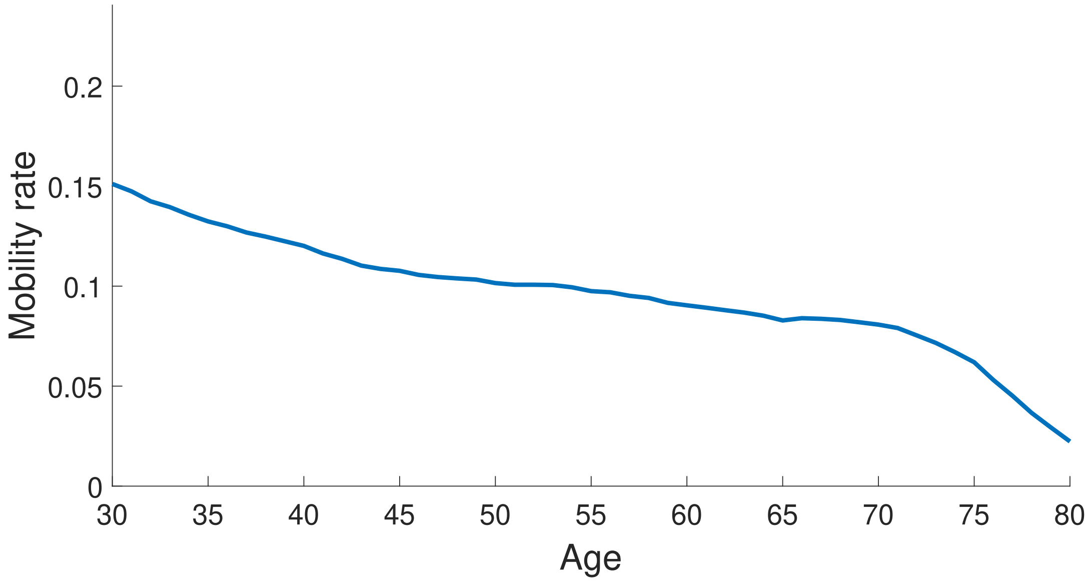
moments of urban areas. The model closely matches the age-averaged population shares, i.e., low-unemployment urban areas are bigger.[20] The table also shows that low-unemployment urban areas have higher average earnings. Notably, the difference between the second and third tercile is relatively small compared to the difference between the first and third tercile. Not only are average earnings low in high-unemployment urban areas but earnings are also relatively unequally distributed. The model matches this fact through worker sorting. High-unemployment urban areas have relatively many low-earnings workers, i.e., those born there. At the same time, workers moving to those urban areas close to retirement have relatively high earnings leading to a relatively high earnings inequality.[21]

The last panel shows that the model also matches substantial rent dispersion across urban areas. Again, as in the data, urban areas in the second and third tercile are relatively similar while rents are substantially higher in urban areas with the lowest unemployment rates. We note that, in the data, rents are yet higher in the first tercile. One possibility is that higher incomes in low-unemployment urban areas lead to higher-quality housing in those urban areas that we cannot measure in the data. Moreover, due to the high population density, building costs may be higher in those urban areas leading to yet higher housing costs.

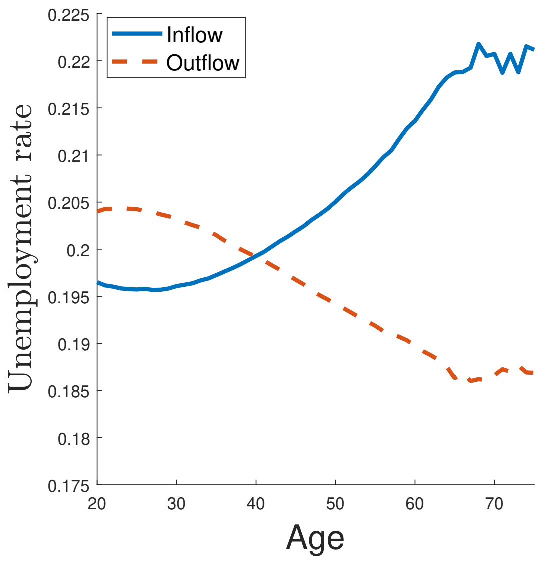
[20] The literature usually estimates heterogeneity in average amenities across urban areas when targeting population sizes. Likely, we do not require these as there is a lot of heterogeneity of amenities at the municipality level within the three unemployment terciles.

[21] This evidence contrasts with the positive correlation found between earnings dispersion and city size in the US economy by various authors; see, for instance, Baum-Snow and Pavan (2013) or Eeckhout et al. (2014). A recent

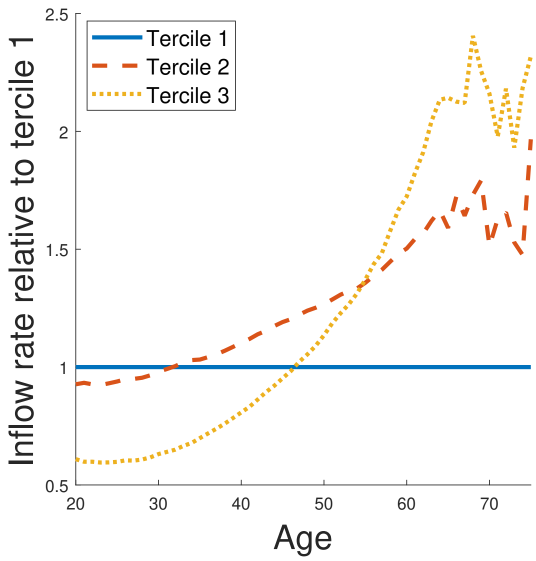
Figure 3: Mobility over the life cycle in the model




(a) Mean mobility by age




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




(c) Inflow rate by age

Notes: The top panel displays the decennial mobility rate of people over the life cycle. The bottom left panel displays the average urban area unemployment rate across all individuals flowing to (separating from) an urban area. The right panel displays the inflow rate of people in an urban area depending on its tercile in the urban area unemployment distribution relative to the inflow rate in the lowest tercile. Source: Model simulations.

Turning to mobility patterns, the blue solid line in Figure 3(a) displays the mobility rate of people over the life cycle in our model economy. Comparing this to its data counterpart in Figure 2(c), we see that the model matches that the mobility hazard rate is decreasing with age, though the

paper by Castells-Quintana et al. (2020) uses data for Urban Areas in OECD countries and estimates that such strong association is weaker outside the US and mainly driven by the richest and largest cities.

decline is faster in the data during early ages. 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 to receive a better offer from a different urban area decreases with age.

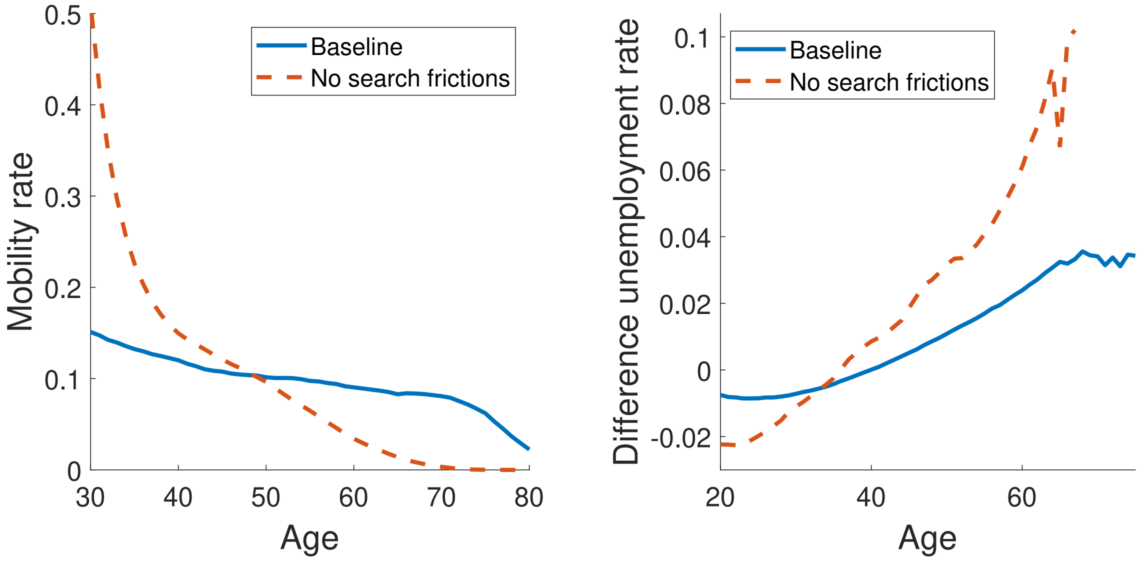
In the data, as highlighted in Figure 2(a), these sorting patterns vary with the life cycle. Figure 3(b) shows that the model matches the pattern closely: The young tend to sort into low-unemployment urban areas, and the elderly tend to sort into high-unemployment urban areas. Similarly, Figure 3(c) shows that the model also matches closely the underlying distribution of inflow rates to different urban areas across ages (compare Figure 2(b)). The model rationalizes these life cycle patterns by 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, for whom good labor market conditions in an urban area are unimportant.

Finally, our model 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 non-retired people moving to a new urban area as non-employed. In the data, this share is 46 percent, i.e., many people move to urban areas even without a concrete job opportunity. The model matches this fact well: 47 percent of movers join the new urban area as unemployed. In parts, the model rationalizes this large fraction by the elderly moving to urban areas with higher unemployment rates as they expect to retire soon and dispersion in idiosyncratic amenities. In addition, in the model, the young move to low-unemployment urban areas even without a concrete job offer as it allows them to search for work in the local job market.

### 5.3 Spatial search frictions and mobility fixed costs

Different from us, the urban literature typically assumes that people consider moving each period and choose optimally across all possible locations after observing the realizations of idiosyncratic amenities across all locations. As discussed before, survey evidence suggests that people make mobility decisions much more infrequently. In addition, to highlight that spatial mobility frictions also help us to understand mobility data, we compare here the baseline model to a recalibrated model without search frictions. We relegate the description of that model to Appendix G.

Figure 4: 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.

The red dashed line in Figure 4(a) shows that this alternative model fails to replicate several aspects of the age-mobility hazard. Mobility is too high for young people while the elderly almost do not move. The latter fact arises from the fixed cost of mobility which are now an "unreasonable high" 5.3 times the average yearly earnings compared to 1.5 in the baseline model.[22] Without search frictions, it is difficult for the model to 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.[23]

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 as Figure 4(b) shows. Here, for better visibility, we represent the sorting from Figure 3(b) 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 match sorting patterns at prime age, as these are partially calibrated using the dispersion of idiosyncratic amenities. Given this level of sorting at prime age, however, the model without search frictions implies a much too steep age gradient in sorting into urban areas with different labor markets. When people can

[22] In a model with only fixed costs, for the U.S. Kennan and Walker (2011) estimate a cost of 312,000 dollars. Relative to income, the inferred costs would be even higher for Spain because the yearly mobility rate is only around 1%. Schluter and Wilemme (2018) also note that spatial search frictions are a possible way to rationalize low mobility.

[23] One may argue that mobility costs are lower for the elderly. However, as the figure highlights, to match the data, we also require higher mobility costs for the young relative to those aged 55 which seems implausible to us.

optimally choose their preferred labor market, the incentives at young ages are highest to move to low-unemployment urban areas. 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 (i) people make mobility decisions infrequently and (ii) mobility opportunities are random instead of chosen optimally.

Finally, the alternative model also implies that people turnover is counter-factually 38% higher in urban areas in the highest unemployment tercile relative to the lowest tercile. The reason is that the unemployed have relatively higher mobility acceptance rates. The baseline model overcomes this by modeling low-unemployment areas as search hubs: they provide more opportunities to move elsewhere. As noted above, we interpret this as arising from people having larger networks in low-unemployment (large) urban areas and firms in those urban areas having often also establishments in other parts of the country.[24]

# 6 Results

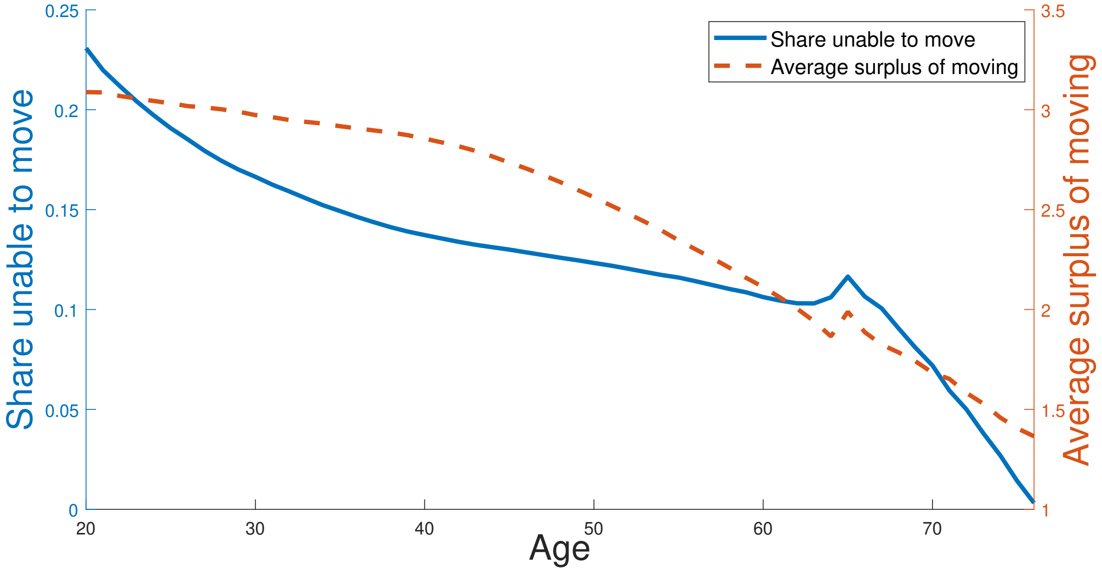
In this section, we study mobility patterns in the benchmark economy. Moreover, we use counter-factual simulations to evaluate the steady-state effects of various policies.

## 6.1 Understanding mobility

We find that search frictions are the main impairment to the mobility of the young while mobility fixed costs are the main impairment to the mobility of the elderly. Regarding spatial sorting over the life cycle, high urban area productivities, rapid productivity growth, and good job markets all contribute to young people moving to low-unemployment urban areas. The resulting high housing rents, in turn, incentivize the elderly to leave these locations. Finally, we find that 58% of mobility results from idiosyncratic differences in amenities.

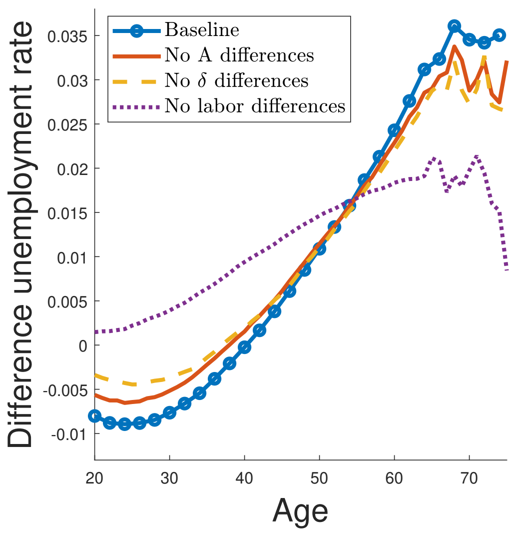
[24]To take an explicit example, the baseline model interprets the many observed flows from Madrid to Barcelona (relative to the flows from a higher unemployment urban area, such as Cadiz, to Barcelona) as resulting from people in Madrid receiving relatively many offers to move. Differently, much of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

Figure 5: Understanding mobility.

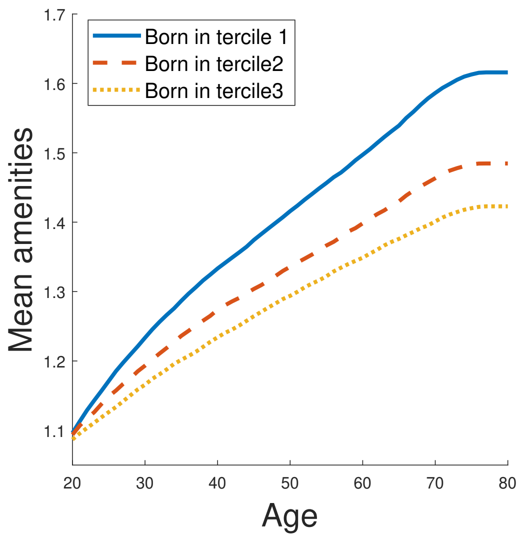



(a) Mobility surplus

Notes: The blue straight line 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, $\kappa$. Source: Model simulations.




(b) Counterfactuals




(c) Amenities

Notes: The left panel 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* $\tilde{\delta}$ *differences* eliminates differences in urban area skill accumulation; *No labor differences* eliminates differences in urban area job loss and job finding rates. The right panel displays the average amenity level of individuals born in urban areas with different unemployment rates. Source: Model simulations.

### 6.1.1 The role of mobility frictions

The solid blue line (left axis) in Figure 5(a) displays the share of people willing to move given a random mobility offer minus the realized mobility rate. The red-dashed line (right axis) displays the average value of moving relative to the migration costs. At the beginning of the life cycle, more than 20% additional people would move across urban areas if they would receive an opportunity. Moreover, their average value of moving exceeds the fixed costs of mobility by a factor of three. As people move over time into locations and jobs with better idiosyncratic characteristics, the value of moving declines and so does the share of people restricted by search frictions. Put differently, search frictions are the main hindrance to the mobility of the young. By implication, a high share of the young population does not move despite large benefits. In contrast, when old, the average surplus of moving is close to the fixed cost of mobility, i.e., fixed costs become the dominant deterrent to mobility.

### 6.1.2 Sorting over the life cycle

To understand the role different aspects of local labor market conditions have on the sorting of people across urban areas over the life cycle, we simulate the model but eliminate each time one aspect of heterogeneity. Figure 5(b) shows the results. The solid red line shows the sorting over the life cycle when all urban areas have the same aggregate productivities. Strikingly, even after eliminating productivity differences across urban areas, most of the life-cycle sorting patterns remain. In our model, the other differences explaining the sorting pattern are dynamic, i.e., they provide benefits to people partly in the future. The figure highlights that differences in urban-area local labor markets (job loss and finding rates) are the single most important factors behind the life cycle sorting pattern.

### 6.1.3 The role of idiosyncratic amenities

In our stationary equilibrium, all mobility must result from idiosyncratic differences between workers. One of these is the aforementioned life cycle. Another are differences in employment states and job qualities and differences in employment offers. Lastly, idiosyncratic amenities create incentives for mobility. Table 5 shows that the latter are, indeed, an important factor in mobility decisions. Eliminating heterogeneity in idiosyncratic non-pecuniary benefits, i.e., setting $\sigma_S = 0$, decreases the mobility rate to 4.0%. In particular, without idiosyncratic amenities, fewer people

Table 5: Understanding mobility

| Model | Mobility rate % | Share moving to better urban areas |
|---|---|---|
| Baseline | 9.62 | 0.26 |
| $\sigma_S = 0$ | 3.99 | 0.38 |

Notes: The table shows the mobility rate and the share of workers who change their location and move to a location in a lower tercile of the unemployment distribution than their current location. It displays these moments in the baseline model and a counterfactual simulation, $\sigma_s = 0$, without idiosyncratic amenities. Source: Model simulations.

would move to urban areas with higher unemployment rates than their current urban areas. Notice that heterogeneity in idiosyncratic amenities is more important to understand mobility than job heterogeneity even though we calibrate more dispersion in the latter. The reason is that a good job draw is more transitory that an amenity draw. That is, losing a job may also occur within an urban area. Moreover, the benefit of a good job draw is tied to working and disappears after retirement.

### 6.2 Welfare costs of being born in a high-unemployment urban area

We find that being born in locations of the lower types entails substantial welfare losses compared to being born in the best locations. Higher productivity, higher experience accumulation, better job opportunities, and more mobility opportunities all contribute to those large losses. Notably, static productivity differences across urban areas explain only a small part of these welfare losses, i.e., the main drivers of welfare differences across location types are dynamic.

Turning to the welfare effects of public policy, we highlight three insights. First, because of search frictions, reducing fixed mobility costs or paying subsidies to young people to live in low-unemployment urban areas, if any, increase welfare dispersion at birth. Second, search frictions also imply that paying transfers to high-unemployment urban areas reduces welfare dispersion at birth without large output losses. Third, labor market reforms that benefit young people mostly benefit those born in low-unemployment urban areas.

#### 6.2.1 Decomposing welfare losses

The first row of Table 6 displays the lifetime income losses of being born (age 20) in the second and third tercile of the urban area unemployment distribution relative to the first tercile.[25] A person born into the second and third tercile has a 9.8 and 17.0 percent lifetime income loss, respectively, compared to a person born in the first tercile.

[25] Appendix H derives the welfare loss analytically for our utility function.

Table 6: Decomposing welfare dispersion

| Model | Welfare T2/T1% | Welfare T3/T1% |
|---|---|---|
| Baseline | 9.77 | 17.03 |
| Same productivity | 8.66 | 15.82 |
| Same experience | 6.16 | 13.17 |
| Same $\phi$, $\lambda$ | 8.62 | 11.97 |
| Same $\omega$ | 7.08 | 12.96 |

Notes: The table displays the percent of lifetime income a person born in the second tercile, $T2/T1$, and the third tercile, $T3/T1$, of the urban area unemployment distribution loses compared to someone born in the first tercile. It displays this result for the baseline model as well as several counterfactual simulations. *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; $\phi$, $\lambda$: all urban areas have the mean job finding and job loss rate across urban areas; *Same* $\omega$: all urban areas have the calibrated search efficiency from the highest unemployment urban area. Source: Model simulations.

People prefer to be born in low-unemployment urban areas because these are more productive, provide higher experience returns to their workers, provide better job search during unemployment and more stable jobs, and provide better search opportunities to move to other urban areas. Table 6 quantifies the welfare effects of each of those factors.

The row entitled "Same productivity" eliminates differences in aggregate productivities, $\mathcal{A}_\ell$, between urban areas. That is, it eliminates the factor most commonly thought to explain differences in desirability across urban areas. The lifetime income loss of a person born in the second and third tercile is reduced to 8.7 and 15.8 percent, respectively, relative to a person born in the first tercile. Put differently, urban area productivity differences explain less than 12% of the welfare dispersion across urban areas at birth. Instead, most of the welfare 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 welfare effects when experience accumulation is the same in all urban areas, i.e., $\tilde{\delta}_\ell = 0$. Differences in the returns to experience have a larger effect on welfare dispersion at birth than urban area productivity differences. After eliminating differences in experience accumulation, the lifetime income loss from being born in the second and third tercile of the urban area unemployment distribution falls to 6.2 and 13.2 percent, respectively.

Turning to differences in labor market frictions, the row entitled "Same $\phi$, $\lambda$" equalizes the job offer rates of unemployed workers and the exogenous job loss rates across urban areas. The welfare effect for people being born in the second tercile is relatively small highlighting that labor market frictions are similar in the first and second tercile of the urban area unemployment distribution. However, the effects for people born in the third tercile are substantial, i.e., the welfare loss from being born in the third tercile reduces to 12.0%.

Finally, the row entitled “Same $\omega$” eliminates differences across urban areas in the search efficiency for mobility opportunities. As highlighted above, low-unemployment urban areas serving as a search hub allow people in those to sort into urban areas with relatively high idiosyncratic amenities. Figure 5(c) 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 welfare losses of being born in high-unemployment urban areas. Quantitatively, the lifetime income loss from being born in the second and third tercile of the urban area unemployment distribution falls to 7.1 and 13.0 percent, respectively.

The model also allows us to evaluate welfare differences across the entire life cycle to better understand the underlying sources of welfare dispersion at birth. To this end, we keep expressing welfare in terms of a person's willingness to pay as a percent of lifetime income (measured from age $t$ onward) and condition on her birthplace instead of the location where she is currently living. Rows three and four of Table 7 (age 45) show that welfare differences across birthplaces at age 45 are similar to those at age 20. The reason is that two forces work against each other. On the one hand, the closer people move to retirement, the smaller becomes the effect of differences in labor markets across urban areas for welfare. On the other hand, most benefits of being born in a low-unemployment urban area (higher skill accumulation, better job market prospects, and higher amenities) accrue in the future. At birth, these future returns are discounted which depresses welfare differences relative to those present at age 45. Turning to retirement, at age 68, those born in low-unemployment urban areas still have higher welfare than those born in high-unemployment urban areas. This may be surprising as better labor markets no longer play a role and, on average, those born in low-unemployment urban areas live in more expensive locations at the time of retirement. However, they also live in locations with high average amenities as their urban area search was relatively more efficient over their life cycle.

#### 6.2.2 Public policies

We now turn to study the impact of policy reforms on welfare dispersion across urban areas at birth. Each policy changes the government's budget, and we employ a proportional wage tax to keep the budget at the 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 very simple policy which is giving subsidies to movers. To be specific, we reduce the fixed costs of moving to zero. The column entitled "No fixed costs" in Table 7 shows the results in this alternative economy.

As expected, we observe an increase in the mobility rate which rises by more than 60%. Maybe surprisingly, however, the welfare dispersion at birth increases slightly. The reason is that a reduction of the mobility fixed costs affects people differently depending on their age. The mobility of young people is not much affected. This is so because the fixed costs are not hindering the migration of young people in a major way, as highlighted by Figure 5(a). For them, mobility is an investment whose return well exceeds the migration fixed costs, and search frictions are the main source of limited mobility. As a consequence, the increase in mobility leaves aggregate output almost unchanged, as Table 7 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, i.e., even those not able to move out of those locations do not benefit indirectly from higher mobility through lower rents. What is more, 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. Therefore, welfare differences across urban areas arising from different birthplaces rise particularly among the retired for whom differences in amenities are the main source of welfare differences.

**Place-based policies** In Spain, policymakers currently discuss two types of place-based policies. First, high housing rents in low-unemployment urban areas create the worry that young people do not move to those areas because they cannot afford to pay for housing. Hence, suggestions have emerged to pay subsidies to young people in low-unemployment urban areas. Second, to improve welfare in high-unemployment urban areas, politicians discuss the possibility of paying transfers to high-unemployment urban areas. Using our model, we address how such policies affect welfare dispersion across urban areas at birth, mobility between urban areas, and labor market outcomes.

We simulate a 30% rent subsidy for all people younger than age 30 who live in the lowest

Table 7: Policies targeted at mobility

| | Baseline | No fixed costs | Subsidy young T1 | Transfer T3 | Job stability |
|---|---|---|---|---|---|
| Welfare % | | | | | |
| T2/T1 age 20 | 9.77 | 10.14 | 10.45 | 9.72 | 10.18 |
| T3/T1 age 20 | 17.03 | 17.31 | 17.73 | 16.13 | 18.61 |
| T2/T1 age 45 | 11.12 | 11.18 | 10.76 | 11.07 | 11.51 |
| T3/T1 age 45 | 16.82 | 16.96 | 16.43 | 16.33 | 18.24 |
| T2/T1 age 68 | 2.17 | 2.76 | 2.02 | 2.19 | 0.83 |
| T3/T1 age 68 | 2.90 | 4.12 | 2.74 | 2.58 | 0.97 |
| Mobility rate % | 9.62 | 16.09 | 9.65 | 9.62 | 7.36 |
| $r_2/r_1$ | 0.88 | 0.88 | 0.86 | 0.88 | 0.85 |
| $r_3/r_1$ | 0.83 | 0.83 | 0.80 | 0.87 | 0.80 |
| $Y$ | 2.37 | 2.37 | 2.37 | 2.37 | 2.49 |
| Mean $\ln s$ % | 6.88 | 7.05 | 6.88 | 6.88 | 6.57 |

Notes: The table compares model outcomes from the baseline model to counterfactual simulations. *No fixed costs*: no fixed mobility costs; *Subsidy young T1*: a subsidy to people younger than age 30 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. $Tx/T1$ 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; *Job stability*: reduces the exogenous job loss rate and job reallocation rate by half and recalibrates the job finding rate such that the unemployment rate is the same as in the baseline; $Mobilityrate$: 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.

unemployment urban area tercile. Column three in Table 7 shows that this policy increases welfare inequality at birth. This is to be expected, as the main beneficiary are those already born in the lowest unemployment urban area tercile. Maybe surprisingly, at first sight, the policy has almost no 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 leads to elderly people moving out of these urban areas and, thereby, the subsidy actually decreases the size of low-unemployment urban areas. The elderly leaving low-unemployment urban areas mitigate the rise in housing rents and, thereby, aggravate the increase in welfare dispersion across urban areas at birth.

Next, we turn to simulate a subsidy to people living in urban areas with an unemployment rate in the highest tercile. The subsidy amounts to 15% of the average housing expenditures. Column four in Table 7 shows that this policy reduces the welfare loss from being born in the highest unemployment urban area tercile by 0.9 percentage points of lifetime income. 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 search frictions play in our framework. That is, as shown in Figure 5(a), search frictions imply that there is 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.

We also note that the beneficial effects of the transfer are mitigated by an increase in housing rental prices in subsidized urban areas. As discussed, the additional housing demand does not come from young people who now want to stay in high-unemployment urban areas but from more elderly people moving to those urban areas. Put differently, the policy benefits mostly those individuals who want to live in a high-unemployment urban area, i.e., the elderly.

**Labor market reform** Currently, Spanish policymakers are discussing improving job stability by reducing the number of temporary work contracts. What is little discussed in this debate are the effects on mobility of the reform and its distributional effects across different urban areas. To understand these issues better, we study a reform that reduces the exogenous probabilities that a job ends, $\lambda$ and $\lambda_d$, by half. A large labor literature studies whether such reforms increase the unemployment rate by reducing job-finding rates or decrease the unemployment rate by reducing job-loss rates. We take no stance on this debate and simply reduce the job offer probability until the aggregate unemployment rate is unchanged. The column entitled "Job stability" displays the results. Beginning with the distributional effects, the reform benefits mostly those people born in low-unemployment urban areas, i.e., the between urban area welfare differences at birth increase. The reason is that more stable jobs make low-unemployment urban areas more attractive as those offer rapid experience gains for the employed.

The table also highlights that increased job stability reduces mobility significantly; a mechanism not studied so far in the labor literature. More job stability implies that workers sort on average into better jobs which reduces the incentives to use geographic mobility to achieve job mobility. A decrease in the mobility rate, in turn, reduces the average idiosyncratic amenity level, i.e., people trade off better jobs for lower amenities. As a result, the welfare losses of being born in a high-unemployment urban area are strongly diminished when people have reached retirement as sorting based on amenities is weaker.

## 7 Conclusion

This paper studies a life cycle model of frictional labor markets and frictional mobility decisions between heterogeneous urban areas to understand mobility between urban areas in Spain and the welfare cost of being born in a high-unemployment urban area. We show that the young allocate on net to low-unemployment urban areas as these pay high average wages, provide high returns to labor market experience, have lower labor market frictions, and facilitate their inhabitants to move to yet better urban areas. In contrast, elderly people value those features little and are pushed out of those urban areas by high rent prices.

Spatial search frictions significantly reduce the mobility of people across urban areas. These frictions hinder particularly the reallocation of young people and are strongest in high-unemployment urban areas. As a result, the place of birth carries large implications for lifetime welfare, i.e., being born in a high-unemployment urban area carries with it large welfare losses.

These frictions also have important implications on the design of policies that wish to address the welfare dispersion at birth. Resulting from the search friction, 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 benefit those already born in those locations and fail to meaningfully increase mobility towards these more successful locations.

Ultimately, to increase mobility towards economically more 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., increase information flows about moving opportunities. However, there exist cross-country programs to facilitate mobility such as the *EURES Targeted Mobility Scheme* that may carry valuable lessons.

# A Data details

**Definitions in the Census:** We classify a person as employed in her current urban area when she reports holding a job.[26] The unemployed are those reporting to search for a job. Finally, those non-employed who report being retired, disabled, or have other reasons not to search for a job are classified as out of the labor force. Given this individual information, we compute the unemployment rate of an urban area as the total number of unemployed individuals relative to those in the labor force. The aggregate unemployment rate has large cyclical fluctuations in Spain. As we are interested in long-run decisions, we compute the time-averaged unemployment rate across the three Censuses at the urban area level.[27]

The 2001 and 2011 Censuses included a question on the location of residence during the previous Census, i.e., 10 years ago. This allows us to compute decennial flows of people who flow into a specific urban area and have lived in a different urban area before, $IN_{it}$, as well as those who flow out from a specific urban area, $OUT_{it}$.[28] To compute rates, we use as convention the size of the urban area in the previous Census, i.e., the inflow rate of an urban area is the sum of all people who have arrived at that urban area over the period of 10 years relative to the size of the urban area at the beginning of that period: $IR_{it} = \frac{IN_{it}}{N_{it-1}}$, and $OR_{it} = \frac{OUT_{it}}{N_{it-1}}$.

**Definitions in the MCVL:** We identify the workplace of the individual using the contribution account codes of the firm, which allows us to identify municipalities with a population of more than 40,000 inhabitants.[29] We group municipalities in urban areas as we did with the Census samples. We exclude job spells of the Basque Country and Navarre residents as well as the self-employed, as the MCVL does not collect data on earnings for these individuals.[30] We also omit job spells in agriculture, fishing, forestry, mining, and extractive industries because their fiscal regime allows them to self-report earnings and the number of working days. Finally, we discard foreign workers because we do not have information about their employment history before migrating to Spain. Similarly, we omit workers born before 1962 as we do not have information on job spells before 1980. This selection results in 329,418 workers and 7,366,678 observations.

The MCVL provides two sources of income information for the reference year of each panel (2006-2008). First, annual uncoded earnings from tax administration records. Second, monthly top-coded earnings from Social Security records[31]. We allocate uncoded yearly earnings across months according to the fraction of top-coded earnings that the worker earns each month. In the monthly data, we regard a worker as employed whenever she has positive social security contributions. In the yearly data, we count a worker as employed when she contributes for at least six months in a year to Social Security. Finally, we define a worker's current employer using the ID of the job with the highest earnings. The employer identifier also allows us to identify job-to-job transitions.

[26] We assume that all people are working in the urban areas where they live. According to the INE, less than 3% of workers were working from home in 2011. Moreover, according to the Ministry of Transport, Mobility, and Digital Agenda, the number of people whose commuting time was longer than 60 minutes comprised 3.7% of the workforce. 90.5% of the workforce needed less than 45 minutes to commute to work.

[27] The ranking of urban areas according to their unemployment rate is very stationary across censuses.

[28] To this end, we include persons who move from and to municipalities who are not part of an urban area. Yet, our data still does not cover all people joining and leaving an urban area as it excludes deaths, those individuals who were younger than 16 years old in the previous Census, and those migrating from and to Spain.

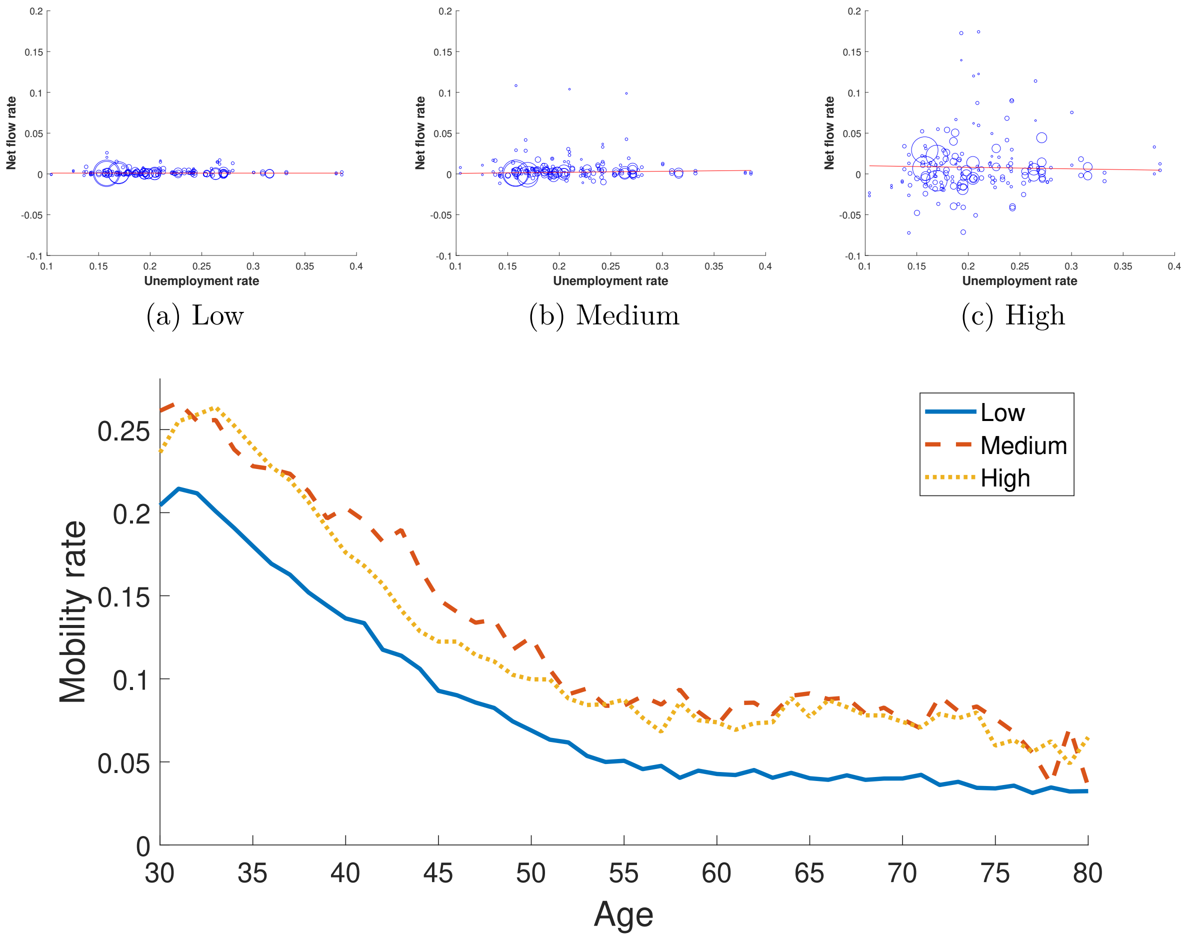
[29] Since the data does not identify municipalities with fewer than 40,000 inhabitants, we have information on 78 out of the 86 existing Urban Areas. In particular, we do not identify the urban areas of Eivissa, La Orotava, Melilla, Ceuta, Blanes, Sant Feliu de Guíxols, Soria, and Teruel.

[30] However, we include Basque Country and Navarre residents when studying labor market transitions.

[31] The data contains top-coded monthly earnings used to calculate social security contributions since 1980. Because of the heavy censoring, we do not use that information.

# B The Role of Education

Figure 6: Mobility by education




(a) Low (b) Medium (c) High

(d) Mobility rate by age

Notes: The top panels display the relationship between peoples' net flow rates and the unemployment rate at the urban area level in Spain. We calculate the unemployment rate as the mean unemployment rate over three Censuses. The lines show size-weighted OLS regression slopes. Low: less than secondary education; Medium: secondary education; High: More than secondary education. The bottom panel shows the mean decennial mobility rate of individuals over age. Source: 1991, 2001, and 2011 Censuses.

Our analysis abstracts from education differences among workers. This appendix shows that the Spanish data does, indeed, suggest that education differences are of second-order importance to understanding mobility patterns.

The top panel of Figure 6 shows that there is no systematic sorting into urban areas with different unemployment rates based on people's education. The bottom panel shows that also people's migration hazards over age look very similar for different education groups. The only difference is a somewhat lower average mobility rate of the lowest educated group throughout the life cycle. This lower mobility rate may present a confounding factor for our analysis if low-educated people were strongly sorted into high-unemployment urban areas. Though they are indeed over-represented in those areas, the differences are small: Their population share is 60% in urban areas in the first decile of the urban area unemployment distribution, 64% in the second, and 67 percent in the third. Given that we find the largest differences in mobility rates between urban areas in the first and second tercile (see, Table 9), these relatively minor differences in education shares explain only a small fraction of the differences in observed mobility rates.

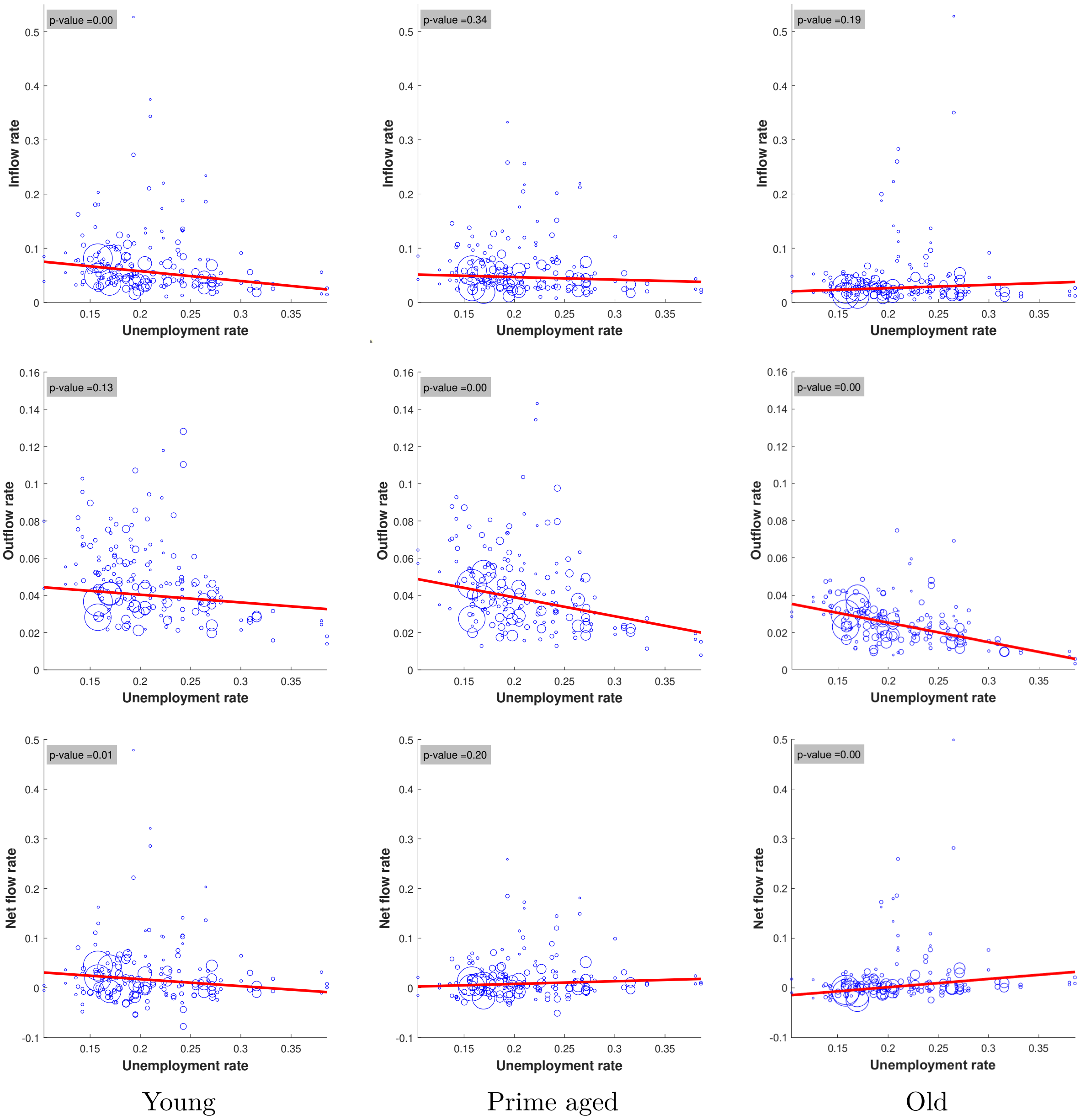
## C Mobility flows by age

Section 3.2 shows that gross mobility is higher in low-unemployment urban areas compared to high-unemployment urban areas and that people sort into urban areas with different unemployment rates over age. The top row of Figure 7 displays the inflow rates at the individual urban area level underlying these patterns. The second row does the same for the outflow rates. To highlight the sorting pattern over age, we divide the population into three age groups.[32] The figure shows that the inflow rates of young people (ages 25–35) fall rapidly with the urban area unemployment rate with very few young people joining urban areas with unemployment rates of 35% or higher.[33] In contrast, outflow rates show only a weak relationship with the unemployment rate. As a result, as the last row shows, the net flow is decreasing in the unemployment rate, i.e., young people move on net to low-unemployment urban areas. Turning to prime-aged workers, the outflow rate displays a stronger negative relationship with the unemployment rate, and the inflow rate shows only a weak negative relationship with the unemployment rate. As a result, the net flow rate is weakly increasing in the unemployment rate. Finally, the outflow rates of the elderly (ages 50+) also display a strong negative relationship with the unemployment rate. and the inflow rate shows a weak positive relationship with the unemployment rate. As a result, the net outflow of old people displays a strong positive relationship with the unemployment rate, i.e., the elderly sort into high-unemployment urban areas.

[32]We define rates using the age-specific flow of people in the numerator and the total urban area size in the denominator. This way, the total flow rate can be decomposed additively into the flow rates displayed in Figure 1.

[33]We discard people younger than age 25 as, given the decennial measure, their mobility may have resulted from the mobility decisions of their parents. Including those people leaves the results unchanged.

Figure 7: Mobility flows, unemployment, and age.




Notes: The figures display the relationship between peoples' mobility flow rates and the unemployment rate at the urban area level in Spain. We calculate the unemployment rate as the mean unemployment rate over three Censuses. The lines show size-weighted OLS regression slopes. Young: age 25-35; Prime-age: ages 36-49; Old: ages 50-80. Source: 1991, 2001, and 2011 Censuses.

# D Local labor market characteristics

Table 8: Local labor markets

| Estimation of earnings equation | Unemp. tercile T1 | Unemp. tercile T2 |
|---|---|---|
| Urban area fixed effect, $\alpha_\ell$ (%) | 9.26*** | 4.71*** |
| | (0.24) | (0.25) |
| $\delta_1$ (%) | 1.15*** | 0.19*** |
| | (0.04) | (0.05) |
| $\gamma_1$ (%) | 8.50*** | |
| | (0.08) | |
| $\gamma_2$ (%) | -0.23*** | |
| | (0.00) | |
| N | 7,364,713 | |
| $R^2$ | 0.0272 | |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

| Employment flows | Unemp. tercile T1 | T2 | T3 |
|---|---|---|---|
| Emp. to unemp. rate (%) | 8.5 | 9.5 | 11.2 |
| Unemp. to emp. rate (%) | 33.2 | 30.4 | 29.4 |
| Job-to-job rate (%) | 12.7 | 11.3 | 10.7 |
| Share job-to-job loss | 0.41 | 0.41 | 0.45 |

Notes: The left panel of the table reports the coefficients for the process of log earnings following equation Equation (D.1). We categorize urban areas in three different unemployment rates terciles where the third tercile serves as the normalization. We measure experience as the number of days with a full-time equivalent labor contract, and we express them in years. The regression includes a constant term as well as controls for age, age squared, sex, education, year dummies, worker fixed effects, and time fixed effects. The right side of the panel reports summary statistics of the labor market of urban areas ranked in three different unemployment terciles. The statistics are based on the population of people who remain in an urban area. The job-to-job transition rate is the share of employed workers who has a new employer ID in the next year. The share with a loss are those job-to-job transitions resulting in lower earnings. Source: MCVL 2006-2008.

This appendix describes labor markets in different urban areas. To that end, we continue with our ranking of urban areas into terciles depending on the unemployment rate. We begin by understanding better the average earnings differences across urban areas. Low-unemployment urban areas may have higher earnings because workers there are particularly highly skilled or they may provide high-paying jobs conditional on workers' skills. Regarding worker skills, Glaeser (1999), Baum-Snow and Pavan (2012), and De La Roca and Puga (2017) show that the effect of work experience on earnings growth systematically varies across urban areas. Following this insight, we assume the following reduced-form relationship for log earnings of worker $i$ in an urban area of tercile $\ell$ at time $t$:

$$w_{i\ell t} = \varphi_i + \tau_t + \alpha_\ell + \sum_{\ell=1}^{2} \delta_\ell \, e_{i\ell t} + \gamma_1 \, \epsilon_{it} + \gamma_2 \, \epsilon_{it}^2 + \boldsymbol{X'_{it}} \, \beta + \varepsilon_{i\ell t}, \tag{D.1}$$

where $\varphi_i$ is a worker-fixed effect, $\tau_t$ is a time-fixed effect, and $X_{it}$ is a vector containing education, age, age squared, and sex. $\alpha_\ell$ is an urban area (of tercile $\ell$) 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 $\epsilon_{it}$ is overall worker experience.[34] The latter captures the returns to experience in the third tercile while $\delta_1$ and $\delta_2$ capture the additional returns in the first and second terciles. We stress, however, at this point that we do not give a structural interpretation to the coefficients of the regression but will interpret them later through the lens of our structural model.

The left panel of Table 8 highlights three facts from the regression results. First, urban areas with low unemployment rates pay high average earnings conditional on worker characteristics. The urban area fixed effect of the first tercile, $\alpha_1$, is 9.3%, whereas the urban fixed effect of the second tercile is 4.7%. Second, earnings are concave in overall experience accumulation. Third, workers experience more rapid earnings growth when working in low-unemployment urban areas.

[34] We follow the reduced-form literature, e.g., De La Roca and Puga (2017), and include worker fixed effects. That literature includes those as workers with different innate abilities may sort across urban areas and because workers with a higher innate ability may find it easier to accumulate experience in the labor market.

In particular, one additional year of experience in an urban area ranked in the lowest and middle tercile of the urban area unemployment distribution raises average earnings by 1.2% and 0.2%, respectively, relative to accumulating the same year in the third tercile.

Urban areas also differ in the job opportunities they provide, as the right panel of Table 8 highlights. Consistently with the findings of Bilal (2021) for France and the U.S. and Kuhn et al. (2021) for Germany and the UK, the flows of going in and out of the workforce are correlated with the area unemployment rate. The employment to unemployment flow rate (EU) in the highest unemployment tercile is 11.2%, whereas it is 8.5% in the lowest tercile. The unemployment to employment (UE) flow rate is higher in low-unemployment urban areas compared to high-unemployment urban areas. Turning to the search efficiency of employed workers, we find a slightly higher job-to-job transition rate (EE) in low-unemployment urban areas compared to high-unemployment urban areas. Yet, differences across urban areas are relatively small. Quite notably, a high share of job-to-job transitions results in earnings losses. Notice that, given our yearly data, many of these EE transitions could be capturing EUE transitions. Together with the sizeable EU flow rates, the average job stability is low in Spain reflecting the high share of temporary work contracts in the economy documented for example by Conde-Ruiz et al. (2019).

## E Characterizing the stationary equilibrium

Before we define the stationary equilibrium, we need to define flows in the economy across urban areas. We denote inflows by $IN(\ell)$ and outflows by $OUT(\ell)$. These flows are computed using the individual's migration policy function and aggregating across individuals. For instance, let $OUT_i^E(\ell, s, e, z)$ denote the amount of $i$ years old worker with state $(\ell, s, e, z)$ who leave a location of type $\ell$. It satisfies:

$$OUT_i^E(\ell, s, e, z) = N_i^E(\ell, s, e, z)\ \Xi_i^E(\ell, s, e, z), \tag{E.1}$$

where $\Xi_i^E(\ell, s, e, z)$ denotes the overall probability of migration, which depends on all possible migration opportunities and the individual's migration decision:

$$\Xi_i^E(\ell, s, e, z) = \mu_\ell^E \sum_{\ell'} \frac{1}{3} \sum_{s'} (1-\phi_{\ell'}) g_i^{EU}(\ell, s, e, z, \ell', s')\ f_S(s') + \\ \mu_\ell^E \sum_{\ell'} \frac{1}{3} \sum_{s'} \phi_{\ell'}\ f_S(s') \sum_{z'} g_i^{EE}(\ell, s, e, z, \ell', s', z')\ f_Z(z'). \tag{E.2}$$

The evolution of the population is given by the law of motion

$$N(\ell)' = N(\ell) + IN(\ell) - OUT(\ell) + N_1(\ell)' - N_T(\ell), \tag{E.3}$$

where $N_1(\ell)'$ is the overall measure of newborns at a location of type $\ell$ and $N_T(\ell)$ is the measure of $T$ years old who died at the end of the previous period. Now we are ready to define the stationary equilibrium.

***Definition* 1.** *A recursive stationary equilibrium, given subsidies $\{b_U, b_R\}$, is a vector of rental prices, $\{r_\ell\}_1^L$, a set of value functions and optimal decision rules for retirees, $\left\{V_t^R, W_t^R, \Omega_t^R, g_t^{R,\mu}, g_t^{R,h}\right\}_{t=R+1}^T$, for unemployed individuals, $\left\{V_t^U, W_t^U, \Omega_t^{UU}, \Omega_t^{UE}, \Omega_R^{UR}, \Psi^{EU}, g_t^{UU,\mu}, g_t^{UE,\mu}, g_t^{U,z}, g_t^{U,h}\right\}_{t=1}^R$, for workers, $\left\{V_t^E, W_t^E, \Omega_t^{EU}, \Omega_t^{EE}, \Omega_R^{ER}, \Psi_t, \Psi_t^{EE}, \Psi_t^{ER} g_t^{EU,\mu}, g_t^{EE,\mu}, g_t^{EE,z}\right\}_{t=1}^{R-1}$ and population measures $\left\{N_t^R\right\}_{t=R+1}^T$, and $\left\{N_t^U, N_t^E\right\}_{t=1}^R$ such that:*

1. *Value functions and policy functions solve individual problems shown in Equations (4.6) to (4.20),*
2. *the housing markets clear, $H_\ell^D = \overline{H}_\ell$, for all $\ell$ where the demand function is given by Equation (4.22),*
3. *all population measures, $\left\{N_t^R\right\}_{t=R+1}^T$, and $\left\{N_t^U, N_t^E\right\}_{t=1}^R$, given by, Equation (4.21), are constant over time and their laws of motion satisfy Equation (E.3).*

**Proposition 1 main text:** In the main text, we use the fact that all urban areas of the same type have the same equilibrium rental price. The intuition for the proposition is as follows: Suppose that there are two locations, 1 and 2, of productivity $\ell$, and that location 1 is cheaper than 2. If it its rental price is cheaper, Equation (4.25) implies that some population group is smaller in location 1: either retirees, unemployed of a particular age and experience, or employed individuals. However, this cannot be, as the inflows to location 1 must be greater than those to location 2 and its outflows must be lower. Let us focus our attention on retirees. Take two retirees identical in all respects (age and current residence) but the first one has the opportunity to migrate to 1 and the second one has the opportunity to migrate to 2. Since migration opportunities across locations of the same productivity type are drawn from a uniform distribution, the law of large numbers ensures that there is always a positive measure of people from any location $\ell$ who have a migration opportunity to either 1 or 2. The gain of moving to 1 is larger than the gain of moving to 2,

$$\Omega_t^R(\ell, s, 1) > \Omega_t^R(\ell, s, 2), \tag{E.4}$$

since 1 is cheaper. Hence, agents need to draw a higher amenity value to migrate to location 2 than to migrate to location 1. Since the distribution of amenity draws is the same across locations, inflows of retirees to location 1 are larger than inflows to location 2. Conversely, outflows from 1 to a given location $\ell$ are lower than the similar outflow from 2. The reason, again, is that retirees located in 1 have to draw a higher amenity value to move to $\ell$ than the similar retiree in location 2. The same reasoning applies to unemployed people of a given age and experience, location of residence, and current amenity value. The key is that, in any given location, there is always a positive measure of people that are offered to move to 1 and another measure of who are offered to move to location 2 under the same labor conditions. Since location 1 is cheaper, people moving to location 2 have to be compensated for the rental differential with a higher amenity value. Thus, the inflows to 2 is lower than the inflows to 1. Similarly happens to employed individuals. Hence, it follows that the population must be strictly larger in location 1, arriving at a contradiction.

# F Calibration Details

Table 9: Moments in model and data

| Moment and parameter | Model T1 | Model T2 | Model T3 | Data T1 | Data T2 | Data T3 |
|---|---|---|---|---|---|---|
| Equation (D.1) | | | | | | |
| Urban area fixed effects (%); $\mathcal{A}_\ell$ | 9.80 | 6.71 | 0.00 | 9.26 | 4.71 | 0.00 |
| Earnings growth in UA (%); $\tilde{\delta}_\ell$ | 1.39 | 0.4 | 0.00 | 1.15 | 0.19 | 0.00 |
| Earnings growth (%); $\psi_1$ | | 8.35 | | | 8.50 | |
| Earnings growth (%); $\psi_2$ | | -0.22 | | | -0.23 | |
| Labor markets | | | | | | |
| EU rate (%); $\lambda_\ell$ | 8.59 | 9.47 | 11.24 | 8.50 | 9.50 | 11.20 |
| U rate (%); $\phi_\ell$ | 16.67 | 20.61 | 27.47 | 16.20 | 20.10 | 27.10 |
| Job-to-Job rate (%); $\Lambda$ | | 10.75 | | | 11.81 | |
| Job-to-Job share losses (%); $\lambda_d$ | | 42.36 | | | 41.97 | |
| Std of job switchers; $\sigma_Z$ | | 0.55 | | | 0.55 | |
| Mobility | | | | | | |
| Relative people turnover; $\omega_\ell$ | 1 | 0.86 | 0.80 | 1 | 0.86 | 0.79 |
| Mobility rate (%); $p^U$ | | 9.61 | | | 9.50 | |
| Ratio of E to U movers; $p^E$ | | 2.62 | | | 2.70 | |
| Mobility ages 76–80; $\kappa$ | | 3.73 | | | 3.62 | |
| Share T1 to T1 prime-age; $\sigma_S$ | | 0.56 | | | 0.55 | |

Notes: The table displays the endogenously model calibrated moments and the corresponding data moments. Those moments that are urban area (UA) specific, are reported for each, otherwise, only one common number is reported.

Table 9 displays additional details to the model calibration from Section 5. It shows for each endogenously calibrated parameter, the moment resulting from the model calibration and the same moment from the data. Overall, the model provides a close fit to the data. The largest deviations are in the earnings equation which we calibrate by indirect inference.

## G A Model without Search Frictions

Section 6.1.1 compares our model to a model without search frictions to show the importance of those frictions for mobility patterns across urban areas. This section describes the model without mobility frictions across urban areas. Local labor markets are modeled identically to the baseline model and so are preferences. Hence, Equation (4.14) to Equation (4.17) take the same form, and we restrict us here to describing the migration stage.[35] For comparability, we will use the same notation as in the main text.

We follow much of the migration literature and assume that people optimally decide each period in which urban area to search given some realization of i.i.d. shocks for each urban area type. The literature usually assumes that these shocks follow extreme value distributions as this simplifies migration decisions. For a better comparison to the baseline model, we keep here the assumption that these shocks are log-normally distributed. Hence, at the migration stage, the value of a retiree of age $t = R+1, \ldots, T-1$, who lives in a location of type $\ell$ and amenity value $s$ solves:

$$V_t^R(\ell, s) = \int\int\int \max\left\{\beta\, W_{t+1}^R(\ell, s), \beta\Omega^R(s', s'', s''') - \kappa\right\} f_S(s')f_S(s'')f_S(s''') \tag{G.1}$$

$$\Omega^R(s', s'', s''') = \max\left\{W_{t+1}^R(1, s'), W_{t+1}^R(2, s''), W_{t+1}^R(3, s''')\right\}. \tag{G.2}$$

$W_{t+1}^R(\ell, s)$ is the value of staying in the current location, and $\Omega^R(s', s'', s''')$ is the value of moving to the best alternative location.

Similarly, the unemployed also choose the optimal place to search. In doing so, they take into account that different locations provide different probabilities to be offered a job, $\phi_{\ell'}$, and that they have the choice to move after having observed the type of job offer:

$$V_t^U(\ell, s, e') = \int\int\int \max\left\{\beta\, W_{t+1}^U(\ell, s, e'), \beta\Omega^U(\ell, s, e', s', s'', s''') - \kappa\right\} f_S(s')f_S(s'')f_S(s''') \tag{G.3}$$

$$\Omega^U(\ell, s, e', s', s'', s''') = \max\left\{\bar{\Omega}^U(\ell, s, e', 1, s'), \bar{\Omega}^U(\ell, s, e', 2, s''), \bar{\Omega}^U(\ell, s, e', 3, s''')\right\} \tag{G.4}$$

$$\begin{aligned}\bar{\Omega}^U(\ell, s, e', \ell', s') = {} & \phi_{\ell'}\int \max\{W_{t+1}^U(\ell, s, e'), W_{t+1}^E(\ell', s', e', z')\} f_Z(z') \\ & + (1-\phi_{\ell'})\max\{W_{t+1}^U(\ell, s, e'), W_{t+1}^U(\ell', s', e')\}\end{aligned} \tag{G.5}$$

Finally, the employed face a similar trade-off as the unemployed with the only difference that they can stay at their current place as employed:

$$V_t^E(\ell, s, e', z) = \int\int\int \max\left\{\beta\, W_{t+1}^E(\ell, s, e', z), \beta\Omega^E(\ell, s, e', z, s', s'', s''') - \kappa\right\} f_S(s')f_S(s'')f_S(s''') \tag{G.6}$$

$$\Omega^E(\ell, s, e', z, s', s'', s''') = \max\left\{\bar{\Omega}^E(\ell, s, e', z, 1, s'), \bar{\Omega}^U(\ell, s, e', z, 2, s''), \bar{\Omega}^U(\ell, s, e', z, 3, s''')\right\} \tag{G.7}$$

$$\begin{aligned}\bar{\Omega}^E(\ell, s, e', z, \ell', s') = {} & \phi_{\ell'}\int \max\{W_{t+1}^E(\ell, s, e', z), W_{t+1}^E(\ell', s', e', z')\} f_Z(z') \\ & + (1-\phi_{\ell'})\max\{W_{t+1}^E(\ell, s, e', z), W_{t+1}^U(\ell', s', e')\}\end{aligned} \tag{G.8}$$

[35] For parsimony, we also omit the value functions in the last period of working life and the last period of life which have different continuation values.

# H Welfare Analysis

Let us define as $\xi_\ell$ the compensation in lifetime income needed for an individual to be indifferent between being born in location types $\ell = 2$, 3, and type 1. Note that the indirect utility function is $u(c, h, s) = \theta^\theta (1-\theta)^{1-\theta} y / \left( r_\ell^{(1-\theta)} \right) + s$, where $y$ is the wage, in the case of an employed worker, or the unemployment subsidy or the retirement pension. $s$ is the amenity value that the current location yields to the individual. Next, define the expected welfare, given the compensation, of being born in $\ell$:

$$EW_\ell(\xi_\ell) \equiv E_{0,\ell} \left\{ \sum_{t=0}^{T} \beta^i \left( (1+\xi_\ell)\, \theta^\theta (1-\theta)^{1-\theta} \frac{y_t}{r_t^{1-\theta}} + s_t \right) \right\}. \tag{H.1}$$

This expectation comprises the fact that labor markets are different across locations and, therefore, there are static differences (so that the initial distribution of employment across newborns is different) but also the expected horizon is different as each location provides different job, migration opportunities and return to experience. The value $\xi_\ell$ is obtained so that

$$EW_\ell(\xi_\ell) = EW_1 \equiv E_{0,1} \left\{ \sum_{t=0}^{T} \beta^i \left( \theta^\theta (1-\theta)^{1-\theta} \frac{y_t}{r_t^{1-\theta}} + s_t \right) \right\}. \tag{H.2}$$

Rewriting Equation (H.1) we have that

$$EW_\ell(\xi_\ell) = \quad (1+\xi_\ell)\; E_{0,\ell} \left\{ \sum_{t=0}^{T} \beta^t \left( \theta^\theta (1-\theta)^{1-\theta} \frac{y_t}{r_t^{1-\theta}} + \frac{s_t}{(1+\xi_\ell)} \right) \right\}, \tag{H.3}$$

$$EW_\ell(\xi_\ell) = \quad (1+\xi_\ell)\; E_{0,\ell} \left\{ \sum_{t=0}^{T} \beta^t \left( \theta^\theta (1-\theta)^{1-\theta} \frac{y_t}{r_t^{1-\theta}} + s_t - \frac{\xi_\ell\, s_t}{(1+\xi_\ell)} \right) \right\}. \tag{H.4}$$

Note that the expected value function of being born in location $\ell$ in period 0 is given by

$$EW_\ell = E_{0,\ell} \left\{ \sum_{t=0}^{T} \beta^t \left( \theta^\theta (1-\theta)^{1-\theta} \frac{y_t}{r_t^{1-\theta}} + s_t \right) \right\}. \tag{H.5}$$

Therefore

$$EW_\ell(\xi_\ell) = (1+\xi_\ell)\; EW_\ell - \xi_\ell\, E_{0,\ell} \sum_{t=0}^{T} \beta^t s_t. \tag{H.6}$$

Hence, $\xi_\ell$ satisfies

$$\xi_\ell = \frac{EW_1 - EW_\ell}{EW_\ell - E_{0,\ell} \sum_{t=0}^{T} \beta^t s_t}. \tag{H.7}$$

Notice that $EW_\ell$ comprises expectations about labor market realizations right when agents are born. The term $E_{0,\ell} \sum_{t=0}^{T} s_t$ varies across locations because of the interaction of migration decisions and the amenities realizations. Thus, we could think of $\xi_\ell$ as the extra lifetime income needed to compensate for the difference in the present yield of income in location 1 plus the difference in the present value of expected amenities relative to the present yield of income in location $\ell$.

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