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DISCUSSION PAPER SERIES

IZA DP No. 15896

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ABSTRACT

Geographic Mobility over the Life-Cycle*

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

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

Keywords: mobility, local labor markets, search frictions, life cycle, dynamic spatial models

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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 are born. Lately, there is a renewed interest in place-based policies to overcome those differences in opportunities.[1] In this paper, we show that policies designed to reduce those differences need to take into account the underlying frictions impeding mobility as well as their heterogeneous effects on mobility over peoples' life cycles.

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

To arrive at these conclusions, we document spatial mobility patterns in Spanish Census data from 1991, 2001, and 2011. We first show that, consistent with the findings of Coen-Pirani (2010) pertaining to U.S. states, net people flows across urban areas are much smaller than gross flows, that is, 80% of all flows represent excess flows. Moreover, this excess reallocation is systematically related to the local unemployment rate: Low-unemployment urban areas have a relatively high excess reallocation rate. Next, we show that people systematically sort across urban areas based on their age. Low-unemployment urban areas attract younger people and lose older people (on net) whereas high-unemployment areas lose younger and attract older people. Finally, we compute peoples' mobility hazards across ages. We find that mobility is highest for young people and declines monotonically with age. However, even elderly people show significant mobility across urban areas.

To understand what makes low-unemployment urban areas particularly attractive to young people, we use administrative Social Security data to characterize differences in local labor markets across low and high-unemployment urban areas. Three dimensions stand out. First, low-unemployment areas pay higher earnings to workers with similar characteristics. Second, workers

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

experience more rapid earnings growth when working in low-unemployment urban areas. Third, low-unemployment areas have lower job destruction and higher job finding rates.

We incorporate these labor market characteristics into a structural life-cycle model with endogenous migration flows across locations and a fixed housing supply to account for observed mobility patterns. Each location has a local frictional labor market where the unemployed and employed search for jobs. Local labor markets differ by their urban area productivity level, the speed at which workers' productivities grow on the job, and job findings and job destruction rates. In addition, people have idiosyncratic tastes for local amenities. Unemployed, employed, and retired people may migrate to other locations but fixed mobility costs and spatial search frictions prevent people to move to their preferred urban area. We think of these search frictions as representing the fact that people consider moving only infrequently as information about moving opportunities does not flow rapidly.

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

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

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

Finally, we simulate reforms to the labor market that ought to benefit, in general, young people to understand their distributional effects. We consider two such policy reforms. The first reform ought to capture a reduction in temporary work contracts, i.e., an increase in job stability. This policy raises the return to employment as its duration increases. As a result, the differential returns of working in a low-unemployment area increase, and the welfare losses of being born in a high-unemployment area rise. Second, we discuss the effects of raising the retirement age by two years. This reform leaves welfare dispersion at birth almost unchanged. On the one hand, a longer working life makes the initial place of birth less determinant for lifetime income which decreases welfare dispersion. On the other hand, it raises the returns to good labor markets which increases the welfare dispersion.

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

Literature On the empirical side, we contribute to the literature studying migration flows between locations. Kennan and Walker (2011) and Bayer and Juessen (2012) are two papers that estimate econometric models linking migration decisions to characteristics of U.S. states. Most similar to us, Coen-Pirani (2010), Lkhagvasuren (2012), and Hansen and Lkhagvasuren (2015) document small net mobility relative to gross mobility rates between U.S. states. In specific, 87% of gross people flows represent excess people reallocation. Our results show that this stylized fact extends to people flows between urban areas in Spain, a smaller geographic unit than a U.S. state. Moreover, we show that there exists a systematic link between excess reallocation and labor market conditions of urban areas as well as between labor market conditions and net people flows once we condition on the life cycle state.

We also relate to the literature that uses structural models to understand the role of job search for spatial reallocation (Nanos and Schluter, 2018; Schluter and Wilemme, 2018; Heise and Porzio, 2021; Jáñez, 2022). Incorporating endogenous housing prices into a spatial search model allows us to explain how young people pushing up housing prices in low-unemployment urban areas leads the elderly to move to high-unemployment urban areas. Moreover, our model features various dimensions of local labor market differences, and we study their relative importance for mobility.

Bilal (2021) for France and the U.S., and Kuhn et al. (2021) for Germany and the UK, also characterize local labor markets across different dimensions. They find that differences in labor market flow rates, particularly differences in the job destruction rates, explain differences in local unemployment rates. De La Roca and Puga (2017) finds that large urban areas offer workers steeper earnings-experience profiles. By combining a model of job search with heterogeneous jobs and endogenous skill accumulation, we show that most of these additional gains in earnings-experience growth reflect that low-unemployment urban areas offer more stable jobs and, thereby, allow workers to faster climb the job ladder.[2] The role of differences in job ladders for migration decisions has also been emphasized by Heise and Porzio (2021) for Germany and by Rendon and Cuecuecha (2010) for cross-border flows between Mexico and the U.S.

Further, this paper contributes to the literature on spatial mobility where housing creates a

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

congestion cost in local labor markets such as Rosen (1979), Roback (1982), or, more recently, Nieuwerburgh and Weill (2010), Monte et al. (2018), Bryan and Morten (2019), Favilukis et al. (2019), and Bilal and Rossi-Hansberg (2021). We add to this literature by emphasizing the importance of mobility search frictions, instead of fixed mobility costs. In particular, we emphasize the importance of search frictions for people reallocation across locations and show that these frictions systematically vary across urban areas. Moreover, we show that the elderly provide a force limiting high rental prices in low-unemployment urban areas. Giannone et al. (2020) and Komissarova (2022) also incorporate the life cycle in a model with congestion costs. The latter uses a two-period overlapping generation model where location amenities respond to migration flows. The former build a spatial OG model where agents can save in the form of financial assets to study net migration flows by age and agent's wealth and housing tenure. Differently from these papers, mobility is restricted by search frictions in our model. We show that, besides helping to understand mobility over the life cycle and between different urban areas, these search frictions imply large welfare losses from being born in a high-unemployment urban area. Zerecero (2021) also studies welfare dispersion arising from being born in different places. He emphasizes the role of a birthplace bias in explaining why people do not leave economically distressed areas, while we emphasize the particularly strong mobility search frictions in those locations.[3]

Finally, we connect to the literature that studies the effects of place-based policies on the macro economy (Glaeser and Gottlieb, 2008; Albouy, 2009; Gaubert, 2018; Fajgelbaum et al., 2019; Gaubert et al., 2021). This literature points out that subsidizing people to live in economically depressed areas reduces economic efficiency as it reduces efficient people reallocation. We show that a moderate subsidy has negligible effects on mobility and aggregate output because search frictions imply that young people in economically depressed areas have on average a high mobility surplus.

2 Data

We employ three different data sets. We describe patterns of geographical mobility using the *Spanish Censuses of Population and Housing*, complemented with data from the Spanish Labor Force Survey (SLFS). To the best of our knowledge, this is the first paper to document mobility in the Spanish Census. To characterize labor markets, we employ Social Security registry data, the Continuous Sample of Employment Histories (*Muestra Continua de Vidas Laborales, MCVL*).

[3] Zabek (2019) and Heise and Porzio (2021) also show the presence of a birthplace bias in mobility data. We also find that people are relatively likely to move to their place of birth in the Spanish data. However, we find that, conditional on moving, the share of people moving to their birthplace is almost flat over the life cycle. It is this life-cycle pattern of mobility that is relevant for us in order to distinguish different mobility frictions.

2.1 Census

The Census is a decennial cross-sectional micro data created by the Spanish statistical agency, *INE*. The structure is similar to its US counterpart described, for example, in Diamond (2016). The data is publicly available since the 1991 Census when a major redesign took place. In each census year (1991, 2001, and 2011), a random set of households are asked to provide information on the current socio-demographic status of all their members aged 16 or older.[4] In total, 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 which comprise around 8% of the total Spanish population.

The Census reports the location of residence at the municipality level whenever a municipality has more than 20,000 inhabitants. Our geographical unit of analysis, however, is the *Urban Area*, 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 and, in particular, a local labor market.[5] Therefore, an urban area can consist of multiple municipalities that are close by.

We narrow our focus on *Large Urban Areas* (LUA), which are those areas whose population is larger than 50,000 inhabitants. There are 86 LUAs in Spain, and its number is stable over the period considered. They account for 69.42% of the total population and about 76% of total employment in Spain.[6] As in other countries, the Spanish population is fairly concentrated in a few urban areas. Four urban areas have a population exceeding one million people (Madrid, Barcelona, Valencia, and Seville) and those four together account for 40% of the population of all urban areas.

We classify a person as employed in her current urban area when she reports holding a job.[7] 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.[8]

[4] We discard individuals that are institutionalized.

[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/#c=home`.

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

[7] 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.

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

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 arrived in a specific urban area and have lived in a different urban area before, AF_{it}, as well as those who separated from a specific urban area, SF_{it}.[9] To compute rates, we use as convention the size of the urban area in the previous Census, i.e., the separation rate of an urban area is the sum of all people who have left that urban area over the period of 10 years relative to the size of the urban area at the beginning of that period: $AR_{it} = \frac{AF_{it}}{N_{it-1}}$, and $SR_{it} = \frac{SF_{it}}{N_{it-1}}$.

2.2 The Spanish Labor Force Survey (SLFS)

The SLFS is a quarterly household survey containing information on 160,000 individuals who are representative of the Spanish population. The first available year of the survey is 1999, and we use the editions between 1999 and 2011. For each individual, we identify her employment status and location of residence during the prior year using a retrospective question. The geographical information is not available at the urban area level but only at the provincial level. This presents a possible limitation when computing mobility patterns in the SLFS. However, according to the Censuses, 90% of mobility between urban areas entails also mobility between provinces.

2.3 Muestra Continua de Vidas Laborales (MCVL)

The *Muestra Continua de Vidas Laborales* is a Spanish administrative data set with longitudinal information on the population of individuals who have any relationship with the Social Security Administration (SSA) for at least one day during the year of reference. This covers all people who either are working or collecting unemployment benefits or a pension.

The MCVL is particularly suitable to study local labor markets because it tracks individuals over their entire careers at the municipality level. The first reference year available is 2006 which provides a 4% random sample of the overall population whose entire labor history in subsequent years is tracked. 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.[10] We group municipalities in urban areas as we did with the Census samples. Importantly, each

[9] 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.

[10] Since the data does not identify municipalities with fewer than 40,000 inhabitants, we have information on 78 out of the 86 existing Large 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.

individual is assigned a unique ID number that allows us to link individuals to the 2007 and 2008 editions. We decide not to use years after 2008 because the Great Recession had a large impact on the Spanish labor market. 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.[11] 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.

We construct both monthly and yearly data sets. The data not only has information on the person in the reference year but contains monthly data on a person's entire monthly employment history which allows us to compute individuals' accumulated work experience in different locations. The MCVL provides two sources of income information for the reference year of each panel (2006-2008). First, annual uncoded earnings from tax administration records. Second, monthly top-coded earnings from Social Security records[12]. We allocate uncoded yearly earnings across months according to the fraction of top-coded earnings that the worker earns each month. Finally, we deflate earnings using the 2009 Consumer Price Index. 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.

To compute working experience, we make use of the fact that the MCVL follows individuals over their entire labor history. We compute for each individual the number of days with a contract in a full-time equivalent job. For interpretive purposes, we express this value in years.

3 Patterns of mobility and local labor market characteristics

To organize the evidence of geographical labor mobility we rank urban areas according to their unemployment rate in the Census. We document three stylized facts about mobility patterns be-

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

[12] 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.

tween urban areas in Spain. First, gross mobility flows across urban areas exceed net flows by a factor of five, which is about the size reported by Coen-Pirani (2010) using US Census data. These "excess" flows are particularly large in low-unemployment urban areas. Second, observed flows have a significant life cycle component.[13] In particular, young people reallocate on net to low-unemployment urban areas whereas older people reallocate on net to high-unemployment urban areas. Third, peoples' mobility hazards are decreasing over the life cycle but stay positive throughout. To better understand why some urban areas are more attractive to young people but not more attractive to the elderly, we highlight in Section 3.3 three differences across low- and high-unemployment local labor markets. Low-unemployment urban areas (i) pay higher earnings irrespective of workers' characteristics, (ii) display earnings growing relatively more quickly with labor market experience, and (iii) display more job stability. First, we turn to describe in detail the mobility patterns according to the Census.

3.1 Urban area characteristics

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

3.2 Mobility across urban areas

As mentioned above, urban areas in Spain show substantial gross people reallocation in the decennial Census data. The size-weighted mean accession rate across urban areas is 14.5%, and the size-weighted separation rate is 11.3%. The same urban area may have significant accession and separation flows much larger than the volume needed to account for its population variation over

[13] Other observables such as education and work status do not show such a sorting pattern. These results are available from the authors upon request.

Table 1: Summary statistics of urban areas

	Unemp. Tercile		
	T1	T2	T3
Unemployment rate (%)			
Average	16.2	20.1	27.1
Population			
Average per City	335,572	200,035	164,857
Number per km^2	1,500	1,153	844
Annual earnings per worker (€2009)			
Average	24,472	19,241	18,493
Housing price per m^2 (€2009)			
Average	1,948	1,254	1,256

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

time. To quantify the importance of urban areas growth for people reallocation, we compute a measure of "excess reallocation" as the difference between peoples' gross flows and net flows (those flows needed to achieve the observed urban area growth). We refer to this statistic as the net people turnover rate:

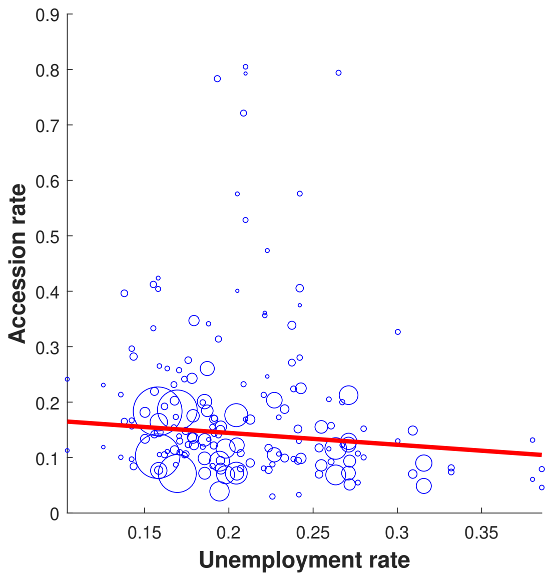
$$NPTR_{it} = AR_{it} + SR_{it} - abs(AR_{it} - SR_{it}). \tag{3.1}$$

In Spain, the size-weighted mean net people turnover rate is 20.1%. Hence, the share of excess people reallocation out of the total reallocation is 80%.

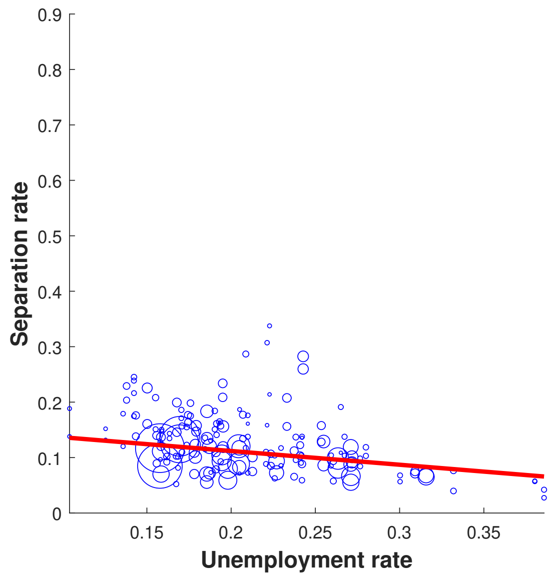
Figure 1 shows that excess people reallocation is systematically related to local labor market conditions of urban areas. Figures 1(a) and 1(b) plot the accession and separation rates of urban areas against their unemployment rates. Low-unemployment urban areas have, on average, higher accession rates than high-unemployment areas. Moreover, low-unemployment areas also have larger separation rates. 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. The net flows hide significant variations in gross people flows. As Figure 1(d) shows, the net people turnover rate is substantially higher at low-unemployment urban areas. Those with an unemployment rate of 0.17 have a predicted net people turnover rate of 22% compared to only 17% for urban areas with an unemployment rate of 0.30. In other words, labor mobility is larger the lower the unemployment rate of the local labor market.

Figure 2 shows the life cycle dimension of the relationship between people flow rates and the unemployment rate at the level of an urban area. To simplify the exposition, we show flow rates

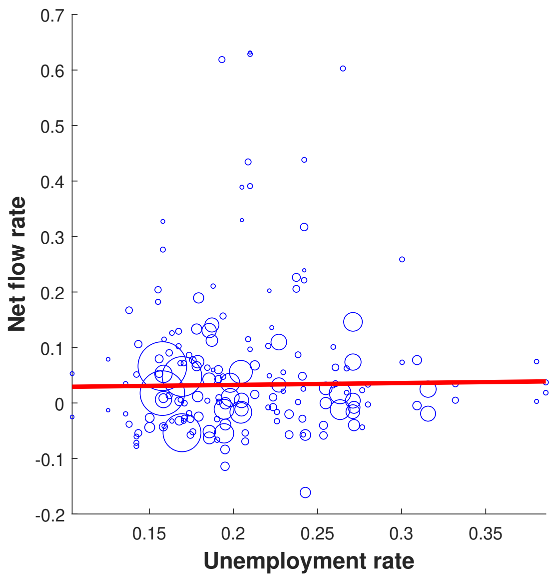
Figure 1: Mobility across Urban Areas.



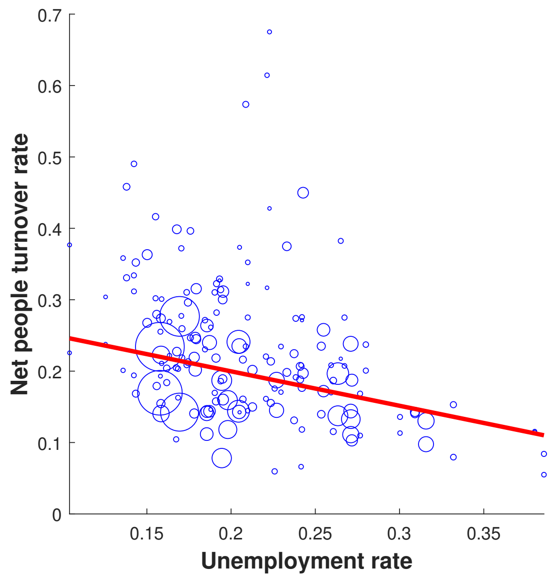
(a)



(b)



(c)



(d)

Notes: The figures display the relationship between people flow rates and the unemployment rate at the urban area level in Spain. We calculate the unemployment rate as the mean unemployment rate over three Censuses. The lines show size-weighted OLS regression slopes. The *net flow rate* is defined as the difference between the accession and separation rates. The *net people turnover rate* is defined as the sum of the accession and separation rates minus the net flow rate. Source: 1991, 2001, 2011 Censuses for three different age groups: young (ages 25-35), prime-aged (ages 36-49), and old (50+).[14] 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 three age-specific flow rates. For those individuals who were in school in the previous Census, we compute the location where they were studying as their area of residence. The first row of Figure 2 shows that the accession rates of young people fall rapidly with the urban area unemployment rate with very few young people joining urban areas with unemployment rates of 35% or higher. In contrast, separation rates show almost no relationship with the unemployment rate. As a result, 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, both the accession and the separation rates are decreasing in the unemployment rate. Put differently, excess people turnover is particularly high for prime-aged workers and this churn is largest for low-unemployment urban areas. The separation rate displays a somewhat stronger negative relationship with the unemployment rate than the accession rate leading to a weak positive relationship between the net flow rate and the unemployment rate. Finally, all urban areas see similar accession rates of old people but their separation rates from low-unemployment areas remain high leading to a net outflow of old people from low-unemployment urban areas.

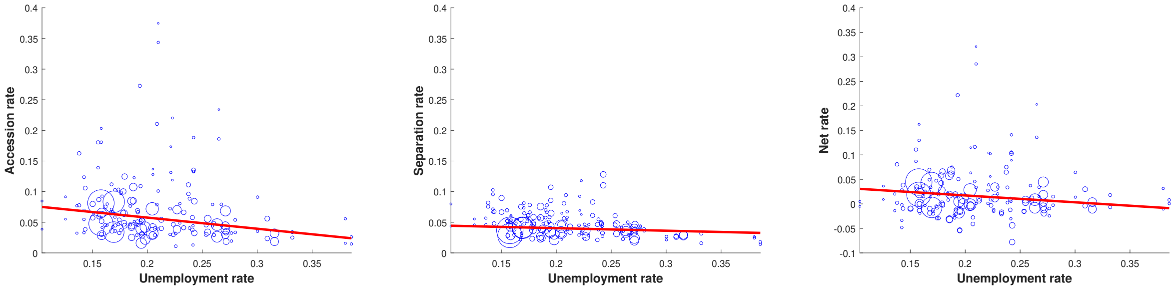
Figure 2 looks at mobility patterns from the urban area point of view. Figure 3, on the contrary, looks at the patterns by peoples' age. Figure 3(a) shows that the average urban area accessed by 25 years old individuals has an average unemployment rate of 0.19, whereas the urban areas where they depart from have an average unemployment rate of 0.2. This difference disappears when they are about 38 years old, the age after which accessed areas have a larger unemployment rate than separating areas. Moreover, the difference rises over age. 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 separating from.

Instead of showing averages, Figure 3(b) provides details on the distribution of arrival rates across urban areas and age. To that end, we again group urban areas into three terciles based on their unemployment rate. The panel displays the age-specific arrival rate of the second and third tercile relative to the first tercile. When young, the arrival rate at the highest unemployment tercile is almost 50% lower than in the lowest tercile. This pattern reverses around age 50, and at age 65, the arrival rate is twice as high in the highest unemployment tercile relative to the lowest tercile.

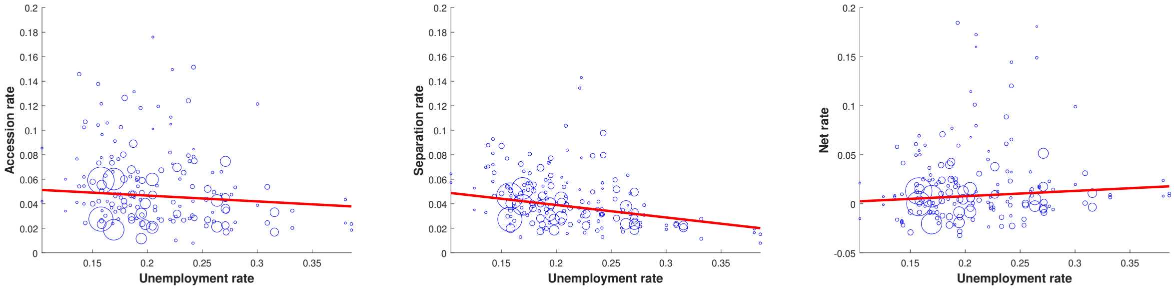
[14] We discard people younger than age 25 as, given the decennial measure, their mobility may have resulted from the mobility decisions of their parents. Including those people leaves the results unchanged.

Figure 2: Mobility, unemployment, and age.

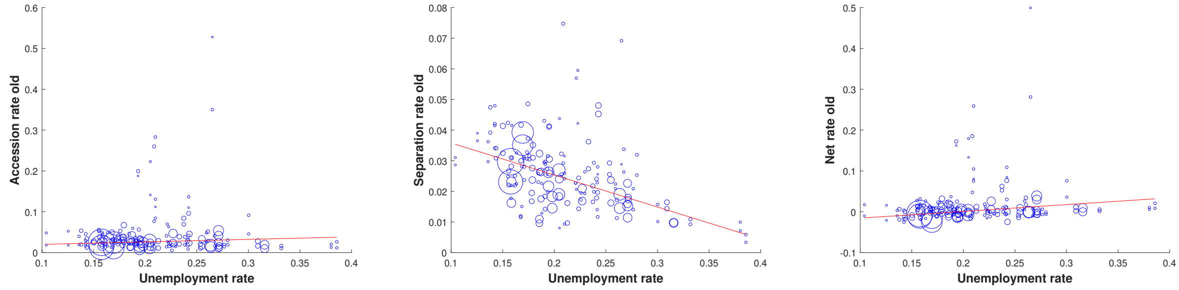
(a) Young



(a) Prime age

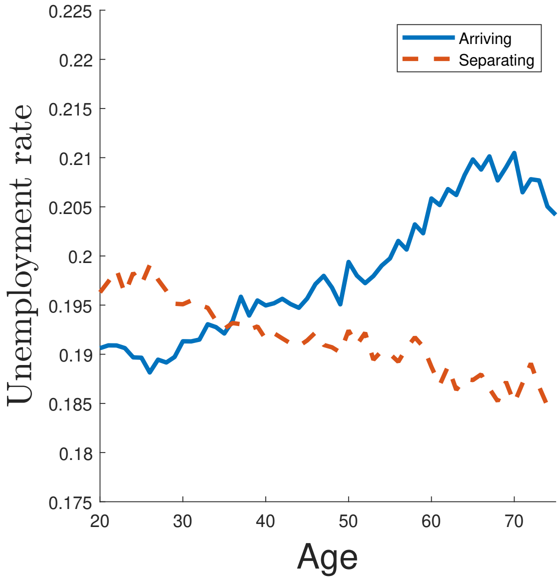


(a) Old

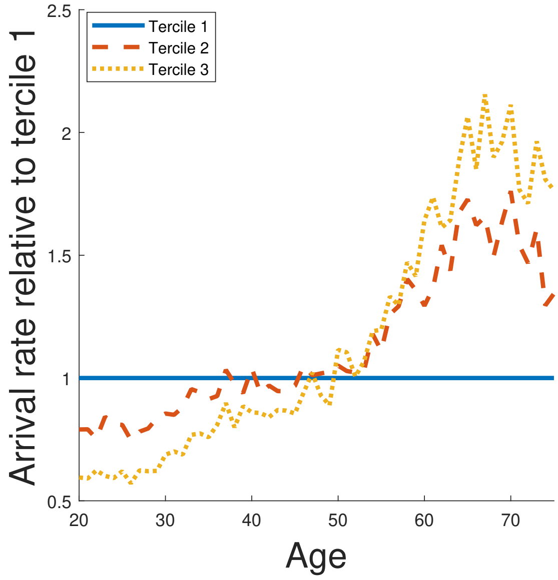


Notes: The figures display the relationship between people flow rates and the unemployment rate at the urban area level in Spain. We calculate the unemployment rate as the mean unemployment rate over three Censuses. The lines show size-weighted OLS regression slopes. The *net flow rate* is defined as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

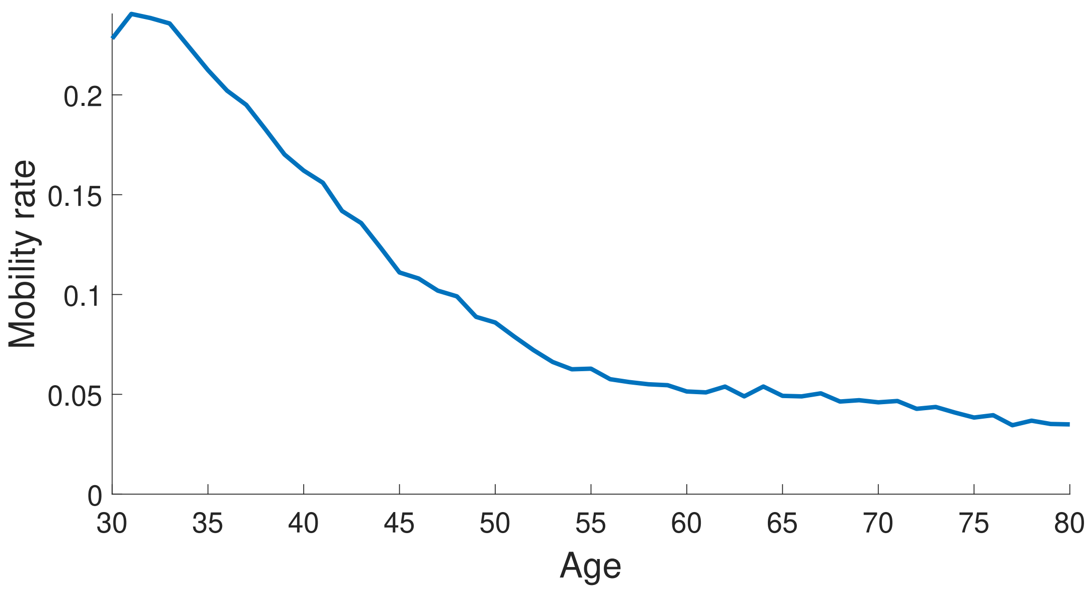
Figure 3: Mobility over the life cycle in the data.



(a) Unemployment at urban area of accession and separation



(b) Accession rate by age



(c) Mean mobility rate by age

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

Finally, Figure 3(c) shows that mobility rates vary substantially over workers' age. The decennial mobility rate falls from 24% at age 31 to less than 5% by age 70. We note that the migration hazard falls monotonically over the life cycle but remains meaningfully positive at all ages. The behavior is similar to job quit hazards, documented for example by Topel and Ward (1992). The labor literature usually interprets a gradually declining hazard as the result of search frictions, and we will use this insight to think about mobility between urban areas.

Besides age, given our focus on the labor market, we would also like to understand the relative contribution of unemployed workers moving to different urban areas for job opportunities in contrast to employed workers who find better jobs. The Census provides us with the employment status of a person in the survey year but not her employment status when she was leaving an urban area. Hence, we turn to the *SLFS* data. Of those people younger than 65, 73% of movers are employed. Put differently, mobility is not primarily driven by people escaping unemployment. This is why we need to study further the labor market characteristics of urban areas.

3.3 Local labor market characteristics

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

$$w_{ij\ell t} = \varphi_i + \tau_t + \alpha_\ell + \sum_{\ell=1}^{2} \delta_\ell \, e_{i\ell t} + \gamma_1 \, \epsilon_{it} + \gamma_2 \, \epsilon_{it}^2 + \boldsymbol{X'_{it}} \, \beta + \varepsilon_{ijt}, \tag{3.2}$$

where φ_i is a worker fixed effect, τ_t is a time fixed effect, and X_{it} is a vector of regressors that control for education, age, age squared, and sex. α_ℓ is an urban area (of tercile ℓ) fixed effect, and $e_{i\ell t}$ is the experience accumulated up to period t in an urban area ranked in the unemployment tercile $\ell = 1, 2$, whereas ϵ_{it} is overall worker experience.[15] The latter captures the returns to experience

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

Table 2: Estimation of earnings equation

	Unemp. tercile	
	T1	**T2**
Urban area fixed effect, α_ℓ (%)	9.26*** (0.24)	4.71*** (0.25)
δ_1 (%)	1.15*** (0.04)	0.19*** (0.05)
γ_1 (%)	8.50*** (0.08)	
γ_2 (%)	-0.23*** (0.00)	
N	7,364,713	
R^2	0.0272	

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

Notes: The table reports the coefficients for the process of log earnings following equation Equation (3.2). We categorize urban areas in three different unemployment rates terciles where the third tercile serves as the normalization. We measure experience as the number of days with a full-time equivalent labor contract, and we express them in years. The regression includes a constant term as well as controls for age, age squared, sex, education, year dummies, worker fixed effects, and time fixed effects. Source: MCVL 2006-2008.

in the third tercile while δ_1 and δ_2 capture the additional returns in the first and second terciles. We are particularly interested in the urban area differences in average pay irrespective of worker characteristics, α_ℓ, and the differences in the returns to labor market experience, δ_1 and δ_2. We stress, however, at this point that we do not give these structural interpretations but will interpret them later through the lens of our structural model.

Table 2 reports the main coefficients from the estimation of Equation (3.2). Three facts stand out. 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%. Second, the earnings reward of experience is concave in overall experience accumulation, as $\gamma_1 = 8.5\%$, whereas $\gamma_2 = -0.23\%$. Thus, an additional year of experience is more valuable at the beginning of working life. Third, workers experience more rapid earnings growth when working in low-unemployment urban areas. This is measured by the estimated value of δ_ℓ. In particular, one additional year of experience in an urban area ranked in the lowest tercile of the urban area unemployment distribution raises average earnings by 1.15% relative to accumulating the same year in the third tercile. Finally, an additional year of experience in the second tercile increases earnings by 0.19% relative to accumulating the same year in the third tercile. That is, as De La Roca and Puga (2017), we find that locations have a static impact on earnings (the location fixed effect α_ℓ) and a dynamic impact captured by the elasticity δ_ℓ.[16]

[16] We take a slightly different view on the main driver of the urban area earnings premium compared to De La Roca and Puga (2017). In their view, it is the size of the urban area. Larger cities give more opportunities for learning

Table 3: Labor Markets across urban areas

	Unemp. tercile		
	T1	**T2**	**T3**
Employment flows			
Job destruction rate (%)	8.5	9.5	11.2
Job finding rate (%)	33.2	30.4	29.4
Job-to-job rate (%)	12.7	11.3	10.7
Share job-to-job with earnings loss	0.41	0.41	0.45

Notes: the table reports summary statistics of the labor market of urban areas ranked in three different unemployment terciles. The statistics are based on the population of people who remain in an urban area. The job destruction rate is the share of employed workers who are non-employed in the next year. The job finding rate is the share of non-employed workers who find a job in the next year. The job-to-job transition rate is the share of employed workers who has a new employer ID in the next year. Source: MCVL 2006-2008.

Urban areas also differ in the job opportunities they provide, as Table 3 highlights. Consistently with the findings of Bilal (2021) for France and the U.S. and Kuhn et al. (2021) for Germany and the UK, the flows of going in and out of the workforce are correlated with the area unemployment rate. The employment to unemployment flow rate (EU) in the highest unemployment tercile is 11.2%, whereas it is 8.5% in the lowest tercile. The unemployment to employment (UE) flow rate is slightly higher in low-unemployment urban areas compared to high-unemployment urban areas but differences are not as pronounced as differences in the EU rates. Turning to the search efficiency of employed workers, we find a slightly higher job-to-job transition rate (EE) in low-unemployment urban areas compared to high-unemployment urban areas. Yet, differences are again smaller than differences in the EU rates. Quite notably, a high share of job-to-job transitions results in earnings losses. Notice that, given our yearly data, many of these EE transitions could be capturing EUE transitions. Together with the sizeable EU flow rates, the average job stability is low in Spain reflecting the high share of temporary work contracts in the economy. As documented by Conde-Ruiz et al. (2019), those contracts produce large worker turnover as some workers may sign different labor contracts every week.

4 A benchmark economy with urban areas

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

from coworkers and, thus, raise individual productivity. Differently, we take a labor market view and rank urban areas by the unemployment rate. Therefore, size is an endogenous object in our analysis that is driven by mobility, which depends on some underlying characteristics of a location.

4.1 Demography, preferences and housing market

The economy is populated by a measure one of people. They live for T periods and are replaced by a newborn Whenever they die. There is no population growth, and the probability of dying before age T is zero. Persons start their life in the labor force and retire after age R. During working life, people are either unemployed or employed.

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

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

where 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 $S \subset \mathbf{R}_{++}$.

The economy is composed of a measure of one 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), land in any location is managed by competing property funds that are perfectly competitive and risk neutral. These funds manage the housing stock. Let us denote as r_{lt} the rental price of housing in location l. Competition among property funds ensures that the price of housing equals the rental price plus the present value of the price next period,

$$p_{lt} = r_{lt} + \beta\, E_t\, p_{lt+1}. \tag{4.2}$$

We assume that those rents are claimed by absentee owners.

4.2 Local labor 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 of type ℓ, in a job j with log productivity z_j, a person of age t earns:

$$\ln w_{j\ell t} = \ln \mathcal{A}_\ell + z_j + a_t, \tag{4.3}$$

$$a_t = e_t + \psi_1 t + \psi_2 t^2, \tag{4.4}$$

$$e_{t+1} = e_t + \tilde{\delta}_\ell, \tag{4.5}$$

where a_t is the person's idiosyncratic log ability. As in its data counterpart shown in Equation (3.2), log earnings depend on urban area fixed effects and productivity. The model allows us to distinguish explicitly between productivity coming from a job, z_j, and worker's ability (in logs), a_t. Notice that we have simplified the process of the worker component in order to reduce the state space. Idiosyncratic productivity is quadratic in age instead of the overall experience. Finally, as in the data, we allow productivity to change with urban area-specific 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. Specifically, the currently unemployed 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 $f_Z(z)$. Simultaneously, 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. To reflect the fact that EE 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 for such reallocation offers are that the worker knows that her current job will disappear because of a temporary contract or a plant closure.[17]

4.3 Mobility across locations

After local labor market shocks, people may have the opportunity to change locations. The gradually decreasing hazard of mobility over age documented in Figure 3(c) supports the view that people make mobility decisions infrequently and, thus, sort into a good match only over time. Hence, similarly to the labor market, we take the view that migration opportunities are the out-

[17]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.

come of a random search process. We think that this process reflects the fact that people think infrequently about the possibility of moving and, on those occasions, their migration opportunity is linked to a particular location. 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. Instead, we think that moving opportunities rather arise by chance. One example of this idea is that specific job opportunities from other locations arrive stochastically. Another example is a person who hears by chance from friends or the media about a new, affordable housing development or the quality of schools and other living conditions at a particular location.

The frequency of such mobility possibilities depends on the current location. That is, as we show below, we infer from the high people churn in low-unemployment urban areas that mobility opportunities arise more frequently for people living in low-unemployment 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. Additionally, we allow that the opportunity to move to a different location depends on the employment state μ_ℓ^J with $J \in \{E, U, R\}$. We assume that migration opportunities are different for employed and unemployed because, on the one hand, the former can rely on networks at work to find new job opportunities at other locations, while, on the other hand, the latter have more time to search for better opportunities.

An opportunity to move to a different location may come with a job offer or as unemployed. The conditional probability of moving with a job offer depends on the labor market conditions in the other location, $\phi_{\ell'}$. In case the offer comes with an employment offer, the offered job type is again a random draw from $f_Z(z)$. A mobility offer entails, in addition to the employment and job offer type, an idiosyncratic location amenity $s' \sim N(0, \sigma_s^2)$ with density $f_S(s')$. If a person decides to move, she pays a utility cost $\kappa \in \mathbf{R}_+$ that can be thought as the time and effort required to move and settle in a new location.

4.4 Value functions

We are going to conjecture that locations of the same productivity level have the same rental price of housing. In Section 4.6 we show that this is, indeed, the case. Recall that there are three stages within each period: First, people work, collect income payments and consume. Second, they receive local labor market shocks which may change their labor status. At the final stage, individuals may receive migration opportunities and decide whether to migrate or not. We describe the individual's problem faced at each stage backward, from the last to the first stage.

4.4.1 Migration stage

Agents receive migration opportunities with probability μ_ℓ^J. Conditional on being able to move, she has the opportunity to move to a location of productivity ℓ' with probability $\pi(\ell')$. If she receives a migration offer, she decides whether to accept it, in which case she pays the utility cost κ. The current value of either choice (migration or not) is discounted with the factor $\beta \in (0,1)$ as the rest of the economic decisions are taken next period. The migration cost, however, is born at the time of migration.

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

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

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

$W_t^R(\ell, s)$ 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 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'. Note that a T years old retiree does not move as there are no gains from doing so since $W_{t+1}^{T+1} = 0$.

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 or, second, it may be the result of being laid off at the previous stage. In the first case, the experience level e' at this stage is equal to her experience level at the beginning of the period, e. In the second case, $e' = e + \tilde{\delta}_\ell$, as she has worked at the beginning of the period.

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

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

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

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

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

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

The value function of individuals who are R years old is a bit different as they know that they will retire next period. Thus,

$$V_R^U(\ell, s, e') = \quad \left(1-\mu_\ell^U\right) \beta \, W_{R+1}^R(\ell, s) + \mu_\ell^U \sum_{\ell'} \Omega_R^{UR}(\ell, s, e, \ell') \, \pi(\ell'), \tag{4.11}$$

$$\Omega_R^{UR}(\ell, s, e, \ell') = \quad \sum_{s'} \max \left\{ \beta \, W_{R+1}^R(\ell, s), \beta \, W_{R+1}^R(\ell', s') - \kappa \right\} f_S(s'). \tag{4.12}$$

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:

$$
\begin{aligned}
V_t^E(\ell, s, e', z) = \quad & \left(1-\mu_\ell^E\right) \beta W_{t+1}^E(\ell, s, e', z) + \\
& \mu_\ell^E \sum_{\ell'} \Big[(1-\phi_{\ell'}) \Omega_t^{EU}(\ell, s, e', z, \ell') + \phi_{\ell'} \Omega_t^{EE}(\ell, s, e', z, \ell')\Big] \pi(\ell'),
\end{aligned} \tag{4.13}
$$

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

$$
\Omega_t^{EU}(\ell, s, e', z, \ell') = \sum_{s'} \max\left\{\beta W_{t+1}^E(\ell, s, e', z), \beta W_{t+1}^U(\ell', s', e') - \kappa\right\} f_S(s'). \tag{4.14}
$$

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

$$
\Omega_t^{EE}(\ell, s, e, z, \ell') = \sum_{z'} \sum_{s'} \max\left\{\beta W_{t+1}^E(\ell, s, e, z), \beta W_{t+1}^E(\ell', s', e, z') - \kappa\right\} f_S(s') f_Z(z'). \tag{4.15}
$$

As in the case of unemployed individuals, the value function of workers who are R years old is a bit different as they know that they will retire next period. Thus,

$$
V_R^E(\ell, s, e, z) = \quad \left(1-\mu_\ell^E\right) \beta W_{R+1}^R(\ell, s) + \mu_\ell^E \sum_{\ell'} \Omega_R^{ER}(\ell, s, e, z\ell') \pi(\ell'), \tag{4.16}
$$

$$
\Omega_R^{ER}(\ell, s, e, z, \ell') = \quad \sum_{s'} \max\left\{\beta W_{R+1}^R(\ell, s), \beta W_{R+1}^R(\ell', s') - \kappa\right\} f_S(s'). \tag{4.17}
$$

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

4.4.2 Local labor market shocks and consumption stages

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

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

$$
\begin{aligned}
W_t^R(\ell, s) = \quad & \max_{c,h} \left\{u(c, h, s) + V_t^R(\ell, s)\right\} \\
\text{s. t} \quad & c + r_\ell h \leq b_R, \\
& c \geq 0,\ h \geq 0.
\end{aligned} \tag{4.18}
$$

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

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

$$\begin{aligned} W_t^U(\ell,s,e) = \quad & \max_{c,h} \Big\{ u(c,h,s) + (1-\phi_\ell)\, V_t^U(\ell,s,e) + \phi_\ell \sum_z \Psi_t^{EU}(\ell,s,e,z)\, f_Z(z) \\ \text{s. t} \quad & c + r_\ell\, h \le b_U, \\ & c \ge 0,\ h \ge 0, \end{aligned} \tag{4.19}$$

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

$$\Psi_t^{EU}(\ell,s,e,z) = \max\Big\{ V_t^U(\ell,s,e), V_t^E(\ell,s,e,z) \Big\} \tag{4.20}$$

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:

$$\begin{aligned} W_t^E(\ell,s,e,z) = \quad & \max_{c,h} \Big\{ u(c,h,s) + \lambda_\ell\, V_t^U(\ell,s,e') + (1-\lambda_\ell)\ \Psi_t(\ell,s,e',z) \Big\} \\ \text{s. t} \quad & c + r_\ell\, h \le w(\ell,e,z,t), \\ & c \ge 0,\ h \ge 0, \\ & e' = e + \tilde{\delta}_\ell, \end{aligned} \tag{4.21}$$

where

$$\Psi_t(\ell,s,e',z) = (1-\Lambda)\, \Psi_t^{EU}(\ell,s,e',z) + \Lambda \Big[(1-\lambda_d)\, \Psi_t^{EE}(\ell,s,e',z) + \lambda_d\, \Psi_t^{ER}(\ell,s,e',z) \Big]. \tag{4.22}$$

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 (4.20). 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

$$\Psi_t^{EE}(\ell,s,e',z) = \sum_{z'} \max\Big\{ \Psi_t^{EU}(\ell,s,e',z), V_t^E(\ell,s,e',z') \Big\}\, f_Z(z), \tag{4.23}$$

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:

$$\Psi_t^{ER}(\ell,s,e',z) = \sum_{z'} \Psi_t^{EU}(\ell,s,e',z')\, f_Z(z). \tag{4.24}$$

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

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

$$N(\ell) = \sum_{t=R+1}^{T} \sum_{S} N_t^R(\ell, s) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}} N_t^U(\ell, s, e) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}\times Z} N_t^E(\ell, s, e, z). \tag{4.25}$$

Likewise, we can define accession and separation flows for a particular location. We denote them as $AF(\ell)$ and $SF(\ell)$. These flows are computed using the individual's migration policy function and aggregating across individuals. For instance, let $SF_i^E(\ell, s, e, z)$ denote the amount of i years old worker with state (ℓ, s, e, z) who separate from a location of type ℓ. It satisfies:

$$SF_i^E(\ell, s, e, z) = N_i^E(\ell, s, e, z)\ \Xi_i^E(\ell, s, e, z), \tag{4.26}$$

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

$$\Xi_i^E(\ell, s, e, z) = \mu_\ell^E \sum_{\ell'} \sum_{s'} \pi(\ell')\,(1-\phi_{\ell'}) g_i^{EU}(\ell, s, e, z, \ell', s')\ f_S(s') + \mu_\ell^E \sum_{\ell'} \sum_{s'} \pi(\ell')\,\phi_{\ell'}\, f_S(s') \sum_{z'} g_i^{EE}(\ell, s, e, z, \ell', s', z')\, f_Z(z'). \tag{4.27}$$

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

$$N(\ell)' = N(\ell) + AF(\ell) - SF(\ell) + N_1(\ell)' - N_T(\ell), \tag{4.28}$$

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. Finally, we can also denote the housing demand at a location of type ℓ as H_ℓ^D and is given by

$$H_\ell^D = \sum_{t=R+1}^{T} \sum_{S} N_t^R(\ell, s)\ g_t^{R,h}(\ell, s) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}} N_t^U(\ell, s, e)\ g_t^{U,h}(\ell, s, e) + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}\times Z} N_t^E(\ell, s, e, z)\ g_t^{E,h}(\ell, s, e, z) \tag{4.29}$$

Now we are ready to define a steady state.

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

1. *Value functions and policy functions solve individual problems shown in Equations* (4.6) *to* (4.24)*,*

2. *the housing markets clear,* $H_\ell^D = \overline{H}_\ell$*, for all* ℓ *where the demand function is given by Equation* (4.29)*,*

3. *all population measures,* $\left\{N_t^R\right\}_{t=R+1}^T$*, and* $\left\{N_t^U, N_t^E\right\}_{t=1}^R$*, are constant over time and satisfy Equations* (4.25) *to* (4.28)*.*

At the steady state, the demographic distribution over all locations is constant and so is the population at each location. Hence, at the steady state, Equation (4.28) implies that migration net flows at each location have to equate the difference between births and deaths.

4.6 Some properties of the steady state

We begin by characterizing consumption and housing decisions. Let y be an individual's income. We have that consumption expenditures are constant shares of income:

$$c = \alpha\, y, \quad h = (1-\alpha)\, \frac{y}{r_\ell}, \tag{4.30}$$

and, hence, the indirect felicity function becomes

$$u(c,h,s) = \alpha^\alpha\, (1-\alpha)^{1-\alpha}\, \frac{y}{r_\ell^{1-\alpha}} + s \tag{4.31}$$

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

$$r_\ell = \frac{(1-\alpha)}{\overline{H}_\ell} \Bigg[\sum_{t=R+1}^{T} \sum_{S} N_t^R\,(\ell,s)\; b_R + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}} N_t^U\,(\ell,s,e)\; b_U + \sum_{t=1}^{R} \sum_{S\times\mathbb{E}\times Z} N_t^E\,(\ell,s,e,z)\; w\,(\ell,e,z,t) \Bigg]. \tag{4.32}$$

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

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

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

Assumption 3. *The probability distribution* $\pi(\ell)$ *is uniform. Thus,* $\pi(\ell) = 1/L$*. The probability of receiving an offer of a particular location of productivity* ℓ *is the same across locations of the same type.*

Proposition 1. *Assumptions 1–3 imply that all locations of the same type,* ℓ*, have the same rental price of housing.*

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 (4.32) 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 accession flows to location 1 must be greater than those to location 2 and its separation flows 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,

$$\Omega_t^R(\ell, s, 1) > \Omega_t^R(\ell, s, 2), \tag{4.33}$$

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, accession flows of retirees to location 1 are larger than accession flows to location 2. Conversely, separation flows from 1 to a given location ℓ are lower than the similar separation flow from 2. The reason, again, is that retirees located in 1 have to draw a higher amenity value to move to ℓ that 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 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 accession flow to 2 is lower than the accession flow to 1. Similarly happens to employed individuals. Hence, it follows that the population must be strictly larger in location 1, arriving at a contradiction.

5 The quantitative model

5.1 Calibration

Table 4 summarizes the calibration. The model period is a year. Households are born at age 20 and live until age 80. We calibrate exogenously parameters of the utility function, governmental programs, urban area housing stocks, and the initial distribution of people over states. We target a 3% yearly interest rate which implies an annual discount factor equal to 0.97. 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. Moreover, our model is about persistent unemployment risk, and unemployment benefits are time-limited and drop to zero after some months. In fact, in the MCVL, we find that the average monthly unemployment benefits of those younger than 65 and non-employed is only 108€. We decide to take an intermediate replacement rate of 15% of the mean wage in our model.

We set the available housing stock in each urban area, $\overline{H}_\ell$, to the total square meters of housing from the Census. Turning to the distribution of people at birth, in a typical overlapping generations model, newborns replace the deceased at the same location. This would be very distorting in this model economy as it would link the location of residence of the elderly with birthplaces. In

Table 4: Calibration

	Unemp. tercile			
Parameter	T1	T2	T3	Target
β		0.97		3% annual discount rate
θ		0.76		Share spend on housing 24%
b_u		0.59		15% of mean wage
b_R		2.98		Monthly benefits of 776€
$\overline{H}_\ell$	1.64	1	0.8	Housing stock in urban areas
$N_1(\ell)$ (%)	0.48	0.27	0.25	Pop. % of 20-22 years old
$\ln \mathcal{A}_\ell$	7.34	7.30	7.30	Tercile wage fixed effects
$\tilde{\delta}_\ell$ (%)	0.57	0.00	0.00	Tercile experience effects
ψ_1 (%)		10.16		Experience profile
ψ_2 (%)		-0.20		Experience profile
λ_ℓ (%)	4.70	5.30	8.40	EU rate of city stayers
ϕ_ℓ (%)	45.0	38.5	28.5	Urban area-level unemployment
Λ (%)		19.50		11 % Job-to-Job rate
λ_d (%)		51.0		41 % Job-to-Job are age losses
		$\mu_\ell^J = \omega_\ell p^J$		
p^U(%)		5.50		Mobility rate of 0.95%
p^E(%)		5.00		Ratio of E to U movers: 2.7
p^R(%)		5.50		$p_R = p_U$
ω_ℓ	2.08	1.00	0.68	Relative worker turnover
κ		5.80		Mobility ages 76–80 = 3.62
σ_Z		0.46		Std of job switchers 0.55
σ_S		0.44		Share T1 to T1 prime-age 55%

Notes: The table displays the model calibration. The left column states the calibrated parameter. The second to fourth columns display the calibrated values for the three terciles of the urban area unemployment distribution. The right column describes the data target.

reality, people have children when they are young where they reside. This is why 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. Regarding the earnings process, we normalize the log productivity of the highest unemployed urban area to one. Next, similar to Equation (3.2), we estimate a regression of workers' log earnings on worker fixed effects, urban area fixed effects, a polynomial in experience, and experience at different urban area terciles. We adjust the parameters of the experience profile and the urban area fixed effects such that this model regression replicates the results from the data. We find that urban area productivity differences are substantially smaller than the urban area earnings fixed effects. The reason is that we explicitly differentiate between urban area productivity and job effects. Low-unemployment urban areas have better labor markets implying workers are on average in better jobs which increases their earnings. For the same reason, we find that urban area heterogeneity in productivity accumulation is smaller than the urban area differences in the earnings-experience profiles.

The labor market search efficiency parameters are calibrated to match statistics pertaining to individuals tracked 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. We find a higher job destruction 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. 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. Thus, the job offer probability of those employed, Λ, is set to match the average job-to-job transition rate. We use the probability that a job offer is a reallocation offer, λ_d to match the fact that 41% of those moving job-to-job experience an earnings loss.[18] We find that about half of job-to-job offers actually result from reallocation offers. Together with an average job destruction 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.

Turning to the frictions hampering reallocation across urban areas, we target moments of average mobility as well as the composition of mobility across employment states and ages. We write the probability of receiving a migration opportunity as $\mu_\ell^J = \omega_\ell \, p_J$, for all ℓ and $J = R, U, E$. Here p_J measures the search efficiency of different employment states, and ω_ℓ the urban-specific search efficiency. We target with p_U a decennial mobility rate of 9.5%. We set the offer probability of those retired as equal to those non-employed. We then calibrate p_E to match that there are 2.6 times more city movers that were before employed relative to city movers that were non-employed. We find that search while non-employed is about 10% more efficient than while employed. Finally, we calibrate ω_ℓ to match the relative net people turnover rates in each location type documented in Section 3. The calibration implies that search is more than twice as efficient in the first relative to the second tercile, and it is 30% less efficient in the third relative to the second tercile. Hence, we refer to low-unemployment urban areas as search hubs. Besides search frictions, the model also features a fixed cost of migration, κ. A high fixed cost decreases particularly mobility at old ages when few periods are left to compensate for paying the fixed costs. Therefore, we set κ to match the average mobility rate during aged 76–80.

In a model without idiosyncratic productivity and amenities, young people would never be

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

willing to leave the lowest unemployment urban area. In our model, the interaction of idiosyncratic productivities with age breaks this logic. This is further interrupted by the existence of idiosyncratic amenities (or nonpecuniary benefits) which may result in young people moving from low-unemployment to high-unemployment areas.[19] More dispersed non-pecuniary benefits increase the share of young people willing to move to higher unemployment urban areas. We calibrate this dispersion, σ_S, such that 30-year-aged switchers leaving the lowest unemployment urban area go with a 55% probability to another such urban area.

5.2 Untargeted moments

Before turning to the analysis of the model, we briefly show that it is able to capture the previously discussed salient characteristics of urban areas and peoples' mobility. We begin with cross-sectional moments of urban areas: low-unemployment urban areas are relatively large, have high earnings, and have high housing prices. Regarding the first, the top panel of Table 5 shows that the model closely matches the age-averaged population shares, i.e., low-unemployment urban areas are bigger.[20]

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

The last panel shows that the model is also able to match 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

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

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

[21] This evidence contrast 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. Moreover, inequality appears to be driven by the very rich who cluster in larger cities.

Table 5: Heterogeneity across urban areas

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

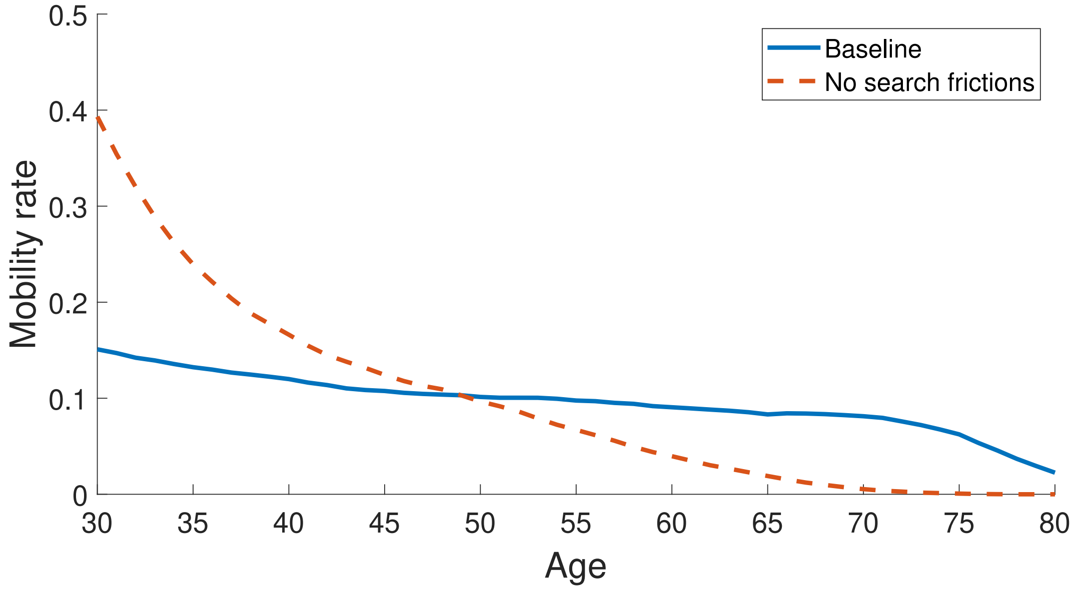
Note: the table reports summary statistics of the demography and labor market of urban areas ranked in three different unemployment terciles (the first tercile stands for the set of urban areas with the lowest unemployment rate). All statistics are normalized by the value in the thrid tercile, $T3$.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

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.

We now turn to mobility patterns. The blue solid line in Figure 4(a) displays the mobility rate of people over the life cycle in our model economy. Comparing this to its data counterpart in Figure 3(c), we see that the model matches that the mobility hazard rate is decreasing with age, though the decline is faster in the data during early ages. Various features of the model are key to delivering the decreasing age-mobility hazard. First, young people have a higher mobility offer acceptance rate because they have a longer horizon to enjoy the benefits of moving. That is, the fixed mobility costs weigh less for people with longer horizons–younger people. Second, as people sort into more productive locations and jobs, the probability to receive a better job offer from a different urban area decreases with age. Third, as a consequence, people sort over time into locations with higher idiosyncratic amenity values. Again, the probability of finding a location with even better amenities, thereby, decreases with age.

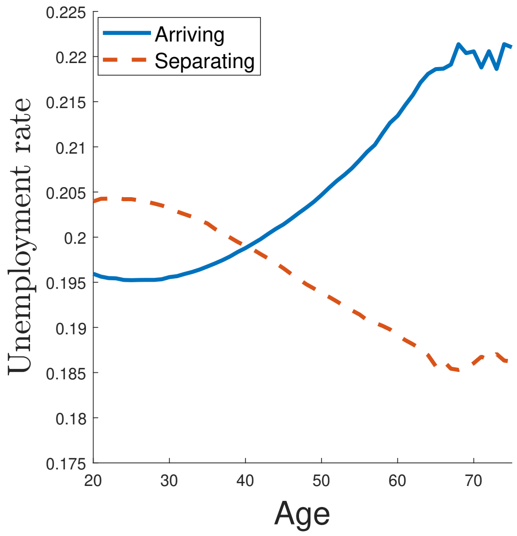
A key prediction of our model is that people sort into different types of urban areas depending on their stage of the life cycle, a pattern we see in the data, as shown in Figure 3(a). Its model counterpart, Figure 4(b), matches closely that for young people, the average unemployment rate in urban areas people are leaving is about 1 percentage point higher than the average unemployment rate in urban areas where they are arriving at. Similarly to the data, this difference in the unem-

Figure 4: Mobility over the life cycle in the model.

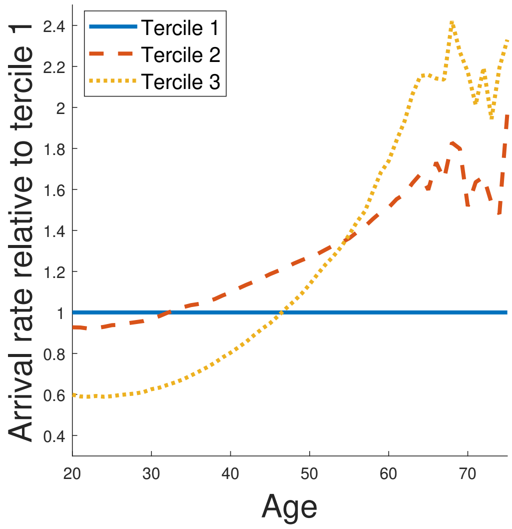


(a) Mean mobility by age

Notes: Decennial mobility rate of people over the life cycle. The blue straight line shows the baseline model and the red dashed line is a recalibrated model without search frictions for mobility. Source: Model simulations.



(b) Unemployment at urban area



(c) Accession rate by age

Notes: The left panel displays the average urban area unemployment rate across all individuals arriving in (separating from) an urban area. The right panel displays the arrival rate of people in an urban area depending on its tercile in the urban area unemployment distribution relative to the arrival rate in the lowest tercile. Source: Model simulations.

ployment rate vanishes around age 40, and the unemployment rate in arriving urban areas becomes higher than the unemployment rate in separating urban areas. By age 65, similar to the data, the average unemployment rate in arriving urban areas is about 3 percentage points higher than the average unemployment rate at separating urban areas and the difference remains flat afterward.

Figure 4(c) displays the distribution of accession rates to different urban areas across ages. Figure 3(b) is the data counterpart. As in the data, people tend to arrive at low-unemployment urban areas when young and high-unemployment urban areas when old. The model matches that young people have a 40 percent lower probability to move to the highest unemployed urban area compared to the lowest unemployment urban area. After age 50, the highest unemployment urban area becomes relatively more likely as a destination area than the lowest unemployment urban area. 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 rent costs. This is particularly true for retirees, for whom good labor market conditions in an urban area are unimportant.

6 Results

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

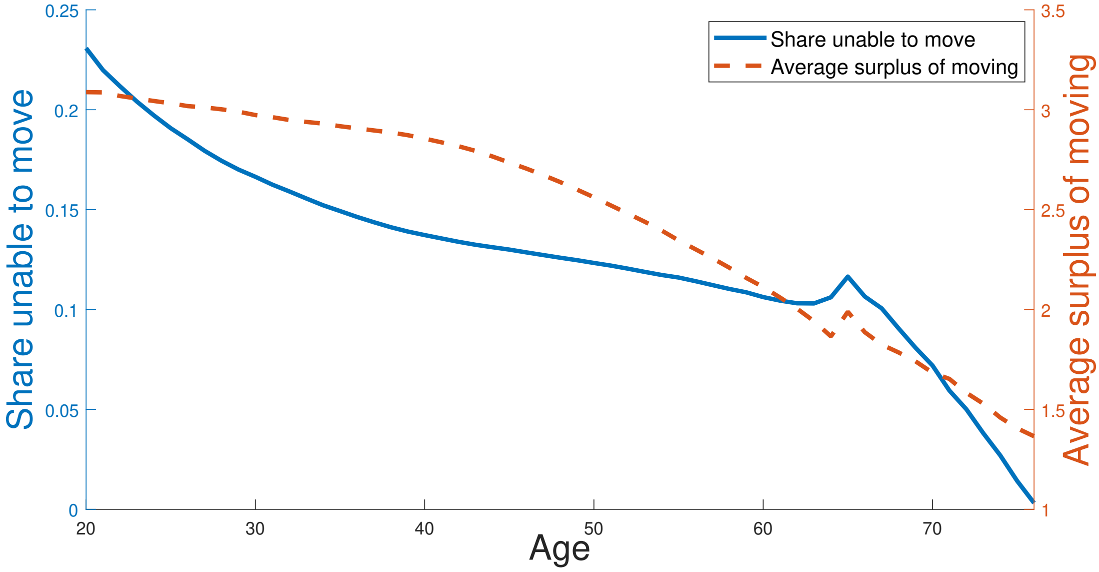
6.1 Understanding mobility

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

6.1.1 The role of mobility frictions

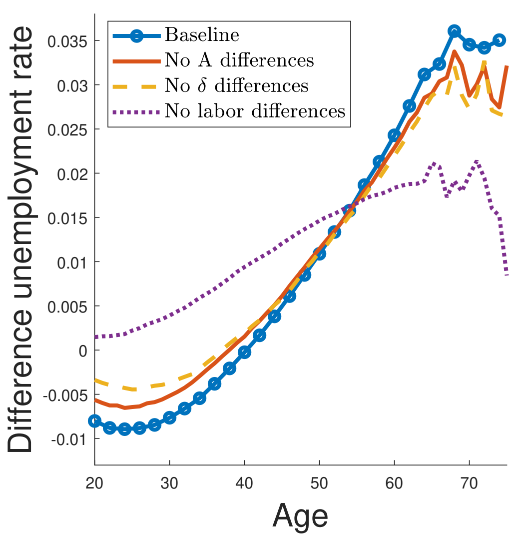
The model features two frictions to mobility: fixed mobility costs and search frictions. Figure 5(a) shows that the effect each of these frictions has on mobility varies with age. The left axis displays the difference between the share of people willing to move given a random mobility offer and the

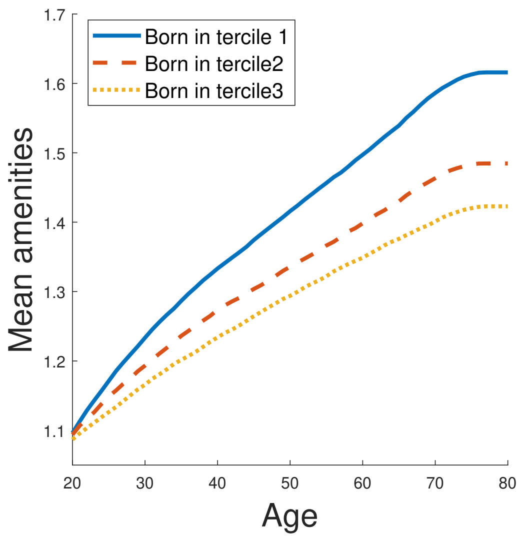
Figure 5: Understanding mobility.



(a) Mobility surplus

Notes: The blue straight line displays the share of people who would accept a random mobility offer minus the share of people actually moving given a random mobility offer. The red dashed line displays the value of those actually moving at their destination location minus the value at their originating location. This excess value is set relative to the fixed mobility costs, κ. Source: Model simulations.





(b) Counterfactuals

(c) Amenities

Notes: The left panel displays the difference between the average urban area unemployment rate across all individuals arriving and separating from an urban area in the baseline model and three counterfactual simulations: *No A differences* eliminates differences in urban area average productivities; *No $\tilde{\delta}$ differences* eliminates differences in urban area skill accumulation; *No labor differences* eliminates differences in urban area job destruction and job finding rates. The right panel displays the average amenity level of individuals born in urban areas with different unemployment rates. Source: Model simulations.

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

Different from us, the urban literature typically assumes that people move at will to any location of their choice and are only hindered by fixed mobility costs. To highlight that mobility frictions are, indeed, important to understand the data, we recalibrate our model without search frictions. To match the average mobility rate we increase the value of the fixed cost of migration. The red dashed line in Figure 4(a) shows that this alternative model fails to replicate several aspects of the age-mobility hazard. Mobility is too high for young people while the elderly almost do not move (as the fixed cost of mobility is higher than in the baseline model). The reason for this result is the age gradient of the excess value of mobility shown in Figure 5(a): The surplus of moving falls with age. Without search frictions, it is difficult for the model to rationalize why young people do not quickly leave high-unemployment urban areas while, at the same time, the elderly still find it optimal to move.

What is more, the model without search frictions would need "unreasonably large" mobility costs. Our recalibration implies a mobility cost of 5.2 times the average yearly wages.[22] In the baseline model, the factor is only 1.5. Finally, in the alternative model without search frictions, people turnover is counter-factually 60% higher in urban areas in the highest unemployment tercile relative to the lowest tercile. That is, it produces too much mobility in less productive locations compared to the data, as the unemployed have relatively higher mobility acceptance rates. This is not the case in our baseline model. As shown in Table 4, we infer from the location-specific people turnover rates that spatial search frictions are lower for low-unemployment locations. As a result, our model implies that low-unemployment areas are 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

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

often also establishments in other parts of the country.[23]

6.1.2 The role of the life cycle and labor market conditions

To understand the role different aspects of local labor market conditions have on the sorting of people across urban areas over the life cycle, we simulate the model but eliminate each time one aspect of heterogeneity. Figure 5(b) shows the results using as the metric the average difference between the average unemployment rate at arriving and separating urban areas. Recall, the baseline model matches this metric in the data closely (see Figure 3(a) and Figure 4(b)).

The solid red line shows the sorting over the life cycle when all urban areas have the same aggregate productivities. Strikingly, even after eliminating productivity differences across urban areas, most of the life-cycle sorting patterns remain. This highlights that other labor market differences are key to understanding what makes low-unemployment urban areas attractive to young people. In our model, these other differences are dynamic, i.e., they provide benefits to workers partly in the future. The figure highlights that differences in urban-area local labor markets (job destruction and finding rates) are the single most important factors behind the life cycle sorting pattern.

6.1.3 The role of idiosyncratic amenities

In our stationary equilibrium, all mobility must result from idiosyncratic differences between workers. One of these is the aforementioned life cycle. The model provides several additional reasons for mobility. First, job opportunities may differ across urban areas for an individual. An unemployed worker may be willing to leave her current urban area when she is offered employment in another urban area. Moreover, an employed worker may move to a different urban area because of a particular promising job-to-job opportunity. Second, dispersion in idiosyncratic amenities across different urban areas, σ_s, incentivizes mobility.

Table 6 quantifies the importance of this latter channel. Eliminating heterogeneity in idiosyncratic non-pecuniary benefits, i.e., setting $\sigma_S = 0$, decreases the mobility rate to 4.0%. In particular,

[23]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. That is, such a model would infer that the fixed costs of moving between Madrid and Barcelona are substantially smaller than the fixed costs of moving from Cadiz to Barcelona.

Table 6: Understanding mobility

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

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

without idiosyncratic amenities, too few people move to urban areas with lower unemployment rates than their current urban areas. Put differently, heterogeneity in idiosyncratic amenities is key for the model to match mobility in the model. Notice that heterogeneity in idiosyncratic amenities is more important to understand mobility than job heterogeneity despite the fact that we calibrate more dispersion in the latter, as shown in Table 4. The reason is that a good job draw is more transitory that an amenity draw. That is, losing a job may also occur within an urban area. Moreover, the benefit of a good job draw is tied to working and disappears after retirement.

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

We find that being born in locations of the lower types entails substantial welfare losses compared to being born in the best locations. A person born in the third or second tercile of the urban area unemployment distribution is willing to pay 17.0 and 9.8 percent of lifetime income, respectively, to be born in the first tercile instead. Higher productivity, higher experience accumulation, better job opportunities, and more mobility opportunities all contribute to those large losses. Notably, static productivity differences across urban areas explain only a small part of these welfare losses, i.e., the main drivers of welfare differences across location types are dynamic.

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

Table 7: Decomposing welfare dispersion

Model	Welfare T2/T1%	Welfare T3/T1%
Baseline	9.77	17.03
Same productivity	8.66	15.82
Same experience	6.16	13.17
Same ϕ, λ	8.62	11.97
Same ω	7.08	12.96

Notes: The table displays the percent of lifetime income a person born in the second tercile, $T2/T1$, and the third tercile, $T3/T1$, of the urban area unemployment distribution loses compared to someone born in the first tercile. It displays this result for the baseline model as well as several counterfactual simulations. *Same productivity*: all urban areas have the aggregate productivity from the highest unemployment urban area; *Same experience*: all urban areas have the experience accumulation process from the highest unemployment urban area; ϕ, λ: all urban areas have the mean job finding and job destruction 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 welfare losses

The first row of Table 7 displays the lifetime income losses of being born (age 20) in the second and third tercile of the urban area unemployment distribution relative to the first tercile.[24] A person born into the second and third tercile has a 9.8 and 17.0 percent lifetime income loss, respectively, compared to a person born in the first tercile.

People prefer to be born in low-unemployment urban areas because these are more productive, provide higher experience returns to their workers, provide better job search during unemployment and more stable jobs, and provide better search opportunities to move to other urban areas. Table 7 quantifies the welfare effects of each of those factors.

The row entitled "Same productivity" eliminates differences in aggregate productivities, $\mathcal{A}_\ell$, between urban areas. That is, it eliminates the factor most commonly thought to explain differences in desirability across urban areas. The lifetime income loss of a person born in the second and third tercile is reduced to 8.7 and 15.8 percent, respectively, relative to a person born in the first tercile. Put differently, urban area productivity differences explain less than 12% of the welfare dispersion across urban areas at birth. Instead, most of the welfare differences across urban areas arise from dynamic benefits that low-unemployment urban areas provide, to which we turn next.

The row entitled "Same experience" shows the welfare effects when experience accumulation is the same in all urban areas, i.e., $\tilde{\delta}_\ell = 0$. Differences in the returns to experience have a larger effect on welfare dispersion at birth than urban area productivity differences. After eliminating differences in experience accumulation, the lifetime income loss from being born in the second and third tercile of the urban area unemployment distribution falls to 6.2 and 13.2 percent, respectively.

[24] Appendix A derives the welfare loss analytically for our utility function.

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 destruction rates across urban areas. The welfare effect for people being born in the second tercile is relatively small highlighting that labor market frictions are similar in the first and second tercile of the urban area unemployment distribution. However, the effects for people born in the third tercile are substantial, i.e., the welfare loss from being born in the third tercile reduces to 12.0%.

Finally, the row entitled "Same ω" eliminates differences across urban areas in the search efficiency for mobility opportunities. As highlighted above, low-unemployment urban areas serving as a search hub allow people in those to sort into urban areas with relatively high idiosyncratic amenities. Figure 5(c) highlights this effect over the life cycle. It displays the mean amenities for cohorts being born in different terciles of the urban area unemployment distribution. By assumption, idiosyncratic amenities are equally distributed in the three terciles at birth. However, over time, people born in low-unemployment urban areas receive more mobility offers and, as a result, sort into urban areas with higher idiosyncratic amenities. Eliminating the heterogeneity in search opportunities, hence, reduces the welfare losses of being born in high-unemployment urban areas. Quantitatively, the lifetime income loss from being born in the second and third tercile of the urban area unemployment distribution falls to 7.1 and 13.0 percent, respectively.

The model also allows us to evaluate welfare differences across the entire life cycle to better understand the underlying sources of welfare dispersion at birth. To this end, we keep expressing welfare in terms of a person's willingness to pay as a percent of lifetime income (measured from age t onward) and condition on her birthplace instead of the location where she is currently living. Rows three and four of Table 8 (age 45) show that welfare differences across birthplaces at age 45 are similar to those at age 20. The reason is that two forces work against each other. On the one hand, the closer people move to retirement, the smaller becomes the effect of differences in labor markets across urban areas for welfare. On the other hand, most benefits of being born in a low-unemployment urban area (higher skill accumulation, better job market prospects, and higher amenities) accrue in the future. At birth, these future returns are discounted which depresses welfare differences relative to those present at age 45. Turning to retirement, at age 68, those born in low-unemployment urban areas still have higher welfare than those born in high-unemployment urban areas. This may be surprising as better labor markets no longer play a role and, on average, those born in low-unemployment urban areas live in more expensive locations at the time of retirement. However, they also live in locations with high average amenities as their urban area search was relatively more efficient over their life cycle.

6.2.2 Public policies

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

Reducing mobility costs We start evaluating a very simple policy which is giving subsidies to movers. To be specific, we reduce the fixed costs of moving to zero. The column entitled "No fixed costs" in Table 8 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 affect very differently people depending on their age. The mobility of young people is not much affected. This is so because the calibrated level of the fixed cost was not hindering much migration of young people in the baseline model economy, as highlighted by Figure 5(a). That is, for young people, mobility depends, mostly, on search frictions. For them, mobility is an investment whose return well exceeds the migration fixed costs. As a consequence, the increase in mobility leaves aggregate output almost unchanged, as Table 8 shows. The reduction in the fixed cost affects, mostly, older workers and retirees who now flock in larger flows to cheaper locations, thus, offsetting the small population loss of young people in those locations. As a result, housing rents are almost unchanged in high-unemployment urban areas, 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. As a consequence, welfare differences across urban areas arising from different birthplaces rise particularly among the retired for whom differences in amenities are the main source of welfare differences.

Place-based policies In Spain, policymakers currently discuss two types of place-based policies. First, high housing rents in low-unemployment urban areas create the worry that young people do

Table 8: Policies targeted at mobility

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

Notes: The table compares model outcomes from the baseline model to counterfactual simulations. *No fixed costs*: no fixed mobility costs; *Subsidy young T1*: a subsidy to people younger than age 30 who live in urban areas in the lowest tercile of the urban area unemployment distribution; *Transfer T3*: a transfer to all people living in the highest tercile of the urban area unemployment distribution. $Tx/T1$ the percent of lifetime income a person born in tercile x of the urban area unemployment distribution loses compared to someone born in the first tercile; $Mobilityrate$: Decennial mobility rate between urban areas; r_x/r_1 Housing rent in tercile x compared to the first tercile of the unemployment distribution; Y: Aggregate income; *Mean* $\ln s$: Mean log of the peoples' amenities. Source: Model simulations.

not move to those areas because they cannot afford to pay for housing. Hence, suggestions have emerged to pay subsidies to young people in low-unemployment urban areas. Second, to improve welfare in high-unemployment urban areas, politicians discuss the possibility of paying transfers to high-unemployment urban areas. Using our model, we address how such policies affect welfare dispersion across urban areas at birth, mobility between urban areas, and labor market outcomes.

We simulate a 30% rent subsidy for all people younger than age 30 who live in the lowest unemployment urban area tercile. Column three in Table 8 shows that this policy increases welfare inequality at birth. This is to be expected, as the main beneficiary are those already born in the lowest unemployment urban area tercile. Maybe surprisingly at first sight, the policy has almost no impact on the mobility rate. In fact, we find that it has practically no impact on the number of under-30-year old living in the lowest unemployment urban areas. The reason is, again, that search frictions make it impractical for them to migrate, despite there being a potentially large gain. One can also see this effect by noting that the policy leaves aggregate output almost unchanged. Instead, the dominant effect of the policy is to increase housing demand by the young who already live in a low-unemployment urban area which increases housing rent dispersion across urban areas. The increase in housing rents in low-unemployment urban areas leads to elderly people moving out of these urban areas and, thereby, the subsidy actually decreases the size of low-unemployment urban areas. The elderly leaving low-unemployment urban areas mitigates the rise in housing rents 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. The subsidy amounts to 15% of the average housing expenditures. Column four in Table 8 shows that this policy reduces the welfare loss from being born in the highest unemployment urban area tercile by 0.9 percentage points of lifetime income. Critiques of place-based policies to high unemployment urban areas usually object to those on grounds that they reduce efficient reallocation of people away from those urban areas. However, we find that the reform has almost no effect on the mobility rate or aggregate output. The reason is, again, the prominent role search frictions play in our framework. That is, as shown in Figure 5(a), search frictions imply that there is a large share of high-surplus movers at young ages. A moderate subsidy for living in the highest-unemployment urban areas simply does not detain these from moving to low-unemployment urban areas when given the opportunity.

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

Labor market reforms Our framework identifies differences in labor markets across urban areas as a key driver behind the welfare losses of being born in a high-unemployment urban area. Currently, Spanish policymakers are discussing two types of labor market reforms that ought to benefit, in general, young people. Our framework allows us to evaluate whether these reforms would widen or narrow the welfare differences conditional on the birthplace.

The first such reform is enhancing job stability by reducing the number of temporary work contracts. We study here a reform that reduces the exogenous probabilities that a job ends, λ and λ_d, by half. A large labor literature studies whether such reforms increase the unemployment rate by reducing job finding rates or decrease the unemployment rate by reducing job destruction rates. We take no stance on this debate and simply reduce the job offer probability until the aggregate unemployment rate is unchanged. The column entitled "Job stability" in Table 9 displays the results. The reform benefits mostly those people born in low-unemployment urban areas, i.e., the between urban area welfare differences at birth increase. The reason is that more stable jobs make low-unemployment urban areas more attractive as those offer the highest returns to employment.

The table also highlights that increased job stability affects overall welfare through its effect of people sorting based on amenities; a mechanism not studied so far in the labor literature. More

Table 9: Labor market reforms

	Baseline	Job stability	Retirement
Welfare %			
T2/T1 age 20	9.77	10.18	9.79
T3/T1 age 20	17.03	18.61	17.09
T2/T1 age 45	11.12	11.51	11.55
T3/T1 age 45	16.82	18.24	17.42
T2/T1 age 68	2.17	0.83	2.01
T3/T1 age 68	2.90	0.97	2.62
Mobility rate %	9.62	7.36	9.56
r_2/r_1	0.88	0.85	0.87
r_3/r_1	0.83	0.80	0.81
Y	2.37	2.49	2.43
Mean $\ln s$ %	6.88	6.57	6.86

Notes: The table compares model outcomes from the baseline model to counterfactual simulations. *Job stability*: reduces the exogenous job destruction rate and job reallocation rate by half and recalibrates the job finding rate such that the unemployment rate is the same as in the baseline; *Retirement*: increases the retirement age by 2 years. $Tx/T1$ 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; $Mobilityrate$: Decennial mobility rate between urban areas; r_x/r_1 Housing rent in tercile x compared to the first tercile of the unemployment distribution; Y: Aggregate income; *Mean* $\ln s$: Mean log of the peoples' amenities. Source: Model simulations.

job stability implies that workers sort on average into better jobs which results in an increase in aggregate income. However, having a good job reduces the incentives to migrate to other urban areas, i.e., the mobility rate decreases markedly. A decrease in the mobility rate reduces the average idiosyncratic amenity level, i.e., people trade off better jobs for lower amenities. As a result, the welfare losses of being born in a high-unemployment urban area are strongly diminished when people have reached retirement.

The second such reform currently discussed is an increase in the retirement age, R. The column entitled "Retirement" simulates a 2-year increase in the retirement age. The reform has almost no effect on the between urban area welfare differences at birth. On the one hand, a longer working life makes the initial place of birth less determinant for lifetime income, thus, decreasing welfare dispersion at birth. On the other hand, the returns to work are highest in low-unemployment urban areas, thus, making the birthplace more important for peoples' lifetime incomes.

7 Conclusion

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

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

We find that policymakers concerned with welfare dispersion at birth may reduce the dispersion by paying transfers to individuals in high-unemployment urban areas. Importantly, resulting from the search friction, a moderate transfer has almost no effect on the outward mobility of young people toward low-unemployment urban areas or aggregate output. Policies that encourage people to move to low-unemployment urban areas mostly benefit those already born in those locations and fail to meaningfully increase mobility towards these more successful locations.

Ultimately, to increase mobility towards economically more successful urban areas, the government would need to address the spatial search friction. We are not aware of governmental programs that specifically target to overcome this friction within a country, e.g., increase information flows about moving opportunities. However, there exist cross-country programs to facilitate mobility such as the *EURES Targeted Mobility Scheme* that may carry valuable lessons.

A 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 $u(c, h, s) = \alpha^\alpha (1-\alpha)^{1-\alpha} y / \left(r_\ell^{(1-\alpha)}\right) + s$, 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:

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

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

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

Rewriting Equation (A.1) we have that

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

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

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

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

Therefore

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

Hence, ξ_ℓ satisfies

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

Notice that EW_ℓ comprises expectations about labor market realizations right when agents are born. The term $E_{0,\ell} \sum_{t=0}^{T} s_t$ varies across locations because of the interaction of migration decisions and the amenities realizations. Thus, we could think of 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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