Geographic Mobility over the Life Cycle*

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July 31, 2024

Abstract

When locations differ in the opportunities they offer their residents and mobility between them 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 differences in opportunities across locations in Spain result mainly from (a) differences in the speed of skill accumulation, (b) differences in job stability and job opportunities, and (c) possibilities for geographic mobility. Search frictions are the main impairment to the mobility of young people while fixed mobility costs are the main impairment for the elderly. Paying transfers to people in distressed economic locations decreases welfare dispersion across urban areas without large adverse effects on mobility. In contrast, several policies that encourage people to move to low-unemployment locations increase welfare dispersion 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, AEI/10.13039/501100011033/, Project PID2022-138706NB-I00 , 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 starting 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 CEX2021-001181-M financiado por MICIU/AEI /10.13039/501100011033, grant PID2020-117354GB-I00, and the Comunidad de Madrid through research grants EPUC3M11 (V PRICIT).

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 people's 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 starting one's career (being born in, from here onwards) in a high-unemployment urban area carries with it large welfare losses. For instance, being born in an urban area with an unemployment rate in the third tercile of the urban area unemployment distribution reduces welfare by an equivalence of 25% of lifetime income relative to being in an urban area that is in the first tercile. Those large welfare losses result from (discounted) lifetime income being 20% lower when born in the third tercile, and the value of amenities being 7% lower.

To arrive at these conclusions, we employ a structural life-cycle model with endogenous migration flows across locations and a fixed housing supply. 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 their idiosyncratic tastes across locations, but they face reallocation frictions. Motivated by reduced-form statistics from Spanish microdata, we model differences in local labor market opportunities in a rich fashion: They may differ in their average productivities, their speed of skill accumulation when working, and their job-finding and job-destruction rates. We find that slower skill accumulation when working in an urban area in the second tercile of the urban area unemployment distribution is the single most important factor explaining lower lifetime incomes for people born there relative to those born in the first tercile. Differently, less stable jobs and lower job-finding rates in urban areas in the third tercile are the single most important factors explaining the lower lifetime incomes of people born in those urban areas. Differences in average productivities between urban areas explain less than 13% of lifetime income differences. Put differently, despite large average earnings differences between urban areas, simply reallocating a worker from a high- to a low-unemployment urban area is not going

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

to instantaneously raise her earnings. Instead, for young people, moving to a low-unemployment urban area carries with it an asset component, as in Bilal and Rossi-Hansberg (2021).

To understand the frictions that prevent young people from reallocating in large numbers to low-unemployment urban areas and taking advantage of these large future benefits, we document four stylized facts about spatial mobility across the life cycle. First, low-unemployment urban areas indeed attract younger people and lose older people (on net). In contrast, high-unemployment areas lose younger and attract older people (on net). However, second, geographic mobility in Spain is limited and much lower than, for example, in the US. The decennial mobility hazard peaks at age 31 at 24% and then declines monotonically thereafter to about 5% at age 55. It continues to decline but its decay slows down with even those 70 years old showing substantial mobility. Third, what is more, mobility rates are higher for people living in low-unemployment urban areas than those living in high-unemployment urban areas. For example, for people younger than age 45, the probability of having moved during the last 10 years is 15% for people who lived in an urban area in the first tercile of the unemployment distribution but only 12% for those in the third tercile. Fourth, we show that of those moving before age 65, 73% were employed prior, i.e., spatial mobility is not only linked to escaping unemployment. Moreover, 45% arrive as unemployed, i.e., there appear to exist benefits to searching for jobs from within a local labor market rather than from afar.

Using the structural model, we show that the life cycle data provides new insights into the underlying frictions that hinder people from reallocating. In particular, apart from a fixed cost associated with mobility, the slowly decaying age-mobility hazard suggests that those frictions are best thought of as spatial search frictions which we think of as informational frictions that hinder the process of evaluating the benefits of moving. Moreover, the fact that sorting across urban areas is slow over the life cycle implies that this search is random rather than directed. Finally, the high reallocation rates of people in low-unemployment urban areas suggest that these urban areas provide better search opportunities.

Search frictions imply that a large number of young people do not leave economically distressed urban areas despite having large potential benefits from moving. In contrast, elderly people move out of low-unemployment urban areas to take advantage of cheaper housing possibilities elsewhere, and mobility fixed costs are the main impairment to them. Put differently, differences in labor markets create demand for relatively expensive urban areas, while retirement creates demand for relatively cheap urban areas.

Spatial search frictions contribute to the large welfare losses from being born in economically distressed urban areas. Moreover, they have profound implications for the policy responses that tackle this welfare dispersion at birth. In particular, policies that give pecuniary incentives to move to low-unemployment areas fail to increase young people's mobility significantly. 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 meaningfully increase the opportunities to move to low-unemployment urban areas. Hence, these reforms mostly benefit those people already born in those areas. The latter policy does so by subsidizing their living costs. The former policy does so by increasing the mobility of people who are already in low-unemployment urban areas as they face relatively weak spatial search frictions. In contrast, simply paying transfers to people living in economically distressed regions is effective in reducing welfare dispersion and has little negative implications on people's mobility. Spatial search frictions are again the reason why mobility changes little: As the young have a high potential mobility surplus from moving to urban areas with lower unemployment rates, a moderate subsidy for staying in their current urban area does not discourage them from moving. We consider policies that pay between 10 and 50 percent of people's rent in high-unemployment urban areas. These policies reduce the welfare loss from being born in these urban areas between one and 6.5 percentage points. The gains could be up to 11.5 percentage points when the housing supply in those high-unemployment urban areas would fully adjust to the increase in housing demand.

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). Using a life cycle framework, we highlight that the elderly provide a force limiting high rental prices in urban areas with good labor markets. Moreover, we show that most of the average earnings differences across urban areas highlighted by this literature arise from dynamic gains accruing to workers over time, particularly a faster climbing of the job ladder in high-paying urban areas, instead of the same worker earning different wages across urban areas.

Here our findings are different from those in Baum-Snow and Pavan (2012). The principal reason is that we find job stability to be much higher in high-paying urban areas once we study urban areas by unemployment rates instead of size which is consistent with recent evidence for other countries provided by Bilal (2021) and Kuhn et al. (2021).

The paper also links to Nanos and Schluter (2018), Heise and Porzio (2023), and Schluter and Wilemme (2023), in trying to understand why people do not reallocate to more promising labor markets. 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.[2] Moreover, we show that the strength of this spatial search friction depends on the current place of residence. We think of these search frictions as encompassing not only informational frictions about labor markets in different locations, as documented by Wilson (2021), but also local housing markets and, in a broad sense, barriers to mobility as those documented by Bergman et al. (2019).

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.[3] Moreover, we show that understanding search frictions as being an integral part of mobility frictions changes the effects of place-based policies that (Glaeser and Gottlieb, 2008; Albouy, 2009; Gaubert, 2018; Fajgelbaum et al., 2019; Gaubert et al., 2021) study. 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 as follows. 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 5.1 discusses the calibration of our benchmark economy and Section 6 presents the results. Finally, Section 7 concludes.

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

[3] 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 to us in identifying different mobility frictions.

2 Data

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

2.1 Census and the Spanish Labor Force Survey (SLFS)

The Census is a decennial cross-sectional microdata set created by the Spanish statistical agency, *INE*. The structure is similar to its US counterpart described, for example, in Diamond (2016). In each census year (1991, 2001, and 2011), a random set of households representing about 8% of the population are asked to provide information on the current socio-demographic status of all their members aged 16 or older.[4]

Our definition of a location is that of an *Urban Areas*, whose definition is similar to that of a commuting zone in the US and is meant to represent the local economy where people work and live.[5] 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. As in other countries, the Spanish population is fairly concentrated in a few urban areas. In particular, Madrid, Barcelona, Valencia, and Seville account together for 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, which allows us to construct inflow and outflow rates for each urban area.

The Census does not allow us to identify the employment status before changing an urban area. To this end, we supplement the data with the SLFS, which is a quarterly representative household survey containing information on 160,000 individuals in Spain. The first available year of the survey is 1999, and we use the editions between 1999 and 2011.[6]

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

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

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

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

3 Patterns of urban areas and mobility

To understand differences in labor-market opportunities across urban areas in Spain, we classify urban areas based on their unemployment rates. In Section 3.1 we report aggregate labor market statistics of urban areas. We show that low-unemployment areas feature higher job-finding rates, lower job-destruction rates, higher earnings growth, and higher average annual earnings. Finally, we show that those urban areas have higher housing prices.

Next, we document four stylized facts about mobility across different urban areas. 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. Third, people's mobility hazards decrease 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 displays summary statistics on urban labor markets. To that end, we group urban areas into three terciles of the urban-area unemployment distribution. The upper row shows that urban areas differ greatly in their unemployment rates; the average rate is 16% in the first tercile, while that of the third tercile climbs to 27%. The next two rows show that, consistent with the findings of

Table 1: Labor market statistics of urban areas

	T1	T2	T3
Unemployment rate (%)	16.2	20.1	27.1
Emp. to Unemp. (E2U) (%)	8.5	9.5	11.2
Unemp. to emp. (U2E) (%)	33.2	30.4	29.4
Job-to-job Rate (J2J) (%)	12.7	11.3	10.7
(%) J2J down	41.0	41.0	45.0
Annual Earnings per Worker	24,472	19,241	18,493

Sources: (a) Unemployment: Time-averaged values from the Census; (b) Flow rates: Time-averaged values from the MCVL 2006-2008. The job-finding rate is the share of non-employed workers who find a job in the next year. The job-destruction rate is the share of employed workers who are non-employed in the next year.

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 employment are correlated with the area unemployment rate. The employment to unemployment flow rate (E2U), on average, is higher for urban areas in terciles 2 and 3, with respect to 1 (9.5 and 11.2, as opposed to 8.5%). In contrast, the unemployment-to-employment flow rate is higher in areas with lower unemployment rates (33.2 in tercile 1, higher than 30.4 and 29.4% in the other two terciles). Finally, average annual earnings per worker are 32% and 4% higher in urban areas in the first and second terciles compared to the third tercile.

Higher average earnings in low-unemployment areas may be the result of those areas providing more productive jobs to their workers, faster earnings growth, or they may reflect the innate abilities of people sorting themselves into those areas. To distinguish between these possibilities, following De La Roca and Puga (2017), we specify the following reduced-form relationship for log earnings of worker i in an urban area of tercile ℓ at time t:[7]

$$\ln w_{i\ell t} = \varphi_i + \tau_t + \alpha_\ell + \sum_{\ell=1}^{2} \delta_\ell \, e_{i\ell t} + \gamma_1 \, \epsilon_{it} + \gamma_2 \, \epsilon_{it}^2 + \boldsymbol{X}'_{it} \, \beta + \varepsilon_{i\ell t}, \tag{3.1}$$

where φ_i is a worker-fixed effect, τ_t is a time-fixed effect, and X_{it} is a vector containing education, age, age squared, and sex. α_ℓ is an urban area (of unemployment tercile ℓ) fixed effect, $e_{i\ell t}$ is the experience accumulated up to period t in an urban area ranked in the unemployment tercile $\ell = 1, 2$, and ϵ_{it} is overall worker experience. The latter captures how earnings grow with experience in the third tercile while δ_1 and δ_2 capture the additional growth in the first and second terciles. We measure experience as the number of days with a full-time equivalent labor contract and we express them in years. Table 2 highlights three key elements of our 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, α_1, is 9.3%, whereas the urban fixed effect of the second tercile is 4.7%. Notably, the urban area fixed effect for the first tercile is substantially smaller

[7] See also Glaeser (1999) and Baum-Snow and Pavan (2012) for similar analyses.

Table 2: Reduced-form earnings equation

	T1	T2
Urban area fixed effect, α_ℓ (%)	9.26***	4.71***
	(0.24)	(0.25)
δ_ℓ (%)	1.15***	0.19***
	(0.04)	(0.05)
γ_1 (%)	8.50***	
	(0.08)	
γ_2 (%)	-0.23***	
	(0.00)	
Worker Controls	Yes	
Job/Sector Controls	No	
City, Worker, Time FE	Yes	
N	7,364,713	
R^2	0.0272	

N = * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

than the average earnings difference between the first and third terciles. Second, workers' earnings grow faster when working in low-unemployment urban areas. In particular, one additional year of experience in an urban area ranked in the first and second tercile of the urban area unemployment distribution is associated with a rise in average annual earnings by 1.5% and 0.19%, respectively, relative to accumulating the same year in the third tercile. Third, earnings are increasing, although concave, in overall experience accumulation. The results are similar to Baum-Snow and Pavan (2012) who study U.S. data where they sort locations by size. As they observe, these reduced-form estimates require strong exogeneity assumptions on mobility to have a causal interpretation.

Our structural model of spatial and job mobility below will allow us to explain a positive urban area fixed effect by (i) some urban areas offering more productive jobs to workers and (ii) workers, given the same quality of jobs, being sorted into better jobs in some urban areas because of better labor markets. Similarly, the model will decompose the observed higher earnings growth in some urban areas into (i) workers' productivity growing faster in those urban areas and (ii) workers climbing the job ladder quicker in some urban areas. Rows four and five of Table 1 suggest that job ladders may play a role. Job-to-job transition rates are somewhat higher in low-unemployment urban areas. This and the fact that jobs last longer in low unemployment areas (as implied by lower employment to unemployment rates) suggest that even if job ladders are similar across all areas, workers are able to climb up faster in low unemployment areas. We note, however, that job ladders do not work that well in the Spanish labor market since, across all urban area types, a large fraction of job-to-job transitions is associated with earnings losses, as the statistic *J2J down* shows. The high share of earnings losses reflects the fact that temporary work contracts dominate the flows of job creation and destruction in Spain, as documented by Conde-Ruiz et al. (2019), which limits the role of job ladders.

Table 3: Summary statistics of urban areas

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

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

Finally, Table 3 displays the statistics of the population and housing market for the different urban areas. It shows that low-unemployment urban areas are on average larger and more densely populated. As a result, the average housing costs are substantially higher in low-unemployment urban areas.

3.2 Mobility across urban areas

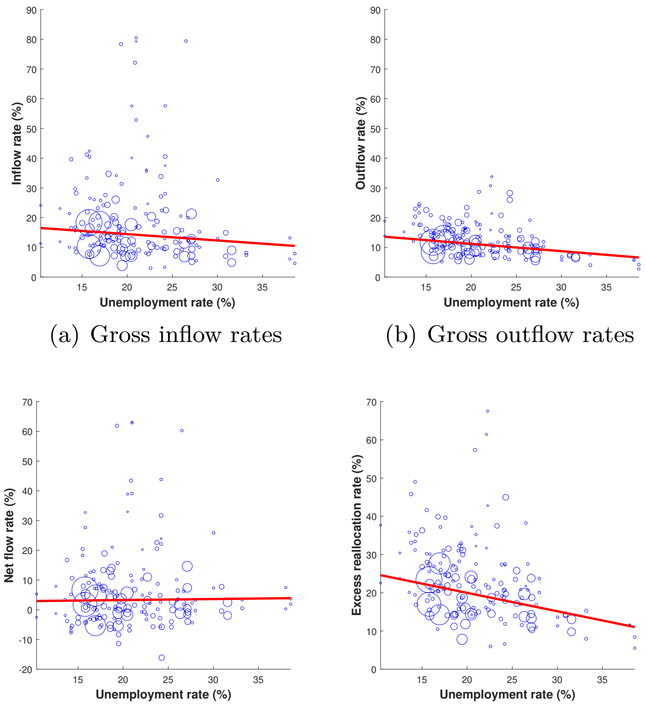
To understand the frictions impeding workers from reallocating across different urban areas, we study people flows across them. The size-weighted mean decennial gross inflow rate, IR, across urban areas is 14.5%, and the size-weighted gross outflow rate, OR, is 11.3%. The same urban area may have significant inflows and outflows, i.e., more gross flows than the net flows needed to account for its population variation over time. We measure "excess reallocation" as the difference between people's gross flows and net flows:

$$ERR_{it} = IR_{it} + OR_{it} - abs(IR_{it} - OR_{it}). \tag{3.2}$$

The size-weighted mean excess reallocation rate is 20.1%. That is, 80% of gross reallocation is excess reallocation. This number is roughly similar to the 87% that Coen-Pirani (2010) and Lkhagvasuren (2012) report regarding mobility across U.S. states, which is a larger geographic unit than an urban area.

Figure 1 links flow rates across urban to their labor market conditions. Low-unemployment urban areas have, on average, higher inflow and higher outflow rates than high-unemployment areas. The relative sizes of both flows are such that the net population growth rate shows no systematic relationship with the unemployment rate at the urban area level, as shown in the third panel. As a result, the excess reallocation rate is substantially higher in low-unemployment urban areas. For instance, those areas with an unemployment rate of 0.17 have a predicted excess reallocation rate of 22% compared to only 17% for urban areas with an unemployment rate of 0.30. The observed correlation between people reallocation and urban area unemployment rate may be caused by the

Figure 1: Mobility across urban areas.



(a) Gross inflow rates (b) Gross outflow rates

(c) Net flow rates (d) Excess reallocation rates

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

Table 4: Excessive reallocation and unemployment

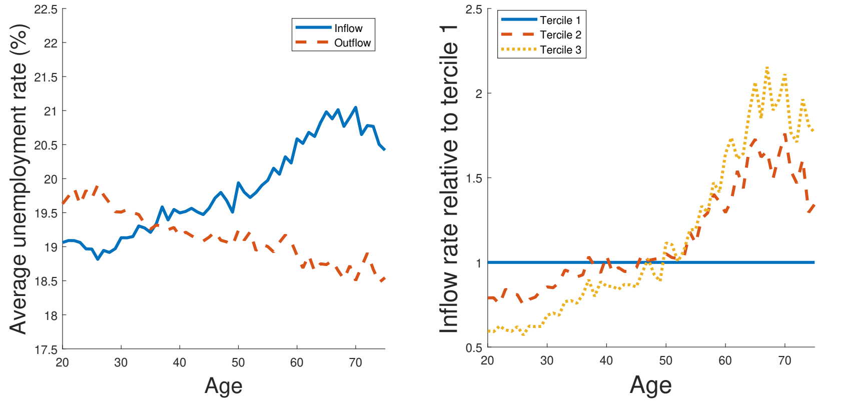
	Excessive reallocation rate	
Unemployment rate	-0.48	-0.75
Further observables	No	Yes
N	168	168
R^2	0.09	0.35

Sources: Census 1991, 2001, and 2011. The further observables are dummies for the urban area shares of 4 age groups, the shares of three education groups, and the share of workers with jobs with high socio-economic status.

characteristics of the people living there instead of the urban area itself. Table 4 shows that this is unlikely to be the case: After controlling for observable population characteristics, the negative relationship between the excessive reallocation rate and the unemployment rate becomes yet stronger. Different from age, Appendix B shows that we do not find evidence of sorting based on education, i.e., we find no evidence that high-skilled workers sort systematically into urban areas with good labor markets.

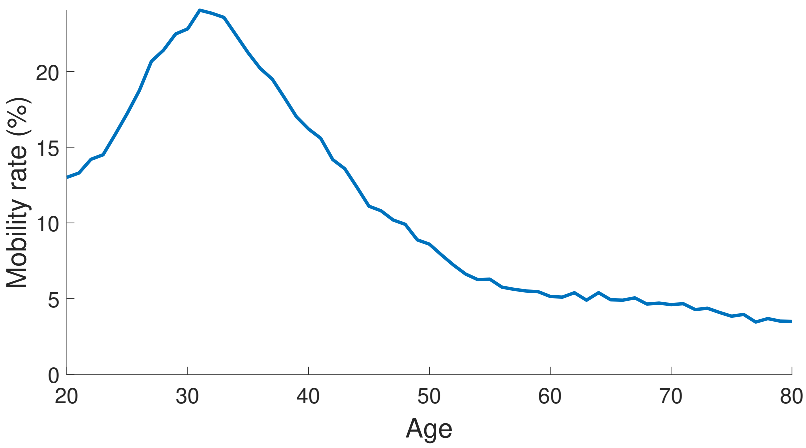
Figure 2(a) shows that an urban area's unemployment rate is an important determinant for the age composition of the flows. At age 25, the average unemployment rate of an urban area people flow into is 0.19, whereas the urban areas where they depart from have an average unemployment rate of 0.20. This difference disappears when they are about 38 years old, after which the average

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



(a) Average unemployment rate of inflow (outflow) urban areas by age

(b) Relative size of inflow rates by age



(c) Mean mobility rate by age

Source: 1991, 2001, and 2011 Censuses.

unemployment rate is higher at places people flow into relative to places they flow out of. By age 65, the average urban area that people are 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. Instead of focusing on the average unemployment rate, Figure 2(b) shows relative inflow rates for three different terciles of the urban-area unemployment distribution. For instance, for those 30 years old, the inflow rate to urban areas in tercile 2 is about 75% of the inflow to tercile 1, whereas the inflow to tercile 3 is about 60%. These figures are reversed for 65-year-old people, where the inflow to tercile 3 doubles the inflow to tercile 1. However, flows are not completely directed as in and out gross flows of people of all ages are significant for all urban areas. These patterns are further illustrated in Figure 7 in Appendix C where we show gross flows of people of different age groups in more detail.

We now turn to document flow rates from the perspective of a person instead of the perspective of an urban area. Figure 2(c) shows the average mobility rate by peoples' ages. The decennial mobility rate, after initially rising, falls from 24% at age 31 to less than 5% by age 70. The paper does not speak to the initial rise which, given the decennial measure represents mostly mobility decisions of parents. Instead, our focus is on explaining the falling mobility hazard after age 31. One notable aspect of this hazard is that the decay is slow after age 55, and mobility remains 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.

Next, we turn to a person's employment status as a determinant of her mobility for which we exploit the SLFS data. 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; that is, the data suggest that people join local labor markets to search for jobs locally, instead of engaging in a global search.

4 A benchmark economy with urban areas

To understand the implications of these patterns, we turn to a structural spatial overlapping generations model of the labor market. Our model economy is a dynamic version of the Roback (1982)-Rosen (1979) model in stationary equilibrium. People make consumption, housing, and 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.

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 lives in the labor force and retire after age R. During their working life, people are either unemployed or employed. When one agent dies it is replaced by a newborn. People value the consumption of a non-housing good, c, and the services of housing, h.

The lifetime utility of person i is

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

where β is the time discount factor, c_{it} is the non-housing consumption at age t, h_{it} denotes housing services, and s_{it} is 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 $S \subset \mathbf{R}_{++}$.[8]

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 ℓ 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 ℓ, $\overline{H}_\ell$, is exogenously given and can be thought of as land. Finally, each type of location consists of an equal measure of individual locations. As in Nieuwerburgh and Weill (2010), absentee landlords own the housing stock and charge a rental price of housing in location l of r_l.

4.2 Local markets

The unemployed receive unemployment benefits b_U 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:

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

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

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

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

where a_t is the person's idiosyncratic log productivity which has a deterministic age component given by ψ_1 and ψ_2.

[8] We abstract from altruism towards children in mobility decisions. Below, we assume that the birthplace of new cohorts is not related to the death place of an exciting cohort, i.e., parents expect their children to be born given the observed distribution of an entering cohort in the data.

Some comments are in order. First, we have abstracted away from any effect of location size on worker's productivity. That is, we have assumed that there are no positive externalities of agglomeration. The literature, such as Eeckhout et al. (2014) or De La Roca and Puga (2017), finds that there is a size premium. However, location size is an endogenous object in our theory. The correlation of size and productivity will appear as an equilibrium function of the fundamentals, which we take to be the characteristics of the local labor markets. Second, differently from our empirical analysis shown in Equation (3.1), we explicitly model an individual's idiosyncratic productivity to depend on her job, z. Similarly to the empirical model, we assume that working in "good" locations gives a static productivity gain, $\mathcal{A}_\ell$, as well as a steeper profile in productivity gain, given by $\tilde{\delta}_\ell$. Differently, for computational simplicity, we assume that her productivity increases with age instead of with overall work experience.

The local labor market opens after employed people work and income payments and consumption take place. Then, agents receive random labor opportunities or may be laid off. As we show in Section 3.2, local labor markets differ in their job offer opportunities and the probability that a worker becomes unemployed. Hence, we allow the currently unemployed to receive a job offer with location-specific probability ϕ_ℓ. A job offer is a random draw of job log productivity, $z \sim N(0, \sigma_z^2)$, where we denote the density of this job offer distribution by $f_Z(z)$. We assume that this density is the same across locations. The currently employed exogenously lose their job with location-specific probability λ_ℓ and become unemployed. Otherwise, they may receive an offer from another job with probability Λ.[9] To capture the fact that job-to-job transitions in Spain frequently lead to earnings losses, we allow for two types of job offers. With probability $1 - \lambda_d$, the worker can choose between her current job, the outside offer, and unemployment, i.e., she will only accept the job when the new job pays a higher wage. However, with probability λ_d, the job offer is a reallocation offer whose only alternative is unemployment if it is rejected. Examples of such reallocation offers are that the worker knows that her current job will disappear because of a temporary contract or a plant closure.[10]

4.3 Mobility across locations

After local labor market shocks are realized, people may have the opportunity to change locations. As discussed above, the shape of the mobility hazard over age documented in Figure 2(c) suggests that people make mobility decisions infrequently. Moreover, administrative survey evidence from

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

[10] 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 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. We think of information frictions as being the cause for people only infrequently considering moving, i.e., migration opportunities are partly 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. Hearing by chance about a job offer from a particular location may be one reason for people considering moving. 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. Consistent with this search view limiting people's mobility opportunities, Wilson (2021) provides evidence that limited knowledge about different local labor markets reduces people's mobility. Moreover, Bergman et al. (2019) find that also other frictions such as the housing search process in the new place play a role in people not considering moving. They find that assisting families to obtain better information about prospective locations increases upward mobility from 15% to around 50%. We allow the frequency of mobility possibilities to depend on the current location and on the employment state μ_ℓ^J with $J \in \{E, U, R\}$. We assume that these migration opportunities are uniformly distributed over the types of alternative places, ℓ', i.e., each occurs with a probability of one-third.

Consistent with the data, an opportunity to move to a different location may come with a job offer or as unemployed. The conditional probability of moving with a job offer depends on the labor market conditions in the other location, $\phi_{\ell'}$. In case the offer comes with an employment offer, the offered job type is again a random draw from $f_Z(z)$. A mobility offer entails, in addition to the employment and job offer type, an idiosyncratic location amenity $\ln s' \sim N(0, \sigma_S^2)$ 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 utility value of all time, effort, and pecuniary costs required to move and settle in a new location. The amenity value of a location stays constant for the entire period a person lives there. To sum up, the net gains of moving balance the pecuniary cost of moving, changes in labor market opportunities, future spatial search opportunities, and the amenity value attached to moving to a new place.

4.4 Value functions

We conjecture that locations of the same productivity level have the same rental price of housing. In Section 4.5 we show that this is, indeed, the case. Recall that there are three stages within each period: First, people work, collect income payments, and consume. Second, 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. We describe the individual's problem faced at each stage backward, from the last to the first stage.[11]

4.4.1 Migration stage

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

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

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

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

Unemployed At the migration stage, an unemployed person's state includes her end-of-period experience level e', her current location, ℓ, and 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 at home or, second, being laid off at the previous stage. In the first case, the experience level e' at this stage is equal to her experience level at the beginning of the period, e. In the second case, $e' = e + \tilde{\delta}_\ell$, as she has worked at the beginning of the period.

Unemployed agents receive an opportunity to migrate to a location of type ℓ' with probability

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

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

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

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

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

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:

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

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

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

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

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

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

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

The migration policy function is $g_t^{EE,\mu}\left(\ell, s, e, z, \ell', s', z'\right)$ if the moving opportunity comes with a job offer and $g_t^{EU,\mu}\left(\ell, s, e, z, \ell', s'\right)$ 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:

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

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

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

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

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

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

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

Employed Workers have a more convoluted problem as they have to make more choices. They become unemployed with probability λ_ℓ. If they do not become unemployed, they may receive a job offer:

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

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 Λ she receives a new job offer and with probability $\Lambda \, (1 - \lambda_d)$ she has the option to stay with her current job or become unemployed. Hence, her upper envelope of choices reads

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

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 D. Let $\mathbb{E}$ be the set of all possible values of experience and Z be the set of labor productivities. The housing demand at a location of type ℓ as H_ℓ^D and is given by

$$H_\ell^D = \sum_{t=R+1}^{T} \sum_{S} N_t^R(\ell, s)\; g_t^{R,h}(\ell, s) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}} N_t^U(\ell, s, e)\; g_t^{U,h}(\ell, s, e) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}\times Z} N_t^E(\ell, s, e, z)\; g_t^{E,h}(\ell, s, e, z)\,, \quad (4.21)$$

where $N_t^R(\ell, s)$, $N_t^U(\ell, s, e)$, and $N_t^E(\ell, s, e, z)$ denote, respectively, the mass of retirees, unemployed and employed working people of certain characteristics, whereas $g_t^{J,h}$ is the housing demand function of those individuals that also depends on their individual state.[12] Thus, aggregate housing demand not only depends on population density but also on its demographic distribution as well as the distribution of working people's productivity. To be more specific, let y be an individual's income. Therefore, consumption expenditures are constant shares of income:

$$c = \theta\, y, \quad h = (1-\theta)\, \frac{y}{r_\ell}. \quad (4.22)$$

Using the market clearing condition of the housing rental market, we find that the rental price of a location of type ℓ depends on the size of the population and also on its demographic and productivity composition:

$$r_\ell = \frac{(1-\theta)}{\overline{H}_\ell} \left[\sum_{t=R+1}^{T} \sum_{S} N_t^R(\ell, s)\; b_R + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}} N_t^U(\ell, s, e)\; b_U + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}\times Z} N_t^E(\ell, s, e, z)\; w(\ell, e, z, t) \right]. \quad (4.23)$$

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

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

[12] For instance $N_t^E(\ell, s, e, z)$ is the mass of employed individuals of age $t \geq R$ in location type ℓ, with job productivity z and idiosyncratic amenity s.

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

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

5 The quantitative model

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

5.1 Calibration

Table 5 summarizes the calibration. Table 10 in Appendix E compares the calibrated moments of the model to their data counterparts. The model period is a year. Our overall strategy is calibrating the model to match selected aggregate statistics of the labor market and some aggregate statistics pertaining to peoples' mobility while letting the model speak in the life cycle and distributional dimensions. Recall that we have characterized urban areas in the data according to their unemployment rate, which is an endogenous object in our theory. Instead, in the model, the fundamental difference across location types are (1) location-specific productivities, as shown in Equations (4.2) to (4.5), differences in job creation and destruction rates and migration opportunities.

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. The value of the discount factor, β, is chosen to target a 3% annual 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 unemployment risk at the yearly frequency, and unemployment benefits are time-limited and drop to zero after some months. In fact, in the MCVL, we find that the average monthly unemployment benefits of those younger than 65 and non-employed is only 108€. We decide to take an intermediate replacement rate of 15% of the mean

TABLE 5: Calibration

	T1	T2	T3	Target
λ_ℓ (%)	4.70	5.30	8.40	EU rate of city stayers
ϕ_ℓ (%)	45.0	38.5	28.5	UA-level unemp.
Λ (%)		19.50		Average 11 % J2J rate
λ_d (%)		51.0		41 % J2J involve wage losses
σ_Z		0.46		Std of wages of job switchers 0.55
$\ln \mathcal{A}$	7.34	7.30	7.30	Tercile wage fixed effect
$\tilde{\delta}_\ell$ (%)	0.57	0.00	0.00	Tercile experience effect
ψ_1 (%)		10.16		Experience profile
ψ_2 (%)		-0.20		Experience profile
p_U (%)		5.50		Average mobility rate of 9.71%
p_E (%)		5.00		Ratio of E to U movers: 2.71
p_R (%)		5.50		$p_R = p_U$
ω_ℓ	2.08	1.00	0.68	Relative worker turnover
κ		$1.5\,w$		Mobility ages 76–80: 3.62%
σ_S		0.44		55% prime age T1 to T1
β		0.97		3% annual discount rate
θ		0.76		Housing median share 24%
b_U		0.59		15% of mean wage
b_R		2.98		Monthly benefit 776€
$\overline{H}_\ell$ (%)	1.64	1.00	0.8	Housing stock in UA (m2)
$N_{1\ell}$ (%)	0.48	0.27	0.25	Pop. % of 20-22 years old

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 across terciles of urban areas, as shown in Table 3. Turning to the distribution of people at birth, we calibrate the distribution of newborns across location types to match the population shares of 20–22 years old in the data. Conditional on the urban area type, we additionally calibrate the share of employed people aged 20–22. Finally, we assign the job types and idiosyncratic amenities at birth as random draws from the respective distributions.

We calibrate the remaining parameters inside the model. The labor market search efficiency parameters are set to match statistics pertaining to individuals in the MCVL who are not switching urban areas. The exogenous job loss probability, λ_ℓ, is set to match the share of EU transitions in the data in each tercile of the distribution of urban areas, as shown in Table 1. We find a higher job loss rate in low-productivity urban areas. The job offer rate in unemployment, ϕ_ℓ, is set to match the average unemployment rate in each urban area tercile. The resulting calibration implies that job search is more efficient in high-productivity urban areas and that these areas have lower unemployment rates. In what follows we will refer either to low-unemployment or high-productivity locations as both features go hand in hand. The job offer probability of those employed, Λ, is set to match the average job-to-job transition rate. We use the probability that a job offer is a reallocation offer, λ_d to match the fact that 42% of those moving job-to-job experience an earnings loss.[13] We find that about half of job-to-job offers actually result from reallocation offers. Together with an

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

Table 6: Model and data estimates of Equation (3.1).

Moment and parameter	Model			Data		
	T1	T2	T3	T1	T2	T3
Urban area fixed effects (%); α_ℓ	9.80	6.71	0.00	9.26	4.71	0.00
Earnings growth in UA (%); δ_ℓ	1.39	0.4	0.00	1.15	0.19	0.00
Earnings growth (%); γ_1		8.35			8.50	
Earnings growth (%); γ_2		-0.22			-0.23	

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, σ_Z. We calibrate the dispersion such that the standard deviation of log wage changes of job-to-job switchers is 0.55, as in the data. Thus, as shown in Table 5, we find that high-productivity locations also have more stable job markets: higher creation and lower job destruction rates.

Regarding the earnings process, we normalize the log productivity of the least productive urban area to one. Next, we calibrate the rest of the parameters of the productivity process shown in Equations (4.2) to (4.5) so that an estimation with model data of Equation (3.1) matches the estimates found with the MCVL data. Table 6 shows that this match is close. As shown in Table 5, we find that urban area productivity differences across areas in the model are small, $\ln \mathcal{A}_1 =$ 7.34, whereas that of types 2 and 3 is 7.30. Likewise, the dynamic effect on productivity, $\tilde{\delta}_\ell$, is virtually the same in types two and three, whereas its value for type one is 0.50%. The model implies substantially larger reduced-form estimates through differences in job stability across labor markets. A more stable job market leads to longer tenures and better realized average job qualities. Moreover, as workers can reject job offers and stay in their current work, a job ladder arises endogenously in equilibrium. Those endogenous effects explain the entire differences in reduced-form estimates between T2 and T3 and most of the differences between T1 and T3.

Differences in job productivities being important to explain average wage differences across Spanish labor markets is consistent with Porcher et al. (2021) who show that more workers are employed at large plants in high-paying urban areas. Different from us, Baum-Snow and Pavan (2012) find that different experience accumulation on the job and city fixed effects explain most of the city-size wage premium in the U.S. By focusing on unemployment differences between urban areas, instead of size differences, we implicitly rank urban areas according to differences in search frictions giving them a high potential to explain average earnings differences by job effects.

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 ω_ℓ 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. In Section 6.1.3 we discuss the importance of each type of friction impeding mobility in our theory compared with the rest of the literature.[14]

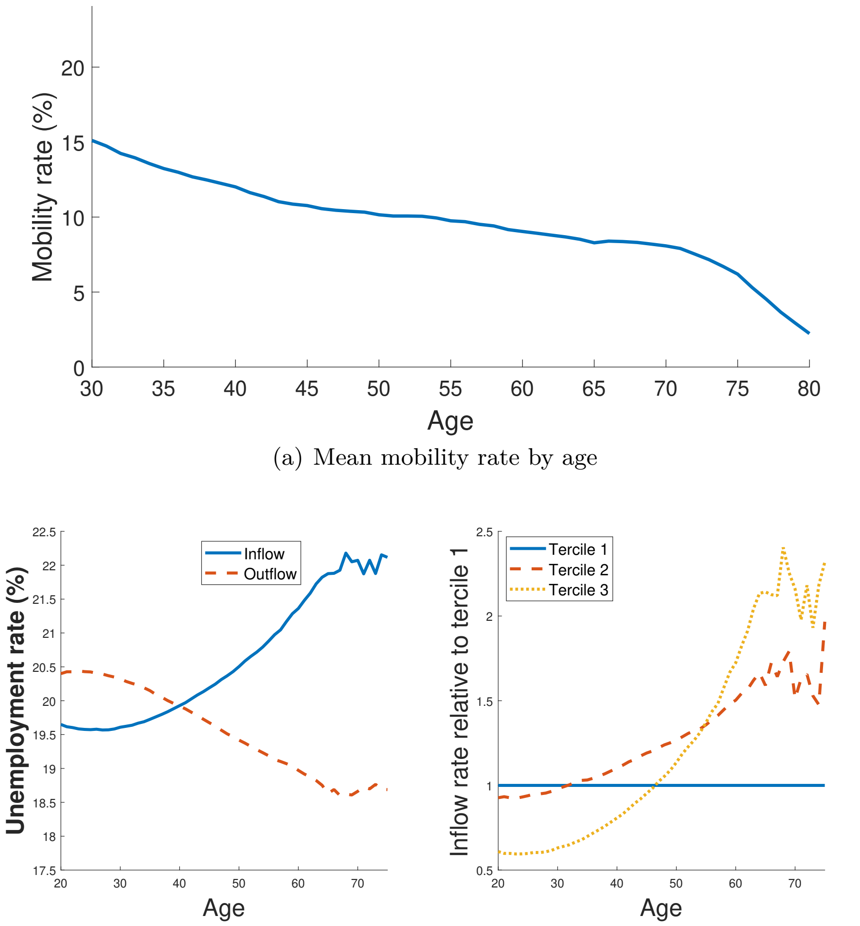
5.2 Untargeted moments

5.2.1 Mobility across urban areas in the model

Here we inspect the mobility patterns over the life cycle implied by our theory. The blue solid line in Figure 3(a) displays the model mobility rate of people over the life cycle where our calibration has targeted the average rate and the rate at old age. Comparing this rate to its data counterpart in Figure 2(c), we see that the model matches the fact that the mobility hazard rate decreases after age 31. Various features of the model are key to delivering the decreasing age-mobility hazard. First, young people have a higher mobility offer acceptance rate because they have a longer horizon to enjoy the benefits of moving. Second, as people sort into more productive locations and jobs and into locations with higher amenities, the probability of receiving a better offer from a different urban area decreases with age. The model, though, produces lower differences in mobility hazards

[14] 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.

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



(a) Mean mobility rate by age

(b) Average unemployment rate of inflow (outflow) locations by age

(c) Relative size of inflow rates by age

by age. For instance, the mobility rate for 30-year-old people is about 22% in the data whereas in the model is 15%. Moreover, the mobility hazard falls more rapidly with age in the data.

In the data, as highlighted in Figure 2(a), the sorting patterns depend on individuals' ages. Figure 3(b) shows that the model matches this dependence 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 closely matches 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. Yet, and consistent with the data, already workers in their mid-40s start sorting into higher unemployment urban areas as they look forward to their retirements.

Finally, the data highlights that employment transitions may play a major role in spatial mobility. Our calibration targets the share of people moving who were previously employed. However, we do not target the share of working-age people moving to a new urban area as non-employed. 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. By allowing people to move to other urban areas as non-employed, our model decouples the mobility friction from the job offer friction that, e.g., Baum-Snow and Pavan (2012), Heise and Porzio (2023), and Schluter and Wilemme (2023) study. In doing so, we emphasize again the role of the life cycle. The young move to low-unemployment urban areas even without a concrete job offer as it allows them to search more efficiently for work from within the local job market. Moreover, starting around age 50, workers move to urban areas with higher unemployment rates as they expect to retire soon.

5.2.2 Urban area characteristics in the model

Mobility patterns have implications for aggregate statistics of locations. Here we turn to inspect whether our theory of mobility produces reasonable location aggregates. Table 7 shows that our theory indeed captures the observed salient characteristics of urban areas, shown in Section 3.1.

The model closely matches the age-averaged population shares, i.e., low-unemployment urban areas are bigger.[15] 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.[16] The calibration targets the observed unemployment rates across terciles and generates endogenously the unemployment-to-employment flow rates. The model matches that these rates are almost the

[15] 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.

[16] 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 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.

Table 7: Heterogeneity across urban areas

	Model	Data	Model	Data
	Population		$U2E$ flow rate	
$T1/T3$	1.93	2.13	1.18	1.13
$T2/T3$	1.20	1.27	0.99	1.03
	Earnings per worker		Housing price	
$T1/T3$	1.21	1.32	1.21	1.55
$T2/T3$	1.09	1.04	1.07	1.00
	$P75/P25$ of earnings			
$T1/T3$	0.96	0.90		
$T2/T3$	0.94	0.91		

same in the third relative to the second tercile but that the rate is somewhat higher in the first tercile.

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. Finally, recall that we have abstracted from agglomeration effects, which would increase rent and size dispersion across locations.

6 Results

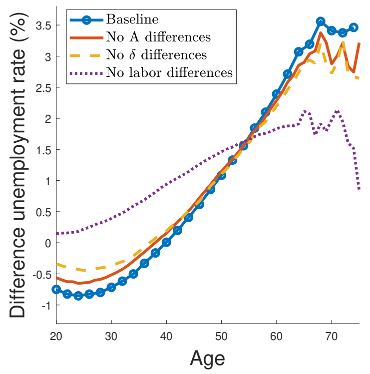
We find that higher dynamic gains, in contrast to higher permanent productivity levels, in low-unemployment urban areas are the main reason young people sort into those urban areas. However, strong spatial search frictions severely limit their ability to move to those labor markets with better opportunities, which leads to large welfare losses to those starting their careers (being born) in high-unemployment urban areas. Policies that aim at facilitating higher mobility mostly fail to address those losses. Instead, paying moderate transfers to high-unemployment urban areas reduces welfare differences with almost no effect on mobility.

6.1 Understanding mobility

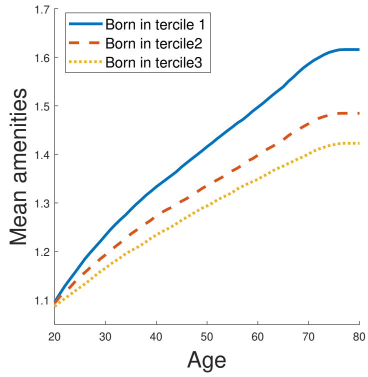
6.1.1 The role of differences in local labor markets

Figure 4(a) eliminates one-by-one differences across local labor markets and shows the resulting sorting patterns over the life cycle. The solid red line shows the sorting over the life cycle when all urban areas have the same aggregate productivities. Notice that most of the life cycle sorting

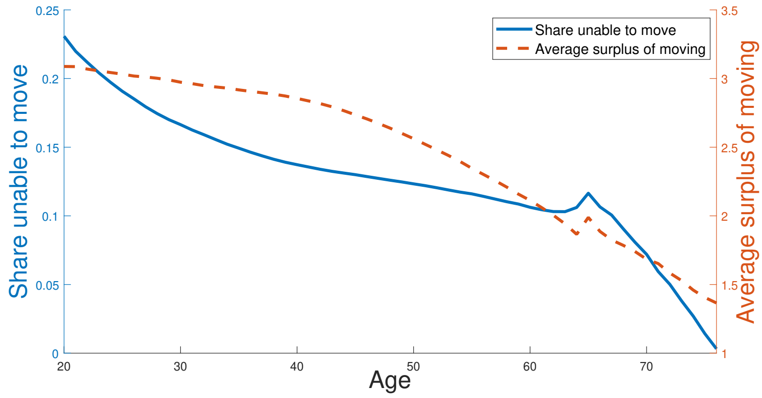
FIGURE 4: Understanding mobility.



(a) Counterfactuals



(b) Amenities



(c) Mobility surplus

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

patterns remain, i.e., average productivity differences fail to explain why young people sort into low-unemployment urban areas. Instead, the key element driving the observed spatial sorting over the life cycle is differences in job-finding and job-destruction rates. Without those differences, the life cycle pattern is much flatter (dotted line). Low-unemployment urban areas allow their inhabitants to find jobs quicker, and those jobs are more stable allowing people to sort into more productive jobs over time. As these gains accumulate dynamically over time, the benefit of moving when young is particularly high.

6.1.2 The role of mobility frictions

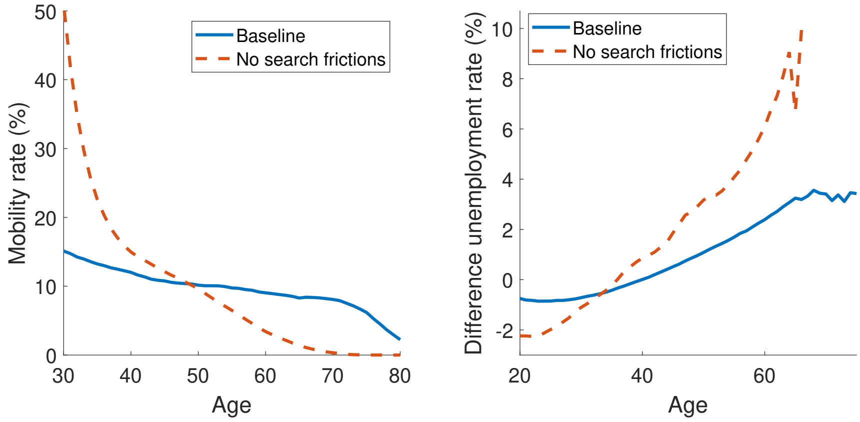
The dynamic gains from living in a low-unemployment urban area raise the question why not even more young people move to those opportunities. To understand the frictions behind limited mobility, the solid blue line (left axis) in Figure 4(c) displays the share of people willing to move given a random 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 received a random 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. Moreover, the potential benefits of moving are highest when the expected lifespan is long as moving is akin to investing in human capital. Hence, the share of people restricted by search frictions falls with age, i.e., search frictions are the main hindrance to the mobility of the young and a high share of the young population does not move despite large benefits. Differently, 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.

6.1.3 Spatial search frictions versus mobility fixed costs

The spatial search frictions are different from most of the urban literature in three important aspects: First, people consider moving only infrequently, second, if they consider moving, their search is random, and, third, the frequency that people consider moving differs across urban areas. In contrast, the literature typically assumes that people consider moving each period and, after observing the distribution of amenities, choose optimally across all possible locations given only fixed mobility costs. As discussed before, survey evidence and evidence provided by Wilson (2021) and Bergman et al. (2019) is consistent with our search view of mobility. Nevertheless, to better understand our identification of search frictions and mobility fixed costs, we compare here our model to a recalibrated model without search frictions where people optimally decide across all locations. In this alternative model, we calibrate the cost of migrating, κ, to match the aggregate mobility rate. We relegate the description of that model to Appendix F.

Search frictions and mobility rates by age The red dashed line in Figure 5(a) shows that the model without search frictions implies too high mobility for young people while the elderly almost do not move. If people can move at will to their desired place they do so as soon as possible (when young) and do not move after retirement because they have done so right at the moment of retirement. Thus, the model cannot rationalize why young people do not quickly leave

Figure 5: 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.

high-unemployment urban areas while, at the same time, the elderly still find it optimal to move. Moreover, fixed costs of mobility are now an "unreasonable high" 5.3 times the average yearly earnings compared to 1.5 in the baseline model.[17] Search frictions provide a rationale for the flatter hazard. They slow down sorting at young ages, and they reduce the calibrated fixed costs which makes it attractive for the elderly to still move.

Random search and spatial sorting by age 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 5(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 optimally choose their preferred labor market, the incentives to move to low-unemployment urban areas are highest at young ages. Similarly, when old, people are much more likely to move to high-unemployment urban areas. In contrast, the data suggest that this sorting process is rather slow, and people do not necessarily move directly to their preferred urban area but, instead, only move there over time. This outcome is natural when (i)

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

people make mobility decisions infrequently and (ii) mobility opportunities are random instead of chosen optimally.

SEARCH EFFICIENCY BY URBAN AREA: CONSEQUENCES FOR MOBILITY BY URBAN AREA The alternative model also implies that people turnover counter-factually 38% higher in urban areas in the highest unemployment tercile relative to the lowest tercile. That is, this model implies larger gross migration flows in high-unemployment areas. The reason for this counterfactual result 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.

To sum up, for a model without search frictions to match the data, we would need three ingredients. The first one would be age-varying fixed mobility costs that should be highest when young, which we find implausible as location attachment should increase with age, not fall. The second ingredient would be age-varying dispersion in amenity shocks to slow down sorting across urban areas at young ages, which we find hard to interpret. The third ingredient is lower fixed costs of mobility in low-unemployment urban areas, which we find a less intuitive interpretation than lower search fictions at said urban areas.[18] We note that two of the three counterfactual implications of a model without mobility frictions are related to the life cycle dimension of our model economy. It is precisely the interaction of life cycle and differences across urban areas that allow us to calibrate the importance of mobility frictions and pecuniary costs.

6.2 SPATIAL DIFFERENCES IN OPPORTUNITIES AND WELFARE

The fact that moving is costly implies that being born in a low-unemployment location should give more opportunities than being born in a high-unemployment location. In our theory, welfare differences depending on birthplace are sizable.

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.

[18]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.

TABLE 8: Decomposing welfare dispersion

	Baseline	Same prod.	Same exper.	Same ϕ, λ	Same ω
Welfare T2/T1%	14.24	12.29	9.37	12.78	10.29
Income T2/T1%	87.77	90.64	94.21	90.39	86.89
Amenities T2/T1%	95.48	94.90	94.37	94.78	101.50
Welfare T3/T1%	25.32	23.18	20.01	17.89	19.18
Income T3/T1%	80.28	82.87	86.12	89.88	79.59
Amenities T3/T1%	93.29	92.78	92.30	92.05	102.40

Welfare is expressed in 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. *Income*: The relative discounted average lifetime income. *Amenities*: The relative discounted average in amenity values. Baseline: the baseline model. *Same productivity*: all urban areas have the aggregate productivity from the highest unemployment urban area; *Same experience*: all urban areas have the experience accumulation process from the highest unemployment urban area; ϕ, λ: all urban areas have the mean job finding and job loss rate across urban areas; *Same* ω: all urban areas have the calibrated search efficiency from the highest unemployment urban area. Source: Model simulations.

6.2.1 Decomposing opportunity differences

The first column of Table 8 displays the welfare losses of starting one's career (age 20) in the second and third tercile of the urban area unemployment distribution relative to the first tercile. We express welfare as the percentage of lifetime income an individual should be paid to be indifferent between being born in the third or second percentile relative to the first tercile.[19] A person born into the second and third tercile has a 14.2 and 25.3 percent lifetime income loss, respectively, compared to a person born in the first tercile. These welfare losses amount to 2.04 and 3.33 times the pecuniary moving cost, respectively.

The welfare differences may arise because lifetime income is higher when being born in a low-unemployment urban area and because those people may enjoy on average higher amenities over the life cycle. The table shows that both are the case. Comparing the third to the first tercile of the urban area unemployment distribution, lifetime income is on average 20% lower, and lifetime amenities are on average 7% lower.

Table 8 decomposes those urban area differences into differences in productivity, in returns to experience, in job search opportunities and job stability, and in search opportunities to move to other urban areas. The row entitled "Same productivity" eliminates differences in aggregate productivities, $\mathcal{A}_\ell$. The welfare loss of a person born in the second and third tercile is reduced to 12.3 and 23.2 percent of lifetime income, respectively, relative to a person born in the first tercile. Put differently, urban area productivity differences, the factor most commonly thought to explain differences in desirability across urban areas, explain less than 13% of the welfare differences and less than 5% of the lifetime income differences across urban areas at birth. Instead, most of these differences across urban areas arise from dynamic benefits that low-unemployment urban areas provide, to which we turn next.

[19] Appendix G derives the welfare loss analytically for our utility function.

The row entitled "Same experience" shows the welfare effects when experience accumulation is the same in all urban areas, i.e., $\tilde{\delta}_\ell = 0$. The welfare loss from being born in the second and third tercile of the urban area unemployment distribution falls to 9.4 and 20.0 percent of lifetime income, respectively. In fact, differences in experience accumulation are the main factor explaining lifetime income differences between urban areas in the first and second tercile of the unemployment distribution. Turning to differences in labor market frictions, the row entitled "Same ϕ, λ" 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 17.9%, and the lifetime income loss falls to 10%.

In the counterfactuals so far, the reductions in welfare losses arise exclusively from reducing income differences across urban areas. Average amenity differences slightly increase as people born in low-unemployment urban areas become more willing to leave those urban areas for those offering better amenities. The row entitled "Same ω" shows that the welfare loss from lower lifetime amenities arises exclusively from differences across urban areas in the search efficiency for mobility opportunities. As highlighted above, low-unemployment urban areas serve as search hubs that allow people to sort into urban areas with relatively high idiosyncratic amenities. Figure 4(b) 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.

Differences in lifetime amenities imply that the birth-place effect creates welfare dispersion even in retirement where income differences no longer exist. For example, at age 68, those born in the third tercile of the unemployment distribution still have a welfare loss equivalent to 3% of their remaining lifetime income relative to those born in the first tercile. The welfare loss for those born in the second tercile is 2.2%. We note that those welfare losses arise despite those born in low-unemployment urban areas living on average in more expensive locations at the time of retirement.

6.3 Public policies

We now turn to study the impact of policy reforms on welfare dispersion across urban areas at birth. To that end, we study steady-state comparisons of these policies. Each policy changes the government's budget, and we employ a proportional wage tax to keep the budget at the (deficit) level of the baseline economy. What is more, by changing housing rental prices, the reforms change peoples' housing expenditures. In our model, changes in rents affect the absent landlords and, thereby, policy reforms change the total amount of resources available to the economy. To avoid this, we assume that all changes in housing rent expenditures are taxed by the government and integrate those taxes into the government's budget.

6.3.1 Reducing mobility costs

We start evaluating a 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 9 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. As highlighted by Figure 4(c), the fixed costs are not hindering the migration of young people in a major way, thus, removing them leaves their mobility mostly unchanged. 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 also leaves aggregate output almost unchanged, as Table 9 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.

6.3.2 Place-based policies

We discuss two types of place-based policies that are of particular interest to Spain. First, high housing rents in low-unemployment urban areas create the worry that young people will not move to those areas because they cannot afford to pay for housing. As a result, the city of Madrid, one

Table 9: Policies targeted at mobility

	Baseline	No fixed costs	Subsidy young T1	Transfer T3 10%	Transfer T3 30%	Transfer T3 50%
Welfare T2/T1%	14.24	14.71	15.78	14.34	14.29	14.25
Welfare T3/T1%	25.32	25.51	26.96	24.31	21.47	18.75
Welfare T3/T1% fixed r		25.51	27.69	23.24	18.33	13.71
Mobility rate %	9.62	16.09	9.64	9.63	9.66	9.66
r_2/r_1	0.88	0.88	0.85	0.88	0.88	0.88
r_3/r_1	0.83	0.83	0.80	0.87	0.95	1.04
Y	2.37	2.37	2.37	2.37	2.37	2.36
Mean $\ln s$ %	6.88	7.05	6.88	6.88	6.90	6.91

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 35 who live in urban areas in the lowest tercile of the urban area unemployment distribution; *Transfer T3*: a transfer to all people living in the highest tercile of the urban area unemployment distribution expressed as a percentage of housing expenditure in T3 without a transfer. $Tx/T1$ the percent of lifetime income a person born in tercile x of the urban area unemployment distribution loses compared to someone born in the first tercile; *Mobility rate*: Decennial mobility rate between urban areas; r_x/r_1 Housing rent in tercile x compared to the first tercile of the unemployment distribution; Y: Aggregate income; *Mean* $\ln s$: Mean log of the peoples' amenities. Source: Model simulations.

of the low-unemployment urban areas, pays a rent subsidy to those younger than age 35. Second, to improve welfare in high-unemployment urban areas, we consider a policy that pays transfers to high-unemployment urban areas. One type of such policy is the European Regional Development Fund which pays nearly 50% of its overall funds assigned to Spain to its fifth poorest region that accounts for only 25% of its population.

We begin by simulating a rent subsidy for young people who live in the lowest unemployment urban area tercile. In 2023, Madrid paid a subsidy of 450€, and, according to the renting portal Idealista, the median rent was 1776€, leading to a 25% rent subsidy. Column three in Table 9 shows that this policy increases welfare inequality at birth. This is to be expected, as the main beneficiaries are those already born in the lowest unemployment urban area tercile. Maybe surprisingly, at first sight, the policy has 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 mitigates somewhat the increase in welfare dispersion. However, the increase in housing rents leads to elderly people moving out of low-unemployment urban areas and, thereby, the subsidy actually decreases the population in those urban areas. This behavior, in turn, mitigates the rise in housing rent dispersion and, thereby, aggravates the increase in 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. We start with a subsidy that amounts to 10% of the pre-reform average housing expenditures in urban areas with the highest unemployment rate. The transfer reduces the average income gap from the first to the third tercile from 23% to 20%. Column four in Table 9 shows that this policy reduces the welfare loss from being born in the highest unemployment urban area tercile by one percentage point. 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 search frictions imply a large share of high-surplus movers at young ages, a moderate subsidy for living in the highest-unemployment urban areas simply does not deter them from moving to low-unemployment urban areas when given the opportunity.

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

The beneficial effects of the transfer are mitigated by an increase in housing rental prices in subsidized urban areas. To quantify this, we solve for the welfare effects when housing rents remain as in the baseline economy, i.e., the housing supply is fully elastic.[20] Table 9 shows that the effect is large: Across the different transfers, the willingness to pay to be born in the first instead of the third tercile of the urban area unemployment rate distribution drops by an additional one to five percentage points when housing costs are fixed.

7 Conclusion

This paper studies the economic consequences of people being born in low- and high-unemployment urban areas in Spain using a life cycle model of frictional labor markets and frictional spatial mobility. Being born in a low-unemployment urban area carries with it large income benefits: lifetime

[20] An alternative way to think about this is that it approximates a world where all people are house owners instead of renters.

discounted income is 20% higher for someone being born in the lowest tercile of the urban area unemployment rate distribution compared to someone being born in the highest tercile. Workers earning more for the same job across different urban areas explains only 5% of those lifetime income differences. Instead, most of the gains are dynamic, i.e., accumulate to workers living in low-unemployment urban areas over time. That is, those workers accumulate more valuable work experience and, quantitatively yet more importantly, spend less time unemployed and have more stable jobs allowing them to faster climb the job ladder.

Apart from higher lifetime income, workers born in low-unemployment urban areas also benefit from more spatial search opportunities that allow them to find locations with better idiosyncratic amenities. Taken together, the welfare gain from being born in the lowest tercile compared to the highest tercile of the urban area unemployment rate distribution is 25% of lifetime income.

These large welfare differences are possible because of strong spatial mobility frictions. We find that the mobility of young people is mainly hampered by spatial search frictions, i.e., people thinking irregularly about moving. Thus, despite large potential gains, many young people remain in urban areas with poor labor market prospects. In contrast, the elderly, who have an incentive to move to high-unemployment urban areas and economize on housing rent, are mostly constrained by the fixed costs associated with mobility.

Understanding mobility frictions as partly arising from search frictions has major implications on the design of policies that wish to address the welfare dispersion at birth. That is, a moderate transfer to people living in high-unemployment urban areas reduces inequality and has almost no adverse effect on the outward mobility of young people toward low-unemployment urban areas or aggregate output. Moreover, policies that encourage people to move to low-unemployment urban areas mostly 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.

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

A Data details

Data aggregation and definitions in the Census: 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 and live. Therefore, an urban area can consist of multiple municipalities that are close by. Urban areas represent 69% of Spain's total population, and 75% of the non-covered people live in rural municipalities with fewer than 20,000 inhabitants. 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.

We classify a person as employed in her current urban area when she reports holding a job.[21] 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.[22]

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}.[23] 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.[24] 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.[25] 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-

[21] 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.

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

[23] 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.

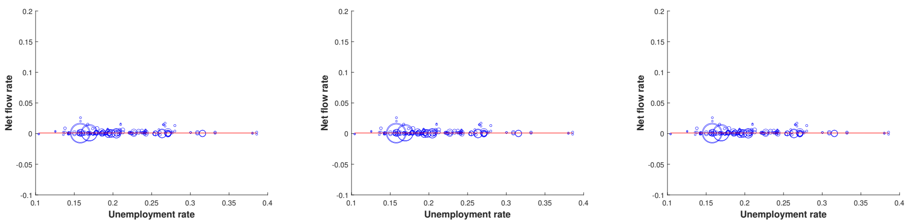
[24] Since the data does not identify municipalities with fewer than 40,000 inhabitants, we have information on 78 out of the 86 existing Urban Areas. In particular, we do not identify the urban areas of Eivissa, La Orotava, Melilla, Ceuta, Blanes, Sant Feliu de Guíxols, Soria, and Teruel.

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

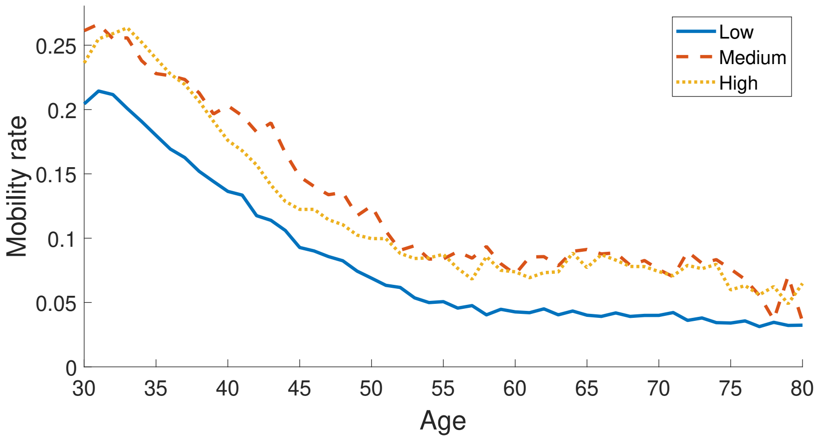
coded earnings from Social Security records[26]. We allocate uncoded yearly earnings across months according to the fraction of top-coded earnings that the worker earns each month. In the monthly data, we regard a worker as employed whenever she has positive social security contributions. In the yearly 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.

B The Role of Education

FIGURE 6: Mobility by education



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



(d) Mobility rate by age and education

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.

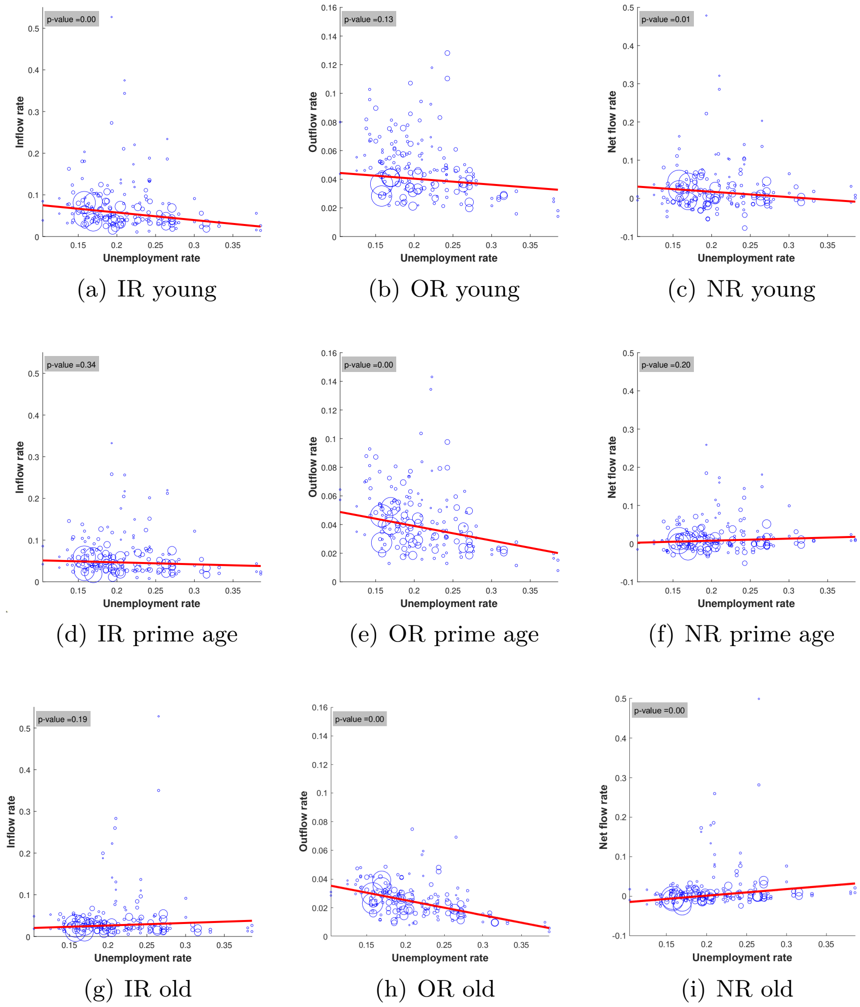
Our analysis abstracts from education differences among workers. This appendix shows that the Spanish data does, indeed, suggest that education differences are of second-order importance to understanding mobility patterns. The top panel of Figure 6 shows that there is no systematic sorting into urban 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% in the third. Given that we find the largest differences in mobility rates

[26]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.

between urban areas in the first and second tercile, these relatively minor differences in education shares explain only a small fraction of the differences in observed mobility rates.

C Mobility flows by age

Figure 7: Mobility flows, unemployment, and age.



(a) IR young (b) OR young (c) NR young

(d) IR prime age (e) OR prime age (f) NR prime age

(g) IR old (h) OR old (i) NR old

Notes: 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.

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.[27] 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.[28] In contrast, outflow rates show only a weak relationship with the unemployment rate. As a result,

[27]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.

[28]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.

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.

D Characterizing the stationary equilibrium

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 σ-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 ℓ is

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

Before we define the stationary equilibrium, we need to define flows in the economy across urban areas. We denote inflows by $IF(\ell)$ and outflows by $OF(\ell)$. In Section 3.2 we described their data counterparts, IR, and OR, relative to population size, to characterize mobility patterns across urban areas. These flows are computed using the individual's migration policy function and aggregating across individuals. For instance, let $OF_i^E(\ell, s, e, z)$ denote the amount of i years old worker with state (ℓ, s, e, z) who leave a location of type ℓ. It satisfies:

$$OF_i^E(\ell, s, e, z) = N_i^E(\ell, s, e, z)\, \Xi_i^E(\ell, s, e, z)\,, \tag{D.2}$$

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:

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

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

$$N(\ell)' = N(\ell) + IF(\ell) - OF(\ell) + N_1(\ell)' - N_T(\ell), \tag{D.4}$$

where $N_1(\ell)'$ is the overall measure of newborns at a location of type ℓ 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,* $\Big\{V_t^R, W_t^R, \Omega_t^R, g_t^{R,\mu},$

$\left.g_t^{R,h}\right\}_{t=R+1}^{T}$, *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* (4.7) *to* (4.20),
2. *the housing markets clear,* $H_\ell^D = \overline{H}_\ell$, *for all* ℓ *where the demand function is given by Equation* (4.21),
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* (D.1), *are constant over time and their laws of motion satisfy Equation* (D.4).

Proposition 1 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 ℓ, and that location 1 is cheaper than 2. If it its rental price is cheaper, Equation (4.23) 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 ℓ 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,

$$\Omega_t^R(\ell, s, 1) > \Omega_t^R(\ell, s, 2), \tag{D.5}$$

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 ℓ 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 ℓ 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.

E Calibration Details

F A Model without Search Frictions

Section 6.1.3 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, Equations (4.14) to (4.20) take the same form, and we restrict

Table 10: Moments in model and data

Moment and parameter	Model T1	Model T2	Model T3	Data T1	Data T2	Data T3
Labor markets						
EU rate (%); λ_ℓ	8.59	9.47	11.24	8.50	9.50	11.20
U rate (%); ϕ_ℓ	16.67	20.61	27.47	16.20	20.10	27.10
Job-to-Job rate (%); Λ		10.75			11.81	
Job-to-Job share losses (%); λ_d		42.36			41.97	
Std of job switchers; σ_Z		0.55			0.55	
Mobility						
Relative people turnover; ω_ℓ	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; κ		3.73			3.62	
Share T1 to T1 prime-age; σ_S		0.56			0.55	

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.

us here to describing the migration stage.[29] 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, $\ell = 1, 2, 3$. 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 ℓ and amenity value s solves:

$$V_t^R(\ell, s) = \int_1\int_2\int_3 \max\left\{\beta W_{t+1}^R(\ell, s), \beta\Omega^R(s', s'', s''') - \kappa\right\} f_S(s')f_S(s'')f_S(s''') \tag{F.1}$$

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

$W_{t+1}^R(\ell, s)$ 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:

$$V_t^U(\ell, s, e') =$$

$$\int_1\int_2\int_3 \max\left\{\beta W_{t+1}^U(\ell, s, e'), \beta\,\Omega^U(\ell, s, e', s', s'', s''') - \kappa\right\} f_S(s')f_S(s'')f_S(s'''), \tag{F.3}$$

[29] 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.

and the value of moving also includes possible job offers:

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

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

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:

$$\begin{aligned}&V^E_t(\ell,s,e',z) = \\ &\int_1\int_2\int_3 \max\left\{\beta\, W^E_{t+1}(\ell,s,e',z),\beta\Omega^E(\ell,s,e',z,s',s'',s''')-\kappa\right\} f_S(s')f_S(s'')f_S(s'''),\end{aligned} \tag{F.6}$$

and, likewise, the value of moving include possible job offers:

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

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

G Welfare Analysis

Let us define as ξ_ℓ 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 ℓ:

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

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 ξ_ℓ is obtained so that

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

Rewriting Equation (G.1) we have that

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

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

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

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

Therefore

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

Hence, ξ_ℓ satisfies

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

Notice that EW_ℓ comprises expectations about labor maret 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 ξ_ℓ 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 ℓ.

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