Should Governments Subsidize Homeownership?

A Quantitative Analysis of Spatial Housing Policies

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Abstract

Should governments promote homeownership? Although such policies are widespread, their welfare implications are not straightforward. While subsidizing homeownership can overcome financial frictions, it can also reduce internal migration and increase the spatial misallocation of labor. To address this question, I build a dynamic spatial equilibrium model with coresidence, homeownership, internal migration, and savings decisions. Homeownership provides utility and insurance against aggregate rental price risk but reduces migration due to the transaction costs associated with selling the property. Migration decisions, in turn, affect homeownership. In particular, non-migrant workers can coreside with their parents, which allows them to save and buy a house earlier than migrants. I develop a new strategy to solve dynamic spatial models with aggregate uncertainty, which models agents' expectations about local endogenous prices and wages using lower-rank factors. The model is estimated for Spain and validated using quasi-experimental evidence from recent place-based homeownership subsidies. I find that mortgage interest deduction policies are welfare-increasing, have majority support, and reduce wealth inequality. However, they decrease internal migration and do not improve the spatial allocation of labor.

Keywords: Housing Policies; Coresidence; Homeownership; Internal Migration; Estimation of Dynamic Spatial Models.

JEL Classification: R13; R21; R23; R28.

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1 Introduction

It is very common for governments to incentivize homeownership through tax benefits and subsidies. While these policies may overcome financial frictions in the mortgage market, their welfare implications are not obvious. Subsidizing young homebuyers in low-productivity locations may tie them to areas with limited job opportunities, since homeowners are less likely to relocate in the future, partly due to the transaction costs associated with selling their property. On the other hand, providing subsidies in productive locations where housing prices are already high can contribute to price increases by further stimulating housing demand. The resulting higher housing costs restrict the ability of lower-income households to access labor markets that offer higher-paying and more stable employment opportunities, and can undermine the original policy objective.[1]

This paper investigates whether governments should promote homeownership and, if so, whether housing policies should be targeted to specific population groups and locations. To address these questions, I develop a dynamic spatial equilibrium model with coresidence, homeownership, internal migration, and saving decisions. Throughout their lifecycle, agents have a set of locations to choose from as their residence, each offering distinct housing prices, wages, and amenities. Additionally, once they make their location choice, they can either buy a house, rent one, or, if they currently live in their birthplace, coreside with their parents. Financial frictions in the credit market imply that agents who want to get a mortgage to become homeowners must first gather sufficient funds for an initial down-payment. Dynamic decisions are taken by forming expectations over local *endogenous* housing prices and wages, which fluctuate in response to multiple aggregate shocks. Moreover, agents face uninsurable idiosyncratic income and unemployment risk that varies across locations.

Solving dynamic spatial equilibrium models with aggregate shocks is a long-standing challenge in urban economics. Standard tools to solve macroeconomic models with aggregate uncertainty, e.g., Krusell and Smith (1998), cannot be easily applied to high-dimensional settings with geography, where aggregate price and productivity dynamics might differ across many locations. I develop a new strategy to solve this class of models by combining insights from Krusell and Smith (1998) and the econometrics literature on factor models (Bai 2009). In particular, I use lower-rank aggregate factors to model agents' expectations about endogenous prices and wages across space, thus reducing the problem's dimensionality. I estimate the agents' forecast rule outside the model, minimizing the computational burden. The forecast rule is accurate, as the prediction of the factor model aligns very closely with the observed data, which is matched in the benchmark equilibrium. In counterfactual exercises, in contrast, the agents guesses are updated to align with the new equilibrium prices and wages.

[1] A list of the main housing policies implemented in OECD countries is reviewed in OECD (2021). Beyond financial frictions in the mortgage market (Engelhardt 1996), rationales for these policies may include the existence of positive externalities associated with homeownership such as crime reduction (DiPasquale and Glaeser 1999, Disney et al. 2023), policy objectives to reduce wealth inequality (Kaas, Kocharkov and Preugschat 2019, OECD 2021), or the high share of homeowners among voters (Ortalo-Magné and Prat 2014).

In the model, the housing and location decisions are interconnected. Homeownership provides direct utility and insurance against rental price volatility, but makes it more costly to migrate, as agents need to sell their house before moving and bear the associated transaction cost. On the other hand, migration decisions themselves influence homeownership outcomes. Young workers who choose not to migrate from their birthplace (*natives*) may forgo potential labor market opportunities elsewhere, but have the option to coreside with their parents, saving on living expenses. This can allow them to accumulate resources for a down-payment and secure a mortgage earlier than *migrants*. Moreover, agents receive housing bequests with some probability over their lifecycle, and become homeowners in their birthplace if they are native while are forced to sell if they are migrants.

I estimate the model using data from Spain, a country with high homeownership, yet low rates of internal migration despite large disparities in income and unemployment risk across locations. Some parameters, including those governing income and unemployment transition probabilities, are estimated externally. The remaining parameters are calibrated to match key moments in the data, such as the lifecycle evolution of homeownership, coresidence, and migration rates, or the median wealth to income ratio.

I use quasi-experimental evidence from a recent policy that subsidized young homebuyers in small cities to validate the model. The place-based design of the policy allows me to find a proper control group in the data, i.e. young residents of slightly larger municipalities where the population was just above the threshold to qualify for the subsidy. In line with the model's prediction, I find that the policy increased homeownership and reduced out-migration rates: new homeowners decrease their annual migration by around 2 percentage points, a substantial effect given the average migration rate of 0.8%. When simulating the same place-based policy in the model, I obtain an untargeted migration elasticity with respect to changes in homeownership status that is very close to the one estimated in the data.

The model also perform well with respect to other non-targeted moments. These include the lifecycle homeownership gap between natives and migrants (around 10-20 percentage points, decreasing with age), the lifecycle migrant income premium (around 10 pp., higher for older workers), and the observed negative relationship between local homeownership rates and Gini wealth inequality across locations (-0.7 correlation). I find that the option to coreside with parents is the main reason behind the higher homeownership rate observed among natives. Coresidence offers natives a way to overcome frictions in the mortgage market, by allowing them to save on housing costs and accumulate funds for the down-payment earlier than migrants, despite earning less on average. Moreover, the negative relationship between local homeownership and wealth inequality is explained by the fact that a higher homeownership rate tends to disproportionally increase wealth at the bottom of the distribution.

Next, I use the model to study the welfare implications of an array of housing policies. Policies in the model are implemented in a fiscal neutral fashion, ensuring a balanced government budget through the adjustment of income taxes. Moreover, prices and wages in each location adjust in equilibrium in response to changes in local housing demand and migration induced by the policy. Agents' expectations about local endogenous prices and wages are consistent with their new stochastic steady state.

First, I consider mortgage interest deductions. This policy, which was in place in Spain until 2013, allows homeowners to annually deduct 1,300 euros in mortgage interests from their labor income taxes. As a result, I find that homeownership increases by 0.8 percentage points, which leads to a reduction in both wealth inequality (-0.95%) and internal migration (-0.86%). Overall welfare increases by 1.64% and the policy has majority support, although it does not improve the spatial allocation of labor. If mortgage interest deductions are only targeted to residents in productive urban locations, then spatial housing price dispersion and wealth inequality increase, and welfare gains are lower with respect to the untargeted policy (0.6%). Due to higher housing prices in equilibrium, homeownership does not increase. Targeting unproductive rural locations, instead, increases labor misallocation and barely affects welfare. In counterfactual simulations without aggregate shocks, the welfare gains from mortgage interest deductions are lower, since the homeownership's insurance value against rental price volatility disappears.

Second, I study the effect of a 3,000 euros rent subsidy to workers younger than 35 and earning less than a low-income threshold (19,500 euros annually). The policy, introduced in 2018, is found to decrease welfare by 1.34%, despite increasing internal migration and reducing the spatial misallocation of labor following the decrease in homeownership. Few agents are better off with the policy (15%), whereas all workers need to pay higher taxes to finance it. Targeting rent subsidies to productive urban or unproductive rural locations marginally mitigates the negative welfare effect of the policy. Support for the targeted policies, however, is even lower than for the untargeted rent subsidies.

Related Literature This paper contributes to the recent literature studying homeownership in the context of quantitative spatial models (Giannone et al. 2023, Greaney 2023, Oswald 2019). While prior works have emphasized the negative influence of homeownership on internal migration, I contribute by providing new causal evidence for this channel using a place-based housing policy. I also study the role of coresidence and housing bequests as novel mechanisms affecting homeownership through migration decisions. Finally, to the best of my knowledge, this is the first spatial equilibrium model analyzing the welfare and aggregate implications of housing policies, beyond relaxing land-use restrictions. The focus on the evaluation of policies in a model with geography, with a particular emphasis on their effects on the spatial allocation of labor, relates to works by Eeckhout and Guner (2017), Fajgelbaum et al. (2019), Ganong and Shoag (2017), and Hsieh and Moretti (2019).

A large macro literature, surveyed in Davis and Van Nieuwerburgh (2015) and Piazzesi and Schneider (2016), models homeownership in general equilibrium. Within this literature, Floetotto, Kirker and Stroebel (2016), Kaas et al. (2021) and Sommer and Sullivan (2018) study the welfare effects of housing policies, while Kaplan, Mitman and Violante (2020) focus on aggregate price fluctuations and their macroeconomic effects. None of these papers, however, model homeownership within a dynamic spatial equilibrium model with aggregate shocks.

Estimating this class of dynamic models with aggregate uncertainty has been a long-standing challenge in urban economics. For example, "dynamic hat algebra" strategies require the economy to approach a stationary equilibrium in which aggregate variables are constant over time, and hence do not allow for aggregate shocks in equilibrium (Artuç, Chaudhuri and McLaren 2010, Caliendo, Dvorkin and Parro 2019, Kleinman, Liu and Redding 2023). Other dynamic spatial equilibrium models (Desmet and Rossi-Hansberg 2014, Desmet, Nagy and Rossi-Hansberg 2018), instead, make the problem effectively static, because agents are either myopic or the future does not affect their optimal decisions. Finally, Bilal (2023) introduces the "Master Equation" representation of the economy, a concept developed in the mathematics mean field games literature (Cardaliaguet et al. 2019), which Bilal and Rossi-Hansberg (2023) use to study aggregate shocks in a dynamic spatial setting with first-order perturbations around the steady state. I develop a new tractable strategy to solve this class of models by combining insights from Krusell and Smith (1998) and the econometrics literature on factor models (Bai 2009). In particular, I use lower-rank aggregate factors to model agents' expectations about local endogenous prices and wages, which reduces the problem's dimensionality while keeping decisions dynamic and allowing for (potentially large) aggregate fluctuations.

This paper is also related to the literature on the influence of internal migration on life-cycle earnings (Bilal and Rossi-Hansberg 2021, De la Roca and Puga 2017, Díaz, Jáñez and Wellschmied 2023, Kennan and Walker 2011). I contribute by investigating new sources of home-biased preferences, namely coresidence and housing bequests. I then study housing policies that, by affecting housing tenure decisions, can change the incentives to stay in the birthplace, thus exerting a significant influence on labor earnings. Differently from Zerecero (2021), home-bias preferences are partly endogenous to the economic environment, and can thus be shaped by the policy-maker.[2] Residual exogenous preferences for the birthplace are estimated to be small, and counterfactual exercises reveal that the coresidence channel encompasses most of the benefits of staying enjoyed by Spanish natives.

Two related papers, Kaplan 2012 and Rosenzweig and Zhang 2019, study the link between coresidence with parents and individual savings behavior. These papers highlight two opposing channels. On the one hand, coresident children are negatively selected in terms of income and have lower precautionary savings motives. On the other hand, sharing of the housing public good during coresidence increases savings. I incorporate these channels and contribute to the literature by adding the coresidence decision into a spatial model where only natives can live with parents. This introduces a new trade-off, whereby coresidents must forgo the benefits of internal migration. Moreover, by also including the homeownership choice, which is subject to a down-payment requirement, I highlight another channel through which savings accrued during coresidence increase lifecycle wealth accumulation.

Finally, this paper connects to the literature examining the relationship between homeownership and wealth inequality (Kaas, Kocharkov and Preugschat 2019, Kindermann and Kohls 2018, Paz-Pardo 2023). I provide new evidence focusing on a single country exploiting

[2] For example, the option to coreside with parents becomes less attractive as housing prices decline.

variation across locations and, taking advantage of the panel dimension of my data, within households, rather than relying on cross-country comparisons. The literature emphasizes that widespread access to homeownership lifts the wealth of the income poor relatively more, and tends to decrease wealth inequality. I evaluate the impact of housing policies on wealth inequality in a model where the allocation of homeowners and renters across space affects the spatial dispersion of prices, which has an additional influence on the housing wealth distribution that can either reinforce or counteract the previous channel.

The remainder of the paper is organized as follows. In Section 2, I present the data and facts. Section 3 provides details on the model's economy. In Section 4, I describe how the model is estimated. Section 5 validates the model. In Section 6, I assess the welfare and distributional implications of housing policies. Finally, Section 7 concludes.

2 Facts on Homeownership and Internal Migration

In this section, I discuss the data and document some key facts about the relationship between homeownership and internal migration in Spain. First, people that become homeowners are less likely to migrate in the future. Second, I show that non-migrants are more likely to be homeowners, and explore the channels of coresidence with parents and housing bequests as candidate explanations for this homeownership gap.

2.1 Geography and Data

Geographic locations are defined as combinations of NUTS-1 regions in peninsular Spain and groups of municipalities within a region classified as either rural or urban.[3] Peninsular Spain comprises six distinct NUTS-1 regions, resulting in a total of 12 locations when combined with urban and rural areas within each region. A map of the locations and more information on their construction is given in Appendix Figure A1.

The empirical analysis focuses on individuals aged between 25 and 64 who are Spanish-born citizens and currently active, i.e. employed or unemployed. A *migrant* is defined as an individual currently residing in a Spanish location that is not their birthplace. A *native* refers to a person who currently resides in their birthplace. As such, migrants and natives should not be seen as fixed types, but rather as the result of choices that may change period by period. Finally, *coresidence* refers to the living arrangement of individuals residing with their parents.[4]

The ideal dataset would be a large panel with comprehensive information on five key dimensions: location (current and birthplace), homeownership, coresidence, income, and

[3] The NUTS classification is a hierarchical system developed by the European Union to divide its territory for statistical purposes. The NUTS-1 refers to major socio-economic regions, with average population size between 3 and 7 millions.

[4] The phenomenon of sharing a flat with a roommate or partner is not considered. Although such living arrangements can result in some housing cost savings due to economies of scale, living with parents often leads to substantially higher savings (Rosenzweig and Zhang 2019).

wealth. While no available dataset perfectly meets these criteria, I use four different data sources to measure specific features in the data. Appendix B gives more information on these four main and additional datasets, and assess their comparability. The main datasets used in the analysis are listed below:

1. Continuous Work History Sample (*Muestra Continua de Vidas Laborales*, or MCVL): This administrative dataset covers the years 2005-2019 and includes 5.25 million observations. It is an individual-level panel with data on location (current and birthplace), coresidence and income.

2. European Union Statistics on Income and Living Conditions (EU-SILC): This survey spans the years 2004-2019 and contains 74,000 Spanish households. It is a household-level panel that includes information on (current) location, homeownership, coresidence, household-level income, and household members' employment status.

3. Survey of Household Finances (*Encuesta Financiera de las Familias*, or EFF): This survey covers the years 2005-2020, comprises 15,000 households, and provides a household-level panel that covers all the important data dimensions. In particular, it is the only dataset with wealth information. However, it is relatively small and has restricted access to location information when the number of local observation is too low, which makes it unsuitable for some estimation procedures.[5]

4. Census of Population and Housing: This dataset includes 1.3 million observations for the year 2011 with detailed information on location, homeownership, and coresidence. However, it is a cross-sectional dataset that does not provide information on internal migration, income, or wealth.

2.2 People Are Less Likely to Migrate After Buying a House

Using a panel regression approach and a diff-in-diff analysis that leverages quasi-experimental variation from a place-based policy, I find that homeownership is associated with a lower probability of future internal migration. Both estimation strategies, which are conducted independently, reach very similar conclusions. The probability of moving reduces by around 1.9 percentage points for homeowners, a substantial effect given the average annual migration rate of 0.82%.

Along the lifecycle, homeownership tends to increase and internal migration rates tend to decline (see Appendix Figure A2). However, as shown in column (1) of Appendix Table A1, I find that homeowners are less likely to migrate than renters even after controlling for age and other observables. While I include year-region fixed-effects to account for local time trends, other unobservables may be biasing the migration elasticity. Therefore, I exploit the panel

[5] Moreover, the EFF does not have individual-level information on coresidents' income. The Bank of Spain, as the EFF data provider, has authorized remote access to restricted geographic information (current and birthplace) in compliance with privacy guidelines. The 2005-2006 wave lacks data on birthplace. Whenever this piece of data is needed for the analysis, I use the 2008-2020 version of the panel.

dimension of the EU-SILC by also including household fixed-effects. I show that household heads that become homeowners are less likely to migrate in the future: the probability of migrating decreases by approximately 1.92 percentage points for homeowners (see column 2 of Table A1), which is significant considering the average annual migration rate of 0.82%.[6] However, the presence of time-varying unobservable factors, not captured by year-region and household fixed-effects, may influence the estimated elasticity.

To identify the causal effect of homeownership on migration rates, I take advantage of the quasi-experimental nature of a 2018 policy that subsidized homeownership for individuals younger than 35 residing in municipalities with less than five thousands inhabitants. The place-based design of the policy allows me to deal with the omitted variable concern by finding a proper control group, i.e. young people belonging to the same age group but living in slightly larger municipalities, where the population was just above the threshold to qualify for the subsidy. Further details on the policy and the data are given in Section 5.1.

I plot in Figure 1 the event studies representing the impact of the policy on homeownership (Figure 1a) and migration rates (Figure 1b).[7] I find that the subsidy increased homeownership among the treated group (relative to the control), which I interpret as the first-stage effect of the policy, and decreased out-migration, which I interpret as the reduced-form effect. As can be seen in columns (1) and (2) of Appendix Table F5, the homeownership rate among the treated increased by 0.115 and the annual migration rate decreased by 0.002 on average.[8] When combining the first-stage and reduced-form estimates, I obtain a migration elasticity with respect to changes in homeownership of -1.83 pp., which is very close to the elasticity estimated with the panel regression.[9]

The absence of significant pre-trends in the event studies, as shown in Figures 1a and 1b, supports the conditional exogeneity assumption of the treatment. As additional exogeneity checks, I run two placebo event studies limiting the sample to individuals aged 37-40. These individuals, just above the age eligibility threshold, could not have accessed the subsidy in any post-treatment years of the event study. Consistent with the exclusion restrictions, the placebo treatment does not significantly affect the outcomes, as shown in Appendix Figures F15a and F15b. I also estimate the migration event study by focusing on young individuals *born* in smaller municipalities, using young people born in marginally larger municipalities as the control. This birthplace-based treatment, arguably more exogenous than one based on current residence, yields estimates comparable to the baseline regression (Appendix Figure F16). Further robustness checks are performed in Section 5.1.

The reduction in internal migration resulting from homeownership has important implications, as changes in location can substantially impact lifetime earnings. Using a migra-

[6]Homeownership is the single most important observable explaining internal migration rates. The only other statistically significant coefficients, although with a lower estimated magnitude, are those associated with age and college education.

[7]The event studies are estimated using specification (17) in Section 5.1

[8]These estimates come from the first-stage and reduced form difference-in-differences version of the event study regressions (17). More details on this diff-in-diff specification can be found in Appendix F.1.

[9]The panel elasticity is -1.92 when using the full set of controls (column 2 of Table A1) and -1.86 when only including the controls used in the event studies of Figure 1 (column 1 of Table 4).

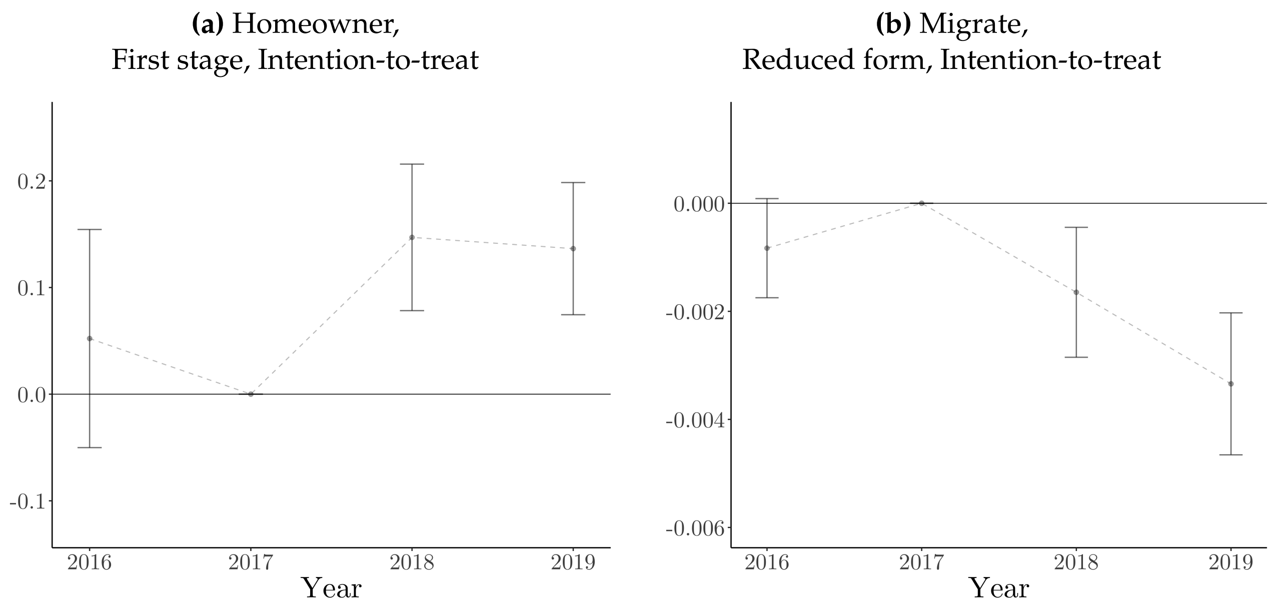


Figure 1: Treated: People aged less than 35 living in small cities (<10k inhabitants). Control group: same age living in slightly larger cities (10k-20k). Treatment year: 2018. Migration across regions (NUTS-1) and rural-urban areas (rural <10k, rural >10k or urban >40k). Included controls and fixed-effects: gender, age, age squared, region, and region-year. Clustered (locations) standard errors. Data: EPF, EPC, EVR 2016-2019.

tion event-study design, I show that internal migrants experience persistent income gains after moving, especially when college-educated and when moving to urban locations (see Appendix Figure A3). Additionally, internal migrants earn about 3% more than local observationally equivalent natives in the cross-section, as can be seen in column (1) of Appendix Table A2. These important data features on local income dynamics are reproduced in the model, where wages are determined locally and are endogenously higher in urban locations.

2.3 Natives Are More Likely to be Homeowners

One might expect that internal migrants, who earn on average higher incomes than observationally equivalent natives, would experience higher rates of homeownership. Yet, I document that natives are more likely to be homeowners than internal migrants. As can be seen in Figure 2a, the homeownership gap after controlling for observable characteristics and adjusting for cohort effects stands at 20 percentage points at younger ages and stabilizes at around 10 pp. along the lifecycle.[10,11]

There are three main candidate explanations for the native-migrant homeownership gap. First, migrants are more likely to change residence again in the future (see Appendix Figure A5), and so may be less willing to settle down and buy a house at younger ages. While self-selection of stayers into homeownership is expected to play a role, it is unlikely to fully account for the extent of the homeownership gap. Notably, the gap persists even at older

[10]The relatively high observed homeownership rate at younger ages should be interpreted taking into account that we are conditioning on individuals not living with parents (25% of the population at age 25).

[11]The reference group is the 1975 cohort. The procedure to adjust for cohort effects is discussed in Appendix A as a comment to Figure A4.

ages, despite migration events becoming relatively infrequent after age 40.

Second, natives are more likely to have inherited the house where they currently live (see Figure 2b). While migrants are equally likely to receive housing bequests as natives, they may be forced to sell the inherited property (and incur the associated transaction costs) if they do not wish to move to their parents' former residence. However, although housing bequests may partially explain the native-migrant homeownership gap in older age groups, when the observed difference in the share of people living in inherited houses is larger, they are unlikely to account for the gap among younger individuals.

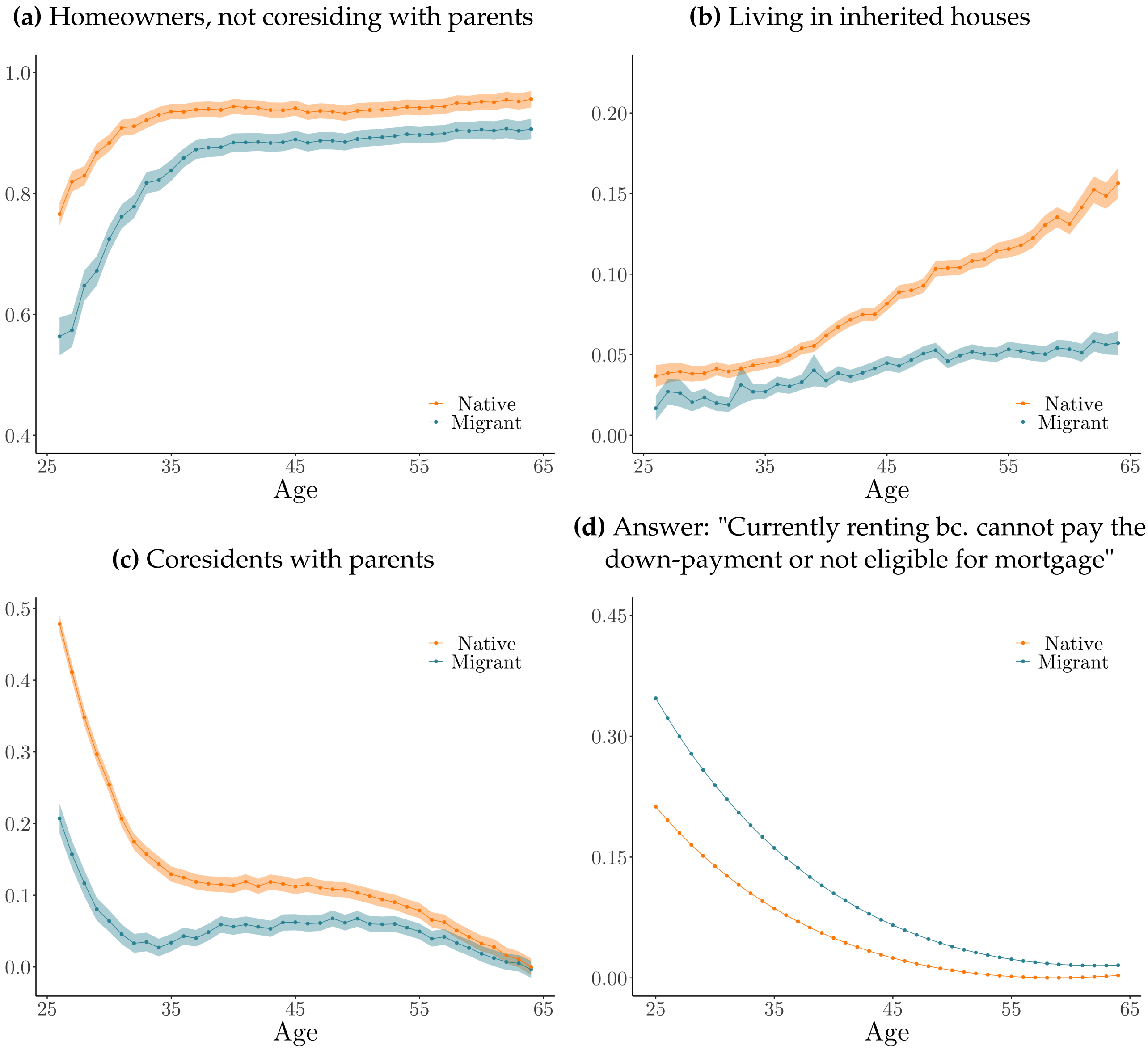


Figure 2: The figures plot age fixed-effects (panels **a** to **c**) and an age polynomial function (panel **d**). Other included fixed-effects are: location, gender, college-educated, married, parent, employed (reference group: male, non-college, single, not parent, employed). Panel **d**: share of surveyed people who say they are currently renting because "I am not eligible for a mortgage" or "I would not be able to afford the down-payment on the house". Confidence intervals at 95% level with heteroskedasticity-robust standard errors are plotted in panels **a** to **c**; not available in panel **d** due to privacy restrictions. Data: Census 2011 (panels **a** to **c**), EFF 2020 (panel **d**).

Finally, natives are more likely to live in the same location as their parents and have the option to coreside with them. As plotted in Figure 2c, the share of young native coresidents is substantially higher than among migrants.[12] By not having to pay housing costs during the coresidence period, it can be easier for natives to save for the mortgage down-payment and become homeowners earlier than migrants. Back-of-the-envelope calculations using expenditure data suggest that natives who are younger than 35 save, on average, between 2,300 and 3,000 euros more in annual housing costs than observationally equivalent migrants (see Appendix Figure A6). As explained in Appendix A, this is also in line with the evidence on the effect of coresidence on children's personal savings described in Rosenzweig and Zhang (2019). Lower income individuals are more likely to coreside with parents, as can be seen in column (3) of Appendix Table A2. Even after accounting for individual fixed-effects, together with age and other observables, there is a negative relationship between income and coresidence (see column (4) in Appendix Table A2). This suggests that the option to live with parents can insure against negative lifetime income shocks.

Survey data in the EFF also reveal that observationally equivalent migrants are less likely to be homeowners than natives due to financial frictions in the mortgage market. Indeed, even after controlling for observables, a higher share of them report being currently renting because they cannot afford to pay the down-payment or are not eligible for a mortgage, although they would like to get one. As can be seen in Figure 2d, this is especially true among young people. The fact that potential migrant homebuyers are more financially-constrained than natives is puzzling if one considers that, as previously noted, there exists a migrant wage premium in the data. To account for this fact, I investigate the role of coresidence in explaining the native-migrant homeownership gap in a spatial model where the homeownership decision is subject to a down-payment constraints and all natives, but only a fraction of migrants, have the option to coreside. The model also features the other two channels proposed as candidate explanations, i.e. the self-selection behavior of stayers into homeownership and the availability of housing bequests.

International Comparison The existence of a homeownership gap between observationally equivalent natives and internal migrants is a new fact documented in this paper. This fact is not unique to Spain: it is also observed in France, Italy, and the United States, as shown in panels (a), (c), and (e) of Appendix Figure A7. The choice of these countries is driven by the availability of Census data on coresidence, homeownership, and both current and birthplace locations within OECD countries, together with data on the observables used as controls. More details on the definition of locations in each country can be found in Appendix A.

As can be seen in panels (b), (d), and (f) of Appendix Figure A7, natives in each of these countries also exhibit a higher propensity to coreside with parents than migrants do. This suggests that, like in Spain, coresidence can be an important driver behind the observed homeownership gap between natives and migrants. Coresidence in France and the United States is less prevalent than in Italy or Spain. Nevertheless, it remains a significant phe-

[12] Some migrants live in the same location as their parents and can coreside with them, often because the entire family migrated when the individual was under 25 years of age. These individuals effectively behave as natives in the model, under the assumption that they treat the location where they grew up as their birthplace. Refer to Section 4.1.3 and Appendix E.4.4 for further discussion.

nomenon among young people, interesting around 15% of individuals aged between 25 and 35 in the U.S. and France (the share is around 40% in Italy and Spain).

2.4 Summary of Facts

Two main facts have been presented. First, people that become homeowners are less likely to migrate in the future, and migration, in turn, positively affects labor earnings. Second, natives are more likely to be homeowners than internal migrants, despite earning lower incomes on average. Three potential explanations emerge for the second fact. First, migrants might relocate again, making them more hesitant to purchase homes. Second, natives have higher chances to live in inherited houses. Finally, natives often live with parents, thereby saving resources which can be directed towards the mortgage down-payment and homeownership. These mechanisms are featured and analyzed in the model.

3 A Spatial Model With Coresidence and Homeownership

This section describes the theoretical framework, a spatial lifecycle model with coresidence, homeownership, migration, and saving decisions. Every period, agents have a set of locations to choose from as their residence, each offering distinct housing prices and wages, which are determined in equilibrium, and fixed amenities. Additionally, they can either buy a house, rent one, or, if they are native, coreside with their parents. Financial frictions in the credit market imply that individuals who need a mortgage to become homeowners must first accumulate enough savings for an initial down-payment. Moreover, agents who buy or sell a house incur some transaction costs.

Individual decisions are interconnected. Homeownership makes it endogenously more costly to migrate, as agents need to sell their house before moving and bear the associated transaction cost, and migrating away from birth location does not allow to coreside with parents. The decisions are also dynamic, and agents form expectations about the future taking into account uninsurable local unemployment risk and labor income risk, as well as aggregate shocks to local *endogenous* housing prices and wages.

3.1 Environment

Time is discrete and denoted by t, while age is denoted by $j \in \{1, ..., J\}$. The period of the model is one year. The economy is populated by a unit-mass of finitely-lived agents that can live in one of D location, indexed by $d \in \{1, ..., D\}$. Agents also choose their housing status h and a consumption good c, which is freely tradable across locations and acts as the numeraire. There exist aggregate shocks that affect local housing prices and wages, and labor income and employment status follow individual-levels stochastic processes. Housing and labor markets are competitive and clear in each location and period. The interest rate r on liquid assets, instead, is fixed and exogenously given. Finally, the government taxes labor income, pays means-tested transfers, and implements housing policies, all while balancing the budget in each period.

3.2 Individual Problem

State Vector Agents are born with four fixed types: birthplace location d_0, education level $e \in \{N, E\}$ (non-college or college), migration type $\tau \in \{1, 2\}$ (non-stayer or stayer), and individual-level fixed productivity θ_e, allowed to vary by education. Age j and time t evolve deterministically over the lifecycle. However, employment status l_{edj} (unemployed or employed) and individual-level persistent productivity z_{ej} change stochastically. They each follow an exogenous process that varies by education and, in the case of employment status, location. Finally, choices in the previous period – assets a_{j-1}, location d_{j-1}, and housing status h_{j-1} (which are drawn stochastically in the first period of the model) – together with prices and wages in each location ($\boldsymbol{p_{dt}}, \boldsymbol{w_{edt}}$), are also part of the individual state vector, denoted by $\boldsymbol{x_j} = (j, d_0, e, \tau, \theta_e, z_{ej}, l_{edj}, a_{j-1}, d_{j-1}, h_{j-1}, \boldsymbol{p_{dt}}, \boldsymbol{w_{edt}})$.

Choices In each period, agents are faced with three distinct choices. First, they make consumption decisions, which determine their assets a_j. Simultaneously, they choose their housing tenure h_j, which, in case they are natives, can either be coresident ($h_j = 0$), renter ($h_j = 1$), or homeowner ($h_j = 2$). In case they are migrants, however, their choices are limited to renting or buying, i.e. $h_j \in \{1, 2\}$. Finally, given housing and consumption decisions in each possible location, agents choose their preferred location d_j, which may or may not align with their birthplace d_0. This choice determines whether the agent is classified as native ($d_j = d_0$) or as migrant ($d_j \neq d_0$).

Financial Frictions Agents that require a mortgage to buy a house must pay the initial down-payment, a fraction χ of the housing value, up front. They can finance the rest with a mortgage with a linear repayment schedule and fixed interest rate r^m. Moreover, individuals who buy or sell a house incur some transaction costs, which are fixed fractions ϕ_b and ϕ_s of the housing value.

Utility Function Within period utility in location d_j is given by

$$\begin{aligned} u(c_j, h_j, d_j, \boldsymbol{x_j}) = \frac{c_j^{1-\gamma}}{1-\gamma} &+ \overbrace{\eta_1 \mathbb{1}\{h_j = 2\}}^{\text{Utility from being homeowner}} - \overbrace{\xi_j \mathbb{1}\{h_j = 0\}}^{\text{Disutility from being coresident}} \\ &- \underbrace{\delta_{e\tau j} \mathbb{1}\{d_j \neq d_{j-1}\}}_{\text{Moving costs}} + \underbrace{\eta_2 \mathbb{1}\{d_j = d_0\}}_{\text{Home-bias}} + \underbrace{A_{d_j}}_{\text{Amenities}} \end{aligned}$$

where γ is the degree of relative risk aversion. Agents value city amenities and derive additional utility from living in their birthplace. This allows for an additional home-bias channel (Zerecero 2021), that complements the ones introduced in this paper, namely coresidence and easier access to bequests for natives. Moreover, agents experience direct utility from homeownership, which captures the psychological sense of stability that comes with owning and maintaining their own house. This assumption is widely made in the literature to explain the observed high rate of homeownership.[13]

The disutility from coresiding with parents, a living arrangement that is only available for natives, captures lack of independence (Kaplan 2012) and is given by

$$\xi_j = \xi_0 + \xi_1 j.$$

Moving costs, taking place when the chosen location is different from the one in the previous period, are given by

$$\delta_{e\tau j} = \delta_0 + \delta_e \mathbb{1}\{e = E\} + \delta_\tau \mathbb{1}\{\tau = 2\} + \delta_1 j + \delta_2 \log(j).$$

The two utility costs are allowed to vary by age, to capture the fact that both migration and coresidence decrease steeply over the lifecycle (see Appendix Figure A2). Migration costs can also vary by education e, since college-educated people are more likely to migrate in the data (see column (2) in Appendix Table A1). Finally, migration costs are allowed to vary by τ (stayer type), since a fraction of the population may have prohibitively high migration costs in all states (Kennan and Walker 2011).

Dynamic Problem The decision process in the model is dynamic. Agents form Markovian expectations over aggregate shocks to local prices and wages ($\boldsymbol{p_t}, \boldsymbol{w_{et}}$) and over individual transition probabilities for employment status and persistent productivity (l_{edj}, z_{ej}). They also take into account that they may receive a housing bequest with exogenous probability $\pi^b_{ed_0 j}$, varying by education, birthplace and age.

The value function associated with optimal housing status h_j and consumption c_j choice in location d_j is given by

$$v_j(\boldsymbol{x_j}, d_j) = \max_{c_j > 0, h_j} \left\{ u(c_j, h_j, d_j, \boldsymbol{x_j}) + \beta \mathbb{E}_{l_{edj+1}, z_{ej+1}, \pi^b_{ed_0 j+1}, \boldsymbol{p_{t+1}}, \boldsymbol{w_{et+1}}} \left[\overline{v}_{j+1}(\boldsymbol{x_{j+1}}) | l_{edj}, z_{ej}, \boldsymbol{p_t}, \boldsymbol{w_{et}} \right] \right\}. \tag{1}$$

The migration choice is made by maximizing $v_j(\boldsymbol{x_j}, d_j)$ across locations,

$$V_j(\boldsymbol{x_j}, \varepsilon_j) = \max_{d_j \in D} \left\{ v_j(\boldsymbol{x_j}, d_j) + \varepsilon_{d_j} \right\}. \tag{2}$$

The expected value function entering the continuation value of $v_j(\boldsymbol{x_j}, d_j)$ is given by

$$\overline{v}_{j+1}(\boldsymbol{x_{j+1}}) = \mathbb{E}_{\varepsilon_{j+1}} V_{j+1}(\boldsymbol{x_{j+1}}, \varepsilon_{j+1}),$$

where $\mathbb{E}_{\varepsilon_j}$ denotes the expectation with respect to the distribution of the vector ε_j with components ε_{d_j}, each measuring idiosyncratic preferences at age j for location d. I assume that ε_j is drawn each period from the Standard Gumbel distribution. Then, following McFadden

[13] See for example Kaas et al. (2021), Oswald (2019), Paz-Pardo (2023). Housing is the only non-tradable good in the model. This assumption is supported by empirical evidence highlighting that housing is the key driver behind local price differences across cities, both in Spain (Forte-Campos, Moral-Benito and Quintana 2021) and in the U.S. (Moretti 2013).

(1973) and Rust (1987), the expected value function admits the closed-form solution

$$\overline{v}_{j+1}(\boldsymbol{x_{j+1}}) = \overline{\gamma} + \log\left(\sum_{d_{j+1}=1}^{D} \exp(v_{j+1}(\boldsymbol{x_{j+1}}, d_{j+1}))\right),$$

where $\overline{\gamma}$ is the Euler-Mascheroni constant.

Finally, agents receive a one-time utility from their homeownership status and accumulated liquid and housing wealth when they exit the model at age J:[14]

$$V_J(a_J, h_J, d_J) = \omega_1 \frac{(a_J + p_{dt}\overline{h}_{deh}\mathbb{1}\{h_J = 2\})^{1-\gamma}}{1-\gamma} + \omega_2 \mathbb{1}\{h_J = 2\}$$

Budget Constraint: Coresidents and Renters Agents entering the period as coresidents or renters can decide to become (or remain) renters or, if they are native, coresidents. In case they choose to rent, their budget constraint is given by

$$a_{j+1} = (1+r)(a_j + y_{edjt} - c_j - \overbrace{\kappa_d p_{dt}\overline{h}_{deh}}^{\text{Rent}}) \geq \mathbf{0},$$

where r is the exogenous interest rate for liquid assets, y_{edjt} is labor income (after tax and transfers), p_{dt} is housing price per square meter, κ_d is the rent to price ratio in location d, and $\overline{h}_{deh}$ is the fixed housing quantity (in square meters) demanded by renters with education e living in d. The budget constraint of agents that decide to coreside, instead, is given by

$$a_{j+1} = (1+r)(a_j + y_{edjt} - c_j) \geq \mathbf{0}.$$

Therefore, coresidents bear no housing costs.[15] Notice that renters and coresidents cannot borrow.

Alternatively, agents with enough cash on hand can become homeowners. To buy a house, agents need to pay the sunk transaction cost of buying $\phi_b p_{dt}\overline{h}_{deh}$ and at least the down-payment requirement $\chi p_{dt}\overline{h}_{deh}$ up front, and can finance the rest, up to $(1-\chi)p_{dt}\overline{h}_{deh}$, with mortgage debt.[16] The mortgage has fixed interest rate r^h and maturity $J - j$:

$$a_{j+1} = (1 + r\mathbb{1}_{a_j \geq 0} + r^h\mathbb{1}_{a_j<0})(a_j + y_{edjt} - c_j - (1 + \underbrace{\phi_b}_{\substack{\text{Transaction cost}\\\text{of buying}}})p_{dt}\overline{h}_{deh})$$

[14]The inclusion of this terminal value condition at age J, which corresponds to 64 years old in the data, accounts for the importance of wealth and homeownership during retirement and for bequest motives. This is needed to match the observed (slow) dissaving behavior of older agents (Oswald 2019).

[15]The evidence discussed in Appendix A as a comment to Figure A6 is consistent with this assumption (Rosenzweig and Zhang 2019).

[16]Fixed housing quantity $\overline{h}_{deh}$ for homeowners is allowed to be different from renters', to capture the fact that the size of homeowners' dwellings is typically larger. It also changes by location and education, as college-educated individuals and rural residents typically live in larger houses.

$$
\begin{aligned}
&a_{j+1} \geq -(1-\chi)p_{dt}\overline{h}_{deh} \\
&a_{j'+1} \geq a_{j'}\left(\frac{(J-1)-j'}{J-j'}\right)\mathbb{1}_{a_{j'}<0} \text{ for } j<j'<J, \\
&a_{J+1} \geq 0.
\end{aligned}
$$

In each future period in which they remain homeowners, agents need to repay their mortgage debt following a linear repayment schedule with prepayment option, which means that each year they have the option to pay more than what they are due to extinguish their debt faster. In case they exercise the prepayment option at age $j' > j$, the mortgage debt maturity automatically changes to $J - j'$, and the linear repayment schedule adjusts with it. This formulation of the budget constraint allows to generate realistic repayment schedules without adding further state variables.[17] Agents cannot exit the model with debt and cannot default on their mortgage.[18]

Budget Constraint: Homeowners Agents entering the period as homeowner can either keep or sell their property. In case they decide to remain homeowners, they don't bear direct housing costs but need to repay their mortgage:

$$
\begin{aligned}
&a_{j+1} = (1 + r\mathbb{1}_{a_j\geq 0} + r^h\mathbb{1}_{a_j<0})(a_j + y_{edjt} - c_j) \\
&a_{j+1} \geq a_j\left(\frac{(J-1)-j}{J-j}\right)\mathbb{1}_{a_j<0} \text{ for } j<J, \\
&a_{J+1} \geq 0.
\end{aligned}
$$

If instead they sell their house, they bear the associated transaction costs $\phi_s p_{dt}\overline{h}_{deh}$ and receive the remaining fraction of the housing value net of the mortgage debt in cash.[19] In case they decide to rent, the budget constraint is given by

$$
a_{j+1} = (1 + r\mathbb{1}_{a_j\geq 0} + r^h\mathbb{1}_{a_j<0})(a_j + y_{edjt} - c_j + (1 - \phi_s - \kappa_d)p_{dt}\overline{h}_{deh}) \geq \mathbf{0}.
$$

If instead they decide to coreside, it is given by

$$
a_{j+1} = (1 + r\mathbb{1}_{a_j\geq 0} + r^h\mathbb{1}_{a_j<0})(a_j + y_{edjt} - c_j + (1 - \overbrace{\phi_s}^{\substack{\text{Transaction cost}\\ \text{of selling}}})p_{dt}\overline{h}_{deh}) \geq \mathbf{0}.
$$

[17] Without the linear repayment schedule, mortgage debt in the model does not decrease as fast over the lifecycle as in the data.

[18] Differently from other countries, defaulting on mortgage debt is considered illegal in Spain. Individuals who are unable to repay their (potentially restructured) mortgage debt can, as a last resort, cancel their debt by transferring their house to the creditor bank through a process known as *dación en pago*. However, it is worth noting that this circumstance is extremely rare in practice, affecting only 1,000 to 2,000 properties annually between 2015 and 2019 (Source: *Registradores de España*). In the estimated model, the yearly evolution of housing prices is such that no agent finds themselves underwater with their mortgage debt. In the event that individuals are unable to repay the debt, they always have the option to sell their house and retain positive assets (see also footnote 19).

[19] The housing price stochastic process and the model parameters are such that in no case it happens that $a_j + y_{edjt} + (1 - \phi_s - \kappa_d)p_{dt}\overline{h}_{deh} \leq 0$.

Budget Constraint: Movers Timing in the model is such that, for agents who decide to migrate, labor income is gained from the previous location and housing costs are paid in the new one. Homeowners who want to move are forced to sell, which endogenously reduces their migration rates. This arises from homeowners' reluctance to pay the transaction costs associated with selling and from the possibility of incurring capital losses. Renters and coresidents don't suffer these costs, and are then more likely to migrate. The budget constraints for movers, omitted here for brevity, are reported in Appendix C.4.

Labor Income In each period, agents can either be unemployed ($l_{edj} = 1$) or employed ($l_{edj} = 2$). The Markovian probability of changing employment status varies by education, location and age. Unemployed people receive constant benefits b, while employed workers are paid for each efficiency unit of labor that they supply exogenously,

$$\varpi_{ed\tau j} = \exp(\theta_e + z_{ej} + \Upsilon_{edj}).$$

The labor endowment is a function of fixed productivity θ_e, deterministic age-profile Υ_{edj}, and persistent shock z_{ej}. I assume that θ_e is drawn from an education-specific normal distribution and that z_{ej} follows a first-order autoregressive process with persistence parameter ϱ_e. The gross labor income paid to employed workers is given by the product of wage per skill $w_{edt}^{\vartheta_{ed}}$ and the labor endowment ϖ_{edj},

$$\tilde{y}_{edjt} = w_{edt}^{\vartheta_{ed}} \varpi_{edj},$$

and varies across types, period, and locations. Endogenous wages w_{edt} vary in response to aggregate shocks, and affect income through the loading coefficient ϑ_{ed}.[20] Therefore, gross log labor income is given by:

$$\ln \tilde{y}_{edjt} = \overbrace{\vartheta_{ed} \ln w_{edt}}^{\text{Local wage process}} + \theta_e + \Upsilon_{edj} + z_{ej}, \tag{3}$$

$$z_{ej} = \varrho_e z_{ej-1} + \upsilon_{ej-1}, \tag{4}$$

where

$$\theta_e \sim N(0, \sigma_{\theta e}^2), \quad \upsilon_e \sim N(0, \sigma_{\upsilon e}^2), \quad \upsilon_{e0} = 0, \quad z_{e0} = 0$$

Housing Prices The square meter price of housing p_{dt} also changes across locations and over time. The evolution of prices is allowed to be correlated with changes in local wages w_{edt} within locations. More details are given in Section 4.2.2 below. Housing rents also evolve over time and are a fixed, location-specific fraction of housing prices, $q_{dt} = \kappa_d p_{dt}$.

Housing Bequests Each period, agents may receive a housing bequest with probability $\pi_{ed_0 j}^b$. This probability can vary by education group, birthplace, and age. If agents who inherit already own a home, they must sell the inherited property. Likewise, if they inherit while

[20] Although local labor markets are perfectly competitive, ϑ_{ed} can be seen as a reduced-form way to capture imperfect wage pass-through of labor productivity, which may vary by education and location. For example, there is evidence that labor market power varies across cities and workers' education group (see Hirsch et al. 2022 for Germany and Luccioletti 2022 for Spain).

living outside their birthplace, they are obliged to sell. This is based on the assumption that the inherited property is located in their birthplace, where their parents previously resided.

Upon selling, agents receive the value of the house $p_{d_0t}\overline{h}_{d_0eh}$ after subtracting transaction costs. This amount is then further divided by a factor of κ^b. This factor represents the average number of siblings with whom the inheritance is split. Hence, the presence of housing bequests increases the incentives to delay purchasing a house and to remain in, or move to, the birthplace. Appendix C.5 contains a version of the maximization problem that makes the role of housing bequests explicit.

3.3 Labor and Housing Markets

The labor and housing markets are competitive and clear in equilibrium in each location d and period t. There is a representative firm in each location that employs college and non-college workers to produce the consumption good. Additionally, a representative construction firm operates in each location and produces housing units, together with a representative real-estate firm that rents out housing units.

The production function of the firm operating in location d is given by

$$Y_{dt} = \Theta_{dt}(\zeta_{dt} L_{Ndt}^{\rho} + (1 - \zeta_{dt}) L_{Edt}^{\rho})^{1/\rho},$$

where Θ_{dt} is the local overall productivity, ζ_{dt} is the local skill-specific productivity, ρ is the CES production function parameter, and L_{edt} is total efficiency units supplied in location d by education group e. Parameters Θ_{dt} and ζ_{dt} are affected by aggregate shocks, as detailed in Section 4.2. The first-order conditions determine wages w_{edt} of college and non-college workers:

$$\widehat{w}_{edt} = \Theta_{dt}(\zeta_{dt}\mathbb{1}_N + (1 - \zeta_{dt})\mathbb{1}_E)(\zeta_{dt} L_{Ndt}^{\rho} + (1 - \zeta_{dt}) L_{Edt}^{\rho})^{\frac{1-\rho}{\rho}} L_{edt}^{\rho - 1},$$

where $\mathbb{1}_E$ and $\mathbb{1}_N$ are indicator functions for the college and non-college first-order conditions, respectively.

Additionally, the inverse housing supply function is given by

$$p_{dt} = \Omega_{dt} H_{dt}^{\psi},$$

where H_{dt} denotes the housing supply stock. This function is obtained from the first-order condition of a representative construction firm that operates with a convex cost technology, as detailed in Appendix C.2. The convexity of the cost function is a reduced-form way to capture the scarcity of buildable land and possible inputs and regulation constraints.

Key parameters are the intercept Ω_{dt}, which captures construction costs that vary across locations and are affected by aggregate shocks (see Section 4.2), and the inverse housing supply elasticity ψ, which reflects the responsiveness of housing prices to changes in the housing stock. A higher ψ means that prices react more to changes in the housing supply, for instance due to the construction restrictions coming from land unavailability or regulations.

Finally, the location-specific price-to-rent ratio, κ_d, is micro-founded in Appendix C.2 as the zero-profit conditions of representative real-estate firms operating in each location.

3.4 Government

The government generates revenue by taxing labor income and provides means-tested transfers, unemployment benefits, and other public goods $\overline{G}_t$. Taxes and transfers are functions $T_t(\cdot)$ and $G_t^g(\cdot)$ of gross labor income $\tilde{y}_{edjt}$. I assume that $\overline{G}_t$ does not affect individuals' utility. In counterfactual exercises, the government additionally implements housing policies with associated expenditure G_t^p, all while keeping the budget balanced.

4 Estimation

This section presents the estimation procedure. Some of the model parameters are estimated with external data sources, whereas the rest are internally calibrated to ensure that a selection of simulated moments align with their data counterparts. These targeted moments include homeownership, coresidence, and migration rates over the lifecycle.

Moreover, I present a strategy to solve the dynamic spatial equilibrium model in the presence of aggregate shocks. In particular, I use a low-dimensional factor model structure to model agents' forecast rules about future local endogenous prices and wages. The forecast rule accurately predicts both benchmark and counterfactual equilibrium prices.

4.1 Model Inputs

This section describes the inputs which are estimated externally, using the sample restrictions described in Section 2.1. People live for 40 years ($J = 40$), from 25 to 64 years old, in one of 12 locations ($D = 12$). The number of locations is kept relatively low for computational reasons.[21]

The model's exogenous inputs include the parameters affecting labor income (unemployment and income risk, taxes and transfers) and the probability of receiving housing bequests. Some additional inputs, such as the exogenous interest rates and the down-payment requirement, are also directly measured from the data. A few remaining parameters, including the inverse housing supply elasticity and transaction costs, are taken from the literature.

4.1.1 Probability of Being Unemployed, Income Process, Taxes and Transfers

As is standard in the literature, a linear regression framework is used to estimate the transition probabilities between employment statuses, while the income process parameters are estimated with a GMM procedure. Moreover, the tax and transfer functions that I assume are also standard choices in the literature.

[21] Doubling the number of locations would quadruple the state space: the model would require solving at 1.3 billion points, up from the current 325 million, thus substantially increasing the computational burden.

Employment Status In each period, agents can either be unemployed ($l_{edj} = 1$) or employed ($l_{edj} = 2$). The Markovian probability of changing employment status varies by education, location and age, and is estimated by running the linear probability regression models:

$$\overbrace{\mathbb{1}_{l_{edj+1}=1}}^{\text{Unemployed next period}} = \alpha_t + \alpha_e + \alpha_d + \alpha_1 j + \alpha_2 \log(j)$$
$$\underbrace{\mathbb{1}_{l_{edj+1}=2}}_{\text{Employed next period}} = \beta_t + \beta_e + \beta_d + \beta_1 j + \beta_2 \log(j).$$

The regressions are separately estimated for employed and unemployed individuals by exploiting the yearly panel dimension of the EU-SILC individual-level dataset, which includes both coresidents and non-coresidents, and sum to one by construction. Education and location fixed-effects, $\alpha_e, \beta_e, \alpha_d$, and β_d, together with age coefficients $\alpha_1, \beta_1, \alpha_2$, and β_2, are used to estimate the Markovian transition probabilities, whereas year fixed-effects α_t and β_t are included to control for aggregate shocks.

The lifecycle transition probabilities from employment to unemployment status across education groups and locations are plotted in Figure 3a. The east urban location is emphasized for reference, while the semi-transparent lines represent other Spanish locations. The probability of being unemployed varies largely across education groups and locations. The unemployment risk is lower for the college-educated and in urban locations within the same NUTS-1 region. There is also an important lifecycle dimension, as unemployment risk tends to be higher at younger ages and decreases over time.

The opposite transition, from unemployed to employed, is plotted in Appendix Figure E11. Re-employment probabilities decrease sharply at older ages, so that the unemployment state becomes more persistent over the lifecycle. Similarly to the probability of becoming unemployed, there is substantial variation across locations and educational groups.

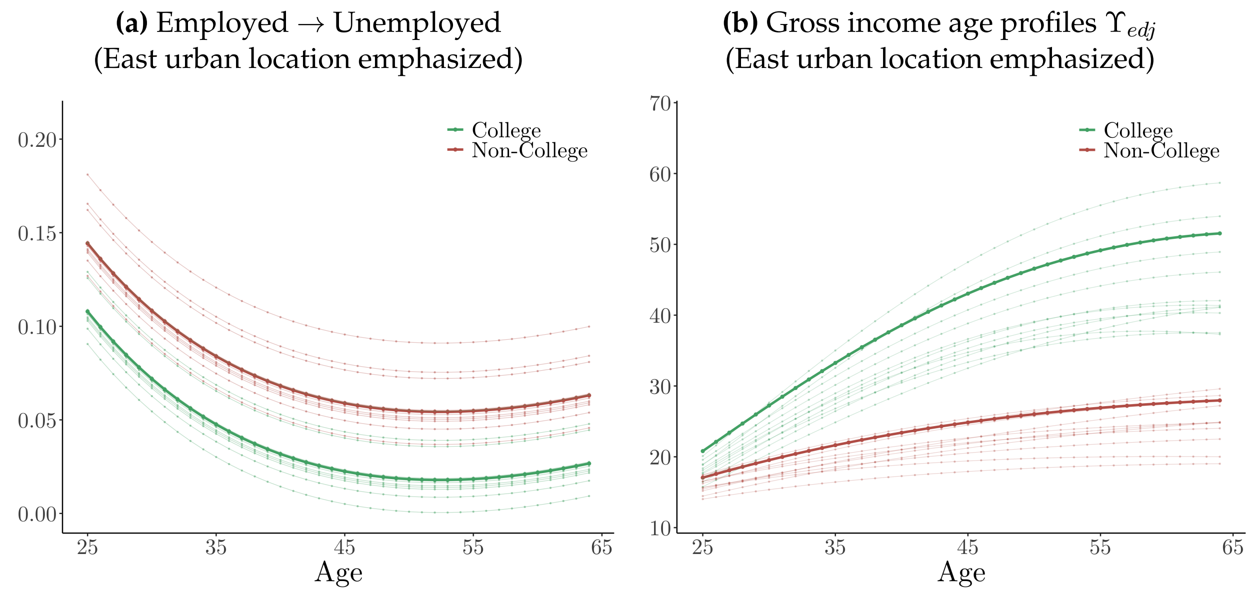


Figure 3: The figures plot age polynomial functions for different locations and education groups (East urban location is emphasized). Data: EU-SILC 2004-2019 (panel **a**), MCVL 2005-2019 (panel **b**).

Income Process In order to estimate the income process of equations (3) and (4), I first residualize gross annual labor income from the observed quantities in equation (3). To do so, I assume that location- and education-specific age profiles are given by

$$\Upsilon_{edj} = \theta_{1ed} j + \theta_{2ed} \log(j)$$

and estimate regression

$$\ln \tilde{y}_{edjt} = \vartheta_{ed} \ln w_{edt} + \theta_{1ed} j + \theta_{2ed} \log(j) + \beta' X_t + u_{ej} \tag{5}$$

using the administrative MCVL data. The additional controls X_t, not present in equation (3), include year and gender fixed-effects. Local wages w_{edt} are measured as the average gross hourly wages by education, location, and year – a quantity that, consistently, is also perfectly matched in equilibrium in the model (see Section 4.2.3). The estimated gross income age profiles Υ_{edj} are plotted in Figure 3b. There are large variations in income lifecycle profiles across location and education groups, with urban locations within NUTS-1 regions and college workers experiencing a substantial premium over rural locations and the non-college educated.

Given regression (5) estimates, residualized labor income is given by

$$\hat{u}_{ej} = \ln \tilde{y}_{edjt} - (\hat{\vartheta}_{ed} \ln w_{edt} + \hat{\theta}_{1ed} j + \hat{\theta}_{2ed} \log(j) + \hat{\beta}' X_t). \tag{6}$$

The income process parameters include the persistence parameters ϱ_N and ϱ_E, the standard deviations of the persistent shocks' innovations σ_{υ_N} and σ_{υ_E}, and the standard deviations of the fixed-effects σ_{θ_N} and σ_{θ_E}. Following Storesletten, Telmer and Yaron (2004), these parameters are estimated by GMM using as population moments the cross-sectional variance of the residualized log income u_{ej} by age. As can be seen in Appendix Figures E12a and E12b, the increasing patterns of earnings inequality over the lifecycle for both college and non-college workers are well captured by the model. More details on the estimation procedure are given in Appendix E.2.

Taxes Given mean gross income $\overline{y}$, the average tax rate at gross income level $\tilde{y}_{edjt}$ is given by:

$$T_t(\tilde{y}_{edjt}) = \max\left\{0, 1 - \varsigma_0 \left(\frac{\tilde{y}_{edjt}}{\overline{y}}\right)^{-\varsigma_1}\right\}.$$

This formulation of the income tax function is standard in the literature (Bénabou 2002, Guner, Lopez-Daneri and Ventura 2016). The parameter ς_0 determines the average tax level, while ς_1 determines the progressivity.

Transfers Following Guner, Kaya and Sánchez-Marcos (2023), means-tested transfers are assumed to change linearly with multiples of mean labor income according to the function:

$$G^g(\tilde{y}_{edjt}) = \max\left\{0, g_1 - g_2 \left(\frac{\tilde{y}_{edjt}}{\overline{y}}\right)\right\}.$$

Parameters g_1 and g_2 are estimated with a linear regression using EU-SILC data. The transfers decline as workers' earnings increase and become zero at around 2.5 times the mean labor income.

4.1.2 Probability of Receiving Housing Bequests

In order to estimate the probability of receiving a housing bequest next period $\pi^b_{ed_0j}$, I turn to the EFF data. This survey asks if respondents have ever inherited one or multiple properties in their lifetime. From this, as detailed in Appendix E.3, we can easily calculate yearly probabilities that align with the cumulative age distribution computed from the data.

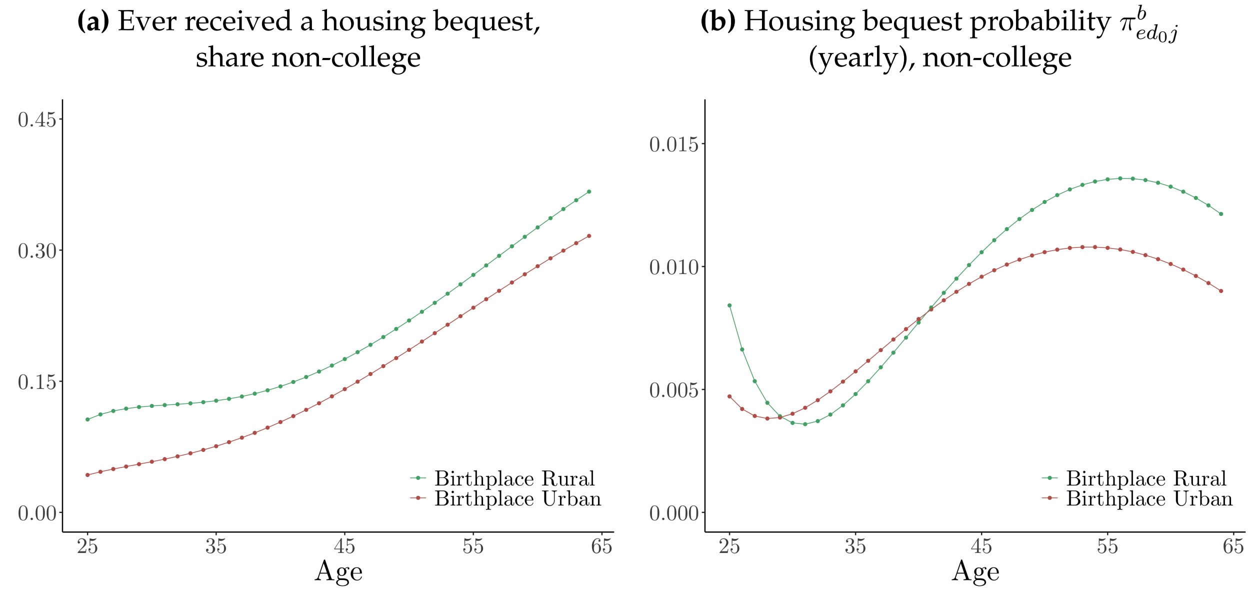


Figure 4: The figures plot the share of people without a college degree who have ever inherited a house during their lifetime (panel a), computed age by age, and the annual probability of receiving a housing bequest (panel b). The equivalent figures for college educated workers are plotted in Appendix Figure E14. Data: EFF 2008-2020.

Our objective is to obtain an individual-level probability of receiving a housing bequest in the next period, both for those who are and aren't currently coresiding. However, only household-level survey information from individuals not residing with their parents is available. Nonetheless, given that individuals currently living with their parents cannot have received a housing bequest from them in the preceding period, the bequest probability can be easily adjusted.[22] Further details are found in Appendix E.3.

Figure 4b plots $\pi^b_{ed_0j}$ for those without college education, while Appendix Figure E14b shows the same probability for college graduates. Panel (a) of Figure 4 depicts the EFF cumulative distribution data, and panel (b) plots the estimated yearly probability. Notice that the yearly likelihood of inheriting a property tends to either increase throughout the life cycle (for those without college education) or to peak roughly at age 45 (for college graduates).

[22] Agents in the model can inherit a house multiple times over their lifetimes, which might be viewed as receiving a significant inheritance. Allowing individuals to only inherit only once, although realistic, would require adding a state variable. Moreover, despite the substantial increase in computational costs, results remain almost identical whether or not a state variable for housing bequests is included (see Appendix E.3).

Additionally, this probability tends to be higher for the college-educated and for people born in rural locations.

4.1.3 Exogenous Parameters

The full set of parameters that are set exogenously is listed in Table 1. These include some parameters which are taken from the literature, namely the coefficient of relative risk aversion γ, the CES production function parameter ρ (Acemoglu and Autor 2011), the inverse housing supply elasticity in Spain ψ (Caldera and Johansson 2013), the transaction costs of buying and selling a house in Spain, ϕ_b and ϕ_s (Kaas et al. 2021), and the ς_0, ς_1 parameters for the Spanish tax function (García-Miralles, Guner and Ramos 2019).[23]

Table 1: Parameters set exogenously.

	Parameter	Value	Source
Relative risk aversion	γ	1.5	Standard
CES production function parameter	ρ	0.406	Acemoglu and Autor (2011), U.S.
Inverse housing supply elasticity	ψ	2.21	Caldera and Johansson (2013)
Transaction costs	(ϕ_b, ϕ_s)	(0.067, 0.067)	Kaas et al. (2021)
Down-payment requirement	χ	0.192	Average 2002-2017
Real interest and mortgage rates	(r, r^m)	(0.014, 0.033)	Average 2002-2017
Housing size (square meters)	$\overline{h}_{deh}$	See text	EPF 2016-2019
Number siblings receiving bequests	κ^b	2.5	Census 1991
Prob. receiving housing bequests	π^b_{edoj}	See text	EFF 2008-2020
Prob. changing employment status	$\pi^{l'}_{ledj}$	See text	EU-SILC 2004-2019
Persistence income process	(ϱ_N, ϱ_E)	(1.00, 1.00)	MCVL 2005-2019
Standard deviation persistent shock	$(\sigma_{\upsilon_N}, \sigma_{\upsilon_E})$	(0.051, 0.056)	MCVL 2005-2019
Standard deviation fixed-effect	$(\sigma_{\theta_N}, \sigma_{\theta_E})$	(0.514, 0.563)	MCVL 2005-2019
Mean gross labor income (thousands)	$\overline{y}$	24.88	MCVL 2005-2019
Tax function	$(\varsigma_0, \varsigma_1)$	(0.898, 0.148)	García-Miralles, Guner and Ramos (2019)
Transfer function	(g_0, g_1)	(0.0227, -0.009)	EU-SILC 2004-2019
Unemployment benefits (thousands)	b	3.3	EU-SILC 2004-2019

Some parameters are computed from the data as simple averages. These include the down-payment requirement χ, the real interest and mortgage rates, r and r^m, housing sizes $\overline{h}_{deh}$, the average number of siblings in the household κ^b, the mean gross labor income $\overline{y}$, and the amount of unemployment benefits b. Finally, some parameters are estimated in the data following the procedures detailed in Sections 4.1.1 and 4.1.2. This is the case for the income process parameters, ϱ_N, ϱ_E, σ_{υ_N}, σ_{υ_E}, σ_{θ_N}, and σ_{θ_E}, the probability $\pi^{l'}_{ledj}$ of changing employment status, the g_0, g_1 parameters for the transfer function, and the probability of receiving a housing bequest π^b_{edoj}. Parameters' values are either reported in Table 1 or, in the case of housing sizes $\overline{h}_{deh}$ and probabilities $(\pi^b_{edoj}, \pi^{l'}_{ledj})$, can be found in Table E4, Figures 3a and 4b, and Appendix Figures E11 and E14.

The initial conditions include agents' fixed types (birthplace, education, migration type, and fixed productivity), initial choices (assets, location, and housing status) and employment status. The initial distributions can vary based on location, education, and native status, but

[23] Kaas et al. (2021) report overall transaction costs of 13.5% for Spain. I assume that these costs are equally split among home-buyers and sellers.

are the same across time. Further details on the estimation of these distributions can be found in Appendix E.4.4.

4.2 Aggregate Uncertainty and Estimation Strategy

This sections outlines the sources of aggregate uncertainty and describes the procedure to compute the equilibrium. In what follows, I drop subscript t for convenience and make explicit when parameters or endogenous objects are affected by aggregate shocks.

4.2.1 Aggregate Shocks

Wages and prices in each location $d = \{1, \ldots, 12\}$ depend on three different location-specific parameters: overall productivity Θ_d, skill-specific productivity ζ_d, and construction costs Ω_d. I define vectors $\boldsymbol{\Theta} = (\Theta_1, \ldots, \Theta_{12})$, $\boldsymbol{\zeta} = (\zeta_1, \ldots, \zeta_{12})$, $\boldsymbol{\Omega} = (\Omega_1, \ldots, \Omega_{12})$, and collect them in $\boldsymbol{\mathcal{Z}} = (\boldsymbol{\Theta}, \boldsymbol{\zeta}, \boldsymbol{\Omega})$.

There exist two exogenous aggregate shocks in the economy: factor 1 and factor 2, denoted by f_1 and f_2. Parameters $\boldsymbol{\mathcal{Z}}$ depend on the realizations of (f_1, f_2), i.e., $\boldsymbol{\mathcal{Z}} = Z(f_1, f_2)$. In equilibrium, local prices p_d, non-college wages w_{Nd}, and college wages w_{Ed} are affected by $\boldsymbol{\mathcal{Z}}$ through the following equations:

$$p_d = \Omega_d H_d^{\psi}, \tag{7}$$

$$w_{Nd} = \Theta_d(\zeta_d L_{Nd}^{\rho} + (1-\zeta_d)L_{Ed}^{\rho})^{\frac{1-\rho}{\rho}} \zeta_d L_{Nd}^{\rho-1}, \tag{8}$$

$$w_{Ed} = \Theta_d(\zeta_d L_{Nd}^{\rho} + (1-\zeta_d)L_{Ed}^{\rho})^{\frac{1-\rho}{\rho}} (1-\zeta_d) L_{Ed}^{\rho-1}, \tag{9}$$

where (ρ,ψ) are fixed parameters, whereas H_d, L_{Nd}, and L_{Ed} denote housing demand, supply of non-college workers, and supply of college workers (in efficiency units), respectively (see Appendix C).

Notice that (H_d, L_{Nd}, L_{Ed}) are equilibrium outcomes that depend on the distribution of agents across individual states, denoted by μ, which in turn depends on individual decisions (e.g. location or housing tenure) and exogenous processes (e.g. employment status). In particular, μ can be written as an (infinitely-dimensional) function that depends on (f_1, f_2) and the model's fixed parameters:

$$\mu = \mathcal{M}(f_1, f_2). \tag{10}$$

Moreover, the vector of endogenous prices and wages $\boldsymbol{q} = (\boldsymbol{p}, \boldsymbol{w_N}, \boldsymbol{w_E})$, with $\boldsymbol{p} = (p_1, \ldots, p_{12})$, $\boldsymbol{w_N} = (w_{N1}, \ldots, w_{N12})$, $\boldsymbol{w_E} = (w_{E1}, \ldots, w_{E12})$, can be rewritten as

$$\boldsymbol{q} = Q(f_1, f_2, \mu), \tag{11}$$

where $Q(\cdot)$ is a known function described by equations (7), (8), and (9). Factors f_1 and f_2 determine parameters in $\boldsymbol{\mathcal{Z}}$, which, together with μ, determine equilibrium prices and wages. Hence, any combination of (f_1, f_2) and μ imply a different set of equilibrium prices and wages.

4.2.2 Forecast Rule

In equilibrium, agents forecast $\boldsymbol{q'}$ to make their optimal dynamic decisions. Given equation (11), this requires forming expectations on future f_1', f_2' and μ' based on aggregate law of motion:

$$(f_1', f_2', \mu') = H(f_1, f_2, \mu).$$

Individuals, however, cannot keep track of the infinitely-dimensional distribution μ to compute its equilibrium law of motion. To make the problem feasible, the dimensionality of μ needs to be reduced. By equations (10) and (11), equilibrium prices and wages can be written as

$$\boldsymbol{q} = \mathcal{Q}(f_1, f_2), \tag{12}$$

where $\mathcal{Q}(\cdot)$ is an infinitely-dimensional function. The question is how to map (f_1, f_2) into prices and wages in each location.

To this end, assume that $\mathcal{Q}(f_1, f_2)$ is approximated by a low-rank factor model of rank 2 (Bai 2009), so that

$$\boldsymbol{q} \simeq \boldsymbol{\lambda_1} f_1 + \boldsymbol{\lambda_2} f_2, \tag{13}$$

where $\boldsymbol{\lambda_k} = (\lambda_{k1}^p, \ldots, \lambda_{k12}^p, \lambda_{k1}^{w_N}, \ldots, \lambda_{k12}^{w_N}, \lambda_{k1}^{w_E}, \ldots, \lambda_{k12}^{w_E})$, for $k = 1, 2$, are the *fixed* loading parameters for each process and location, and (f_1, f_2) are the two aggregate (country-level) *time-varying* and orthogonal factors. In particular, local prices and wages by education can be approximated as combinations of common underlying factors and process- and location-specific parameters, as:

$$\begin{aligned} p_d &\simeq \lambda_{1d}^p f_1 + \lambda_{2d}^p f_2, \\ w_{Nd} &\simeq \lambda_{1d}^{w_N} f_1 + \lambda_{2d}^{w_N} f_2, \\ w_{Ed} &\simeq \lambda_{1d}^{w_E} f_1 + \lambda_{2d}^{w_E} f_2. \end{aligned}$$

Furthermore, assume that the exogenous aggregate factors follow two mutually-independent AR(1) processes,

$$f_1' = \varrho_1 f_1 + \upsilon_1, \tag{14}$$

$$f_2' = \varrho_2 f_2 + \upsilon_2. \tag{15}$$

$$\upsilon_1 \sim N(0, \sigma_{f_1}^2), \;\; \upsilon_2 \sim N(0, \sigma_{f_2}^2).$$

Hence, each period economy can move from any realization of (f_1,f_2) to a new one. Agents know how aggregate states (f_1,f_2) evolve, and can map each realization of (f_1,f_2) into prices and wages in each location using (13). In particular, if agents know parameters ($\boldsymbol{\lambda_k}$, ϱ_1, ϱ_2, σ_{f_1}, σ_{f_2}) and observe current factors (f_1,f_2), then they can form expectations about future prices and wages in each location following the rule:

$$\boldsymbol{q'} = \boldsymbol{\lambda_1} f_1' + \boldsymbol{\lambda_2} f_2' + \boldsymbol{\upsilon_q}, \tag{16}$$

where $\boldsymbol{\upsilon_q}$ is the approximation error in equation (13).

In Section 4.2.3, I describe the procedure to solve the benchmark equilibrium using the forecast rule (16) and the aggregate shocks' laws of motion (14) and (15). In Section 4.2.4, I show hot to solve for the counterfactual equilibrium where housing policies are introduced. In Appendix D.3, I draw a connection between the low-rank forecast rule and forecast rules in the Krusell and Smith (1998) tradition, as well as highlighting the limitations of traditional Krusell and Smith-type strategies in the present high-dimensional spatial setting. In Appendix D.4 I justify the use of the low-rank forecast rule (16) by performing a series of accuracy tests, both in the benchmark and in the counterfactual equilibria. Finally, in Appendix D.7 I provide a formal definition of the equilibrium.

4.2.3 Estimating the Benchmark Equilibrium

In the benchmark equilibrium, I can choose $\boldsymbol{\mathcal{Z}}$ to perfectly match the time series of prices and wages in the data. This is done by inverting equilibrium equations (7), (8), and (9), given the model's parameters and the benchmark equilibrium quantities (H_d, L_{Nd}, L_{Ed}), which are simulated by imposing the equilibrium prices and wages observed in the data. As a result, for each realization of (f_1, f_2), I calculate a set $\boldsymbol{\mathcal{Z}}$ so that the model economy matches observed prices and wages in equilibrum.[24]

Moreover, since I know that the $\boldsymbol{q}$ vector of prices and wages observed in the data are equilibrium objects in the benchmark, I can directly estimate equation

$$\boldsymbol{q} = \boldsymbol{\lambda_1} f_1 + \boldsymbol{\lambda_2} f_2$$

outside of the model. I perform the estimation using the interactive fixed-effects procedure described in Bai (2009)[25]. As can be seen in Appendix Figures D8, D9, and D10, the prediction of the factor model aligns very closely to the prices and wages matched from the data. This is not surprising, since this class of factor models are designed to predict the evolution of the data as best as possible, subject to the low-rank restriction. Further details on the estimates can be found in Appendix D.5.

Finally, given the estimated (f_1, f_2) factors, I can estimate their exogenous AR(1) process externally using equations (14) and (15).[26] I assume that each factor follows a three-points

[24]In particular, I have $3 \times 12 \times T$ equations (where $T = 10$ is the number of periods that I use to estimate the process for the aggregate shocks, ranging years 2010-2019) and $3 \times 12 \times T$ parameters $\boldsymbol{\mathcal{Z}}$ = ($\boldsymbol{\Theta}$, $\boldsymbol{\zeta}$, $\boldsymbol{\Omega}$). Therefore, I can choose the parameters $\boldsymbol{\mathcal{Z}}$ that perfectly rationalize the observed time series for local prices and wages as equilibrium outcomes.

[25]The estimation procedure of the factors and the loading parameters proposed in Bai (2009) involves principal component analysis. The objective of the procedure is to find the matrix of rank 2 that bests approximates the unrestricted 36×10 matrix of fixed effects that would perfectly capture the evolution of local prices and wages over time.

[26]I obtain estimates $\varrho_1 = 0.922$, $\varrho_2 = 0.753$ (standard errors 0.055 and 0.094, respectively), and $\sigma_{f_1} = 0.188$, $\sigma_{f_2} = 0.454$.

Markov chain, which I estimate as discrete approximation of the AR(1) processes.[27] Therefore, all the right-hand side variables and exogenous laws of motion for factors in the forecast rule (16) can be readily estimated from the data.

In Appendix D.1, I present an algorithm to solve the benchmark equilibrium. The estimation of the forecast rule in the benchmark equilibrium does not require simulating the model economy multiple times until convergence in the agents' guesses is achieved. Instead, the rule is estimated only once outside of the model, thanks to the fact that observed prices and wages can be perfectly matched in equilibrium. This hugely simplifies estimation, since solving efficiently for the benchmark economy is necessary to be able to calibrate the model's parameters.

This computational advantage distinguishes my approach from canonical strategies based on Krusell and Smith (1998), which typically require multiple simulations to estimate the forecast rules in the benchmark equilibrium. More details on the connection between the low-rank forecast rule and rules in the Krusell and Smith (1998) tradition are given in Appendix D.3. Appendix D.4 justifies the use of the low-rank forecast rule by performing a series of accuracy tests when predicting benchmark equilibrium prices and wages.

4.2.4 Estimating Counterfactuals

In the counterfactual exercises where housing policies are introduced, a new stochastic steady-state equilibrium is solved. Equilibrium prices and wages are different from the benchmark, even if the processes for the exogenous aggregate shocks remain the same. This occurs because policies affect individual decisions, thus modifying the distribution of agents μ across individual states (e.g. the share of people renting in a specific urban location). Equilibrium prices and wages are updated using equations (7), (8), and (9), where parameters $\boldsymbol{\mathcal{Z}}$ are taken as given and are set equal to their benchmark values.

Since equilibrium prices and wages have changed, the forecast rule (16) estimated from the data is no longer valid and needs to be updated. The factors and parameters governing the exogenous laws of motions (14) and (15) are unchanged in the counterfactual. Instead, I iteratively update the ($\boldsymbol{\lambda_1}$, $\boldsymbol{\lambda_2}$) parameters until the agents' guesses are consistent with the new equilibrium prices and wages, under all the different realizations of the aggregate shocks (f_1, f_2).

In Appendix D.2, I present an algorithm to solve the counterfactual equilibrium. Differently from the benchmark, estimating the forecast rule in the counterfactual equilibrium requires simulating the model economy multiple times until convergence in the agents' guesses is achieved. This is similar to canonical strategies based on Krusell and Smith (1998). The procedure, however, is not computationally taxing, as the other model parameters have already been estimated and are kept fixed at their benchmark values, so that the counterfactual equilibrium can be solved using a single outer loop. Appendix D.4 justifies the use of the low-rank

[27] When solving the model, agents form expectations on future factor realizations based on current realizations and Markov chain probabilities. Moreover, Markov chains are linearly interpolated in the simulations, which results in different probabilities attached to specific values of (f_1', f_2') depending on the exact (f_1, f_2) realizations.

forecast rule by performing a series of accuracy tests when predicting counterfactual equilibrium prices and wages.

4.3 Calibration

This section describes the calibration strategy. Given the exogenous inputs and the agents' forecast rule, I internally calibrate the remaining parameters to match key moments in the data – including coresidence, homeownership, and migration rates over the lifecycle.

4.3.1 Calibrated Parameters

The remaining model parameters, listed in Table 2, are estimated with the simulated method of moments.[28] Some of the calibrated parameters affect the utility function: the discount factor β, the utility from being a homeowner η_1 and living in the birthplace η_2, and the terminal utility from holding wealth and a house, ω_1 and ω_2. The share of stayer types π_τ, the migration and coresidence cost δ, ξ parameters, and amenities A_{d_j} are also calibrated.

Table 2: Calibrated parameters.

	Parameter	Estimate		Parameter	Estimate
Utility			**Migration cost function**		
Discount factor	β	0.990	Intercept	δ_0	1.876
Utility homeowner	η_1	0.216	Age	δ_1	0.007
Utility home-bias	η_2	0.007	Log age	δ_2	0.745
Terminal value wealth	ω_1	0.001	College	δ_e	-0.056
Terminal value homeowner	ω_2	0.000	**Coresidence cost function**		
Other			Intercept	ξ_0	0.148
Share stayers	π_τ	0.800	Age	ξ_1	0.001

The calibrated parameters indicate that agents gain direct utility from homeownership ($\eta_1 = 0.216$) and from residing in their birthplace ($\eta_2 = 0.007$), beyond the economic benefits these choices provide. When translated into economic terms, an agent consuming the average consumption level would be willing to give up 53.9% of their consumption (10,260 euros) to obtain the utility benefits of homeownership, and 3.2% of their consumption (610 euros) to enjoy the utility of living in their birthplace. In this setting where other advantages of being native, namely the option to coreside and easier access to housing bequests, are explicitly modelled, pure preferences coming from home-bias do not play a quantitatively large role.[29]

Agents in the model also experience disutility when migrating or coresiding with parents. A newborn non-college person consuming the average consumption level would be willing

[28] In particular, I use an exponential natural evolution strategy. This is a numerical optimization algorithms that makes updates based on the natural gradient instead of the plain gradient, and belongs to the family of derivative-free algorithms known as black box optimizers. The Julia package `BlackBoxOptim` is used for estimation.

[29] This is different from Zerecero (2021), where all the benefits from being natives are loaded in the home-bias preference parameter.

to give up 96.2% of their consumption (18,330 euros) not to pay the one-off migration utility cost. Moreover, they would sacrifice 43% of their consumption (8,200 euros) not to experience the disutility from coresiding. The estimated discount factor is close to standard values in the literature ($\beta = 0.99$).

A large share of the population (80%) is estimated to be of the "stayer" type, i.e. with prohibitively high migration costs. Koşar, Ransom and Van der Klaauw (2022) use the NY Fed's Survey of Consumer Expectations to elicit respondents' migration probabilities for a set of hypothetical scenarios. They find very large non-pecuniary moving costs for 52% of the population ("rooted") and infinitely large moving costs for 12% of the population ("never-movers"). These estimates may serve as a lower bound for Spain, given that the Spanish internal migration rate is lower than in the U.S.[30]

4.3.2 Targeted Moments

The internally calibrated parameters are estimated to match key moments in the data. The simulated moments and their data counterparts are listed in Table 3. They include the share of homeowners (overall and among coresidents), the share of coresidents, the migration rate among the college-educated, the share of people not migrating, and the median wealth to income ratio at age 50. They also include statistics that capture the lifecycle evolution of housing status and migration. Specifically, the targeted moments are homeownership, coresidence, and migration rates during the initial 10 ages in the model (25-34) as well as the last 10 ages (55-64). The migration flows across locations are also targeted, and are reported in Appendix Table E3.

Table 3: Targeted moments. Data: Census, EU-SILC, MCVL, EFF.

	Data	Model		Data	Model
Lifecycle Homeownership Rates			**Homeownership**		
Ages 25-34	0.481	0.459	Share homeowners, not coresidents	0.900	0.919
Ages 55-64	0.880	0.919	Share homeowners	0.735	0.731
Lifecycle Coresidence Rates			**Internal Migration**		
Ages 25-34	0.400	0.416	Migration rate, college-educated	0.010	0.010
Ages 55-64	0.060	0.060	Share never migrating	0.894	0.889
Lifecycle Migration Rates			**Other**		
Ages 25-34	0.015	0.015	Share coresidents	0.184	0.205
Ages 55-64	0.005	0.005	Median wealth-income ratio, age 50	7.002	7.549

The moments of Table 3 are simple averages or ratios. Their estimation in the data and model is straightforward, with the exception of the share of individuals who never migrate. The challenge arises due to the short 4-year panel dimension of the EU-SILC, which makes the data unsuitable for estimating the proportion of individuals who never relocate throughout

[30]The annual migration rate is around 3% across U.S Metropolitan Statistical Areas and 2% across States (Molloy, Smith and Wozniak 2011), whereas it is 0.8% across Spanish locations.

their lifecycle. To address this issue, I also use information from the longer MCVL panel. A detailed explanation of this inference procedure can be found in Appendix E.4.2.

As can be seen in Table 3, the model captures well the lifecycle evolution in housing tenure and migration rates. As in the data, homeownership increases over the lifecycle, whereas coresidence and migration rates decrease. The cross-sectional data moments, related to housing tenure choices, migration, and wealth, are also well captured in the model. Moreover, the model replicates the migration flows to different locations observed in the data (Table E3).

Some moments relate more strongly to some parameters than others. Migration and coresidence rates are connected to the corresponding migration and coresidence cost function parameters. In particular, intercepts (δ_0, ξ_0) are related to the average migration and coresidence rates, whereas age coefficients (δ_1, δ_2, ξ_1) are related to their evolution over the lifecycle. Moreover, the migration college coefficient δ_e is identified by the migration rate among the college-educated. The homeownership rates over the lifecycle, instead, are closely linked to the period and terminal utility from homeownership parameters (η_1, ω_1). Finally, the share of stayers π_τ is identified by the share of people never migrating, and the median wealth to income ratio is closely related to the discount factor β.

5 Validation

I validate the model by showing that it replicates a set of untargeted moments. First, I run a policy within the model that mirrors a place-based homeownership subsidy that was recently introduced in Spain. As a result of the increase in homeownership following the policy, the model yields a migration elasticity that is similar to the one estimated in the data. Second, I find that the model reproduces the lifecycle homeownership gap between natives and migrants and the income premium enjoyed by migrants over the lifecycle. As a final non-targeted moment, the model reproduces the observed negative relationship between local homeownership rates and wealth inequality across locations.

5.1 Place-Based Subsidy for Young Homebuyers

In the model, homeownership reduces internal migration through the existence of monetary transaction costs associated with selling a house. To validate this key channel in the model, I take advantage of the quasi-experimental nature of a policy that subsidized homeownership for young individuals residing in small municipalities. I run the same policy in the model and, as a result of the increase in homeownership following the subsidy, I find a negative migration elasticity that is close to the one estimated in the data. Notably, transaction costs – the key parameter driving homeowners' lower mobility in the model – are externally set and taken from the literature (Kaas et al. 2021), which makes the elasticity a fully untargeted moment.

The policy, introduced in early 2018, gives a subsidy to first-time home buyers in cities with less than five thousand inhabitants consisting of 10,800 euros, or up to 20% of the house price if the amount is lower. To qualify, the buyer has to be under 35 years old, earn a gross annual income of less than 19,400 euros, and use the purchased house as their primary residence. Furthermore, the house's price cannot exceed 100,000 euros.[31]

After purchasing the home with this subsidy, the buyer has the freedom to sell it under specific conditions: relocating for job reasons, acquiring another home in the same or in a different location, or if five years have passed since the subsidy was granted. Should one relocate without meeting these conditions before the five-year mark, a proportional repayment of the subsidy is required. For instance, moving after two years without qualifying for one of the exceptions requires returning 5,400 euros of the subsidy.

Policy in The Data To analyze the policy's impact in the data, it is crucial to identify the small municipalities where the policy was introduced. The MCVL does not distinguish between cities with population below 40,000. Instead, I use the Residential Variation Statistics (*Estadística de Variaciones Residenciales*, or EVR) and the Continuous Register Statistics (*Estadística del Padrón Continuo*, or EVR) datasets. These combined datasets provide data on the universe of Spanish movers and stayers, respectively, and include an indicator for residents in cities with population lower than 10,000. However, they lack information on homeownership, which is needed to analyse the first-stage impact of the policy, and on income, which could be used to restrict the treatment to the low-income recipients.

To address the first limitation, I estimate the first-stage using the Household Budget Survey (*Encuesta de Presupuestos Familiares*, or EPF). This dataset not only includes an indicator for those living in cities with a population of less than 10,000, but also crucially gives information on homeownership status. To account for the second limitation, the treatment does not condition on any income data. Treated individuals are residents of cities with fewer than 10,000 inhabitants who are younger than 35, not all of which are eligible for the policy. For instance, some of them might live in cities with populations between 5,000 and 10,000 or earn more than 19,400 euros, rendering them ineligible. Therefore, the analysis should be understood as an intention-to-treat exercise. The datasets cover the years 2016 to 2019, encompassing two years before and after the implementation of the policy in early 2018.

The event studies estimated in the data take the form:

$$y_{it} = \alpha_{\text{small1}} + \alpha_t \times \alpha_{\text{small2}} + \alpha_r + \alpha_{rt} + \alpha X_{it} + \epsilon_{it}, \tag{17}$$

where y_{it} is the outcome, which is either the homeownership status (first-stage) or the individual migration event (reduced form), α_{small} is an indicator function for the set of treated cities (municipalities with less than 10,000 inhabitants), and α_t, α_r, and α_{rt} are year, region, and region-year fixed-effects, respectively. In the baseline specification, additional controls X_{it} include gender, age and age squared. Migration occurs when the following year's lo-

[31] The policy, originally introduced to increase emancipation among young people and to reduce rural depopulation, has been renewed in 2021 with slight modifications, including a higher municipality size threshold of 10,000 inhabitants. For data availability reasons and to isolate the effect of the policy from the impact of the COVID-19 pandemic, the analysis focuses on the 2016-2019 period, i.e. two years before and after the first introduction of the policy.

cation of residence is different from the current one. The sample is restricted to individuals younger than 35, the age eligibility threshold for the subsidy, and to individuals living in municipalities with less than 20,000 inhabitants. This ensures a suitable control group: residents aged below 35 from slightly larger municipalities than the population threshold required for the subsidy, specifically those with populations between 10,000 and 20,000.

The two event studies for the first-stage and the reduced form, centered around the 2018 policy year, are depicted in Figures 5a and 5b. Consistent with the model's predictions, I observe that the policy increased homeownership and decreased out-migration. As can be seen in columns (1) and (2) of Appendix Table F5, the homeownership rate among the treated increased by 0.115 and the annual migration rate decreased by 0.002 on average. These estimates come from the first-stage and reduced form difference-in-differences version of regression (17). More details on this diff-in-diff specification can be found in Appendix F.1 and equation (32).

The lack of significant pre-trends in the event studies (Figures 5a and 5b) is in line with the conditional exogeneity assumption of the treatment. As further exogeneity checks, I run two placebo event studies where the sample is restricted to people aged 37-40, who are just above the age eligibility threshold and could not have received the subsidy in any of the two post-treatment years of the event study. The treatment and control groups are otherwise defined as in the baseline regressions, i.e. people living in municipalities below or above 10,000 inhabitants (but less than 20,000 inhabitants). In line with the exclusion restrictions, the placebo treatment does not have a significant effect on the outcomes (Appendix Figures F15a and F15b).

Moreover, I estimate the migration regression by restricting the sample to people *born* in municipalities with less than 20,000 inhabitants, and defining α_{small} in regression (17) as an indicator function for people *born* in municipalities with less than 10,000 inhabitants. The birthplace treatment, arguably more likely to be exogenous than a treatment based on current residence, produces results that are similar to the baseline regression (see Appendix Figure F16).[32] In all specifications, COVID-19 years are excluded to isolate the impact of the policy from the disruptive effect on homeownership and migration decisions caused by the pandemic. Event-study specifications that include the COVID-19 years until 2021 can be found in Appendix Figures F15c and F15d.

I combine the first-stage and reduced-form estimates to obtain a migration elasticity with respect to changes in homeownership. As reported in column (2) of Table 4, new homeowners decrease their annual migration by around 1.83 percentage points as a result of the policy, a substantial effect given the average migration rate of 0.008. This is in line with estimates obtained from running a separate regression with household fixed-effects and the same control variables using the EU-SILC panel, a different dataset encompassing years 2004-2019 and all locations (column 1 of Table 4). The elasticity estimated with the panel is very similar to the one obtained from the policy experiment (-0.0186 instead of -0.0183).

[32]The birthplace treatment specification can only be estimated for the reduced form, and not for the first-stage, for data availability reasons.

I argue that the estimated reduction in migration rates following the increase in homeownership due to the policy reflects the causal effect of homeownership on internal migration. Beyond the exogeneity issues previously discussed and addressed, another potential concern challenges this interpretation. Specifically, the policy's influence on reduced migration might be direct, that is, it may not be entirely mediated by the policy's effect on homeownership. In such a scenario, the observed increase in homeownership may partially arise from individuals who opt to remain as a result of the policy, which also enables them to purchase a house. This could primarily be driven by the policy's repayment rules, which require that a homebuyer who relocates within five years for non-professional reasons and without acquiring another house must make a proportional repayment of the subsidy. Such rules may thus deter new home-buyers from moving for reasons which are not directly related with their status as homeowners (e.g., transaction costs of selling).

To address this concern, I turn to the model. By simulating a version of the policy that does not have these (mild) repayment requirements, I estimate an elasticity that is virtually identical to the one I obtain when simulating the actual policy (-0.018). Moreover, by additionally simulating the policy in a counterfactual equilibrium without transaction costs of selling the house ϕ_s, the key friction that limits homeowners' mobility, I find no reduced form effects of the policy on migration rates. Therefore, I conclude that a reverse causality effect of migration on homeownership is not driving the results, and that estimates from the quasi-experiment reflect the causal effects of homeownership on migration rates.

Policy in The Model The place-based subsidy to young low-income homebuyers living in small cities is simulated in the model. To do so, I need to add an additional state variable that takes on three values: not eligible for the policy, eligible and not recipient, and recipient. This distinction is needed because people who already received the subsidy cannot ask for it again, since the policy only applies to first-time homebuyers. Moreover, in the version of the policy that reproduces the repayment rules, recipients of the policy may be obliged to pay part of the subsidy back in case they move, while non-recipients are not.

The eligibility criteria reflect the income and age thresholds from the 2018 policy. This place-based policy is implemented exclusively in locations Northwest rural, Center rural, and South rural, the rural locations with the lowest mean housing prices. Within these locations, average housing prices fluctuate between 100,000 and 150,000 euros, aligning more closely with the policy's 100k eligibility threshold than other rural areas. Yet, not every resident in these three locations meeting the age and income requirements is automatically eligible. When modeling the policy, only a random 8.75% share of them is considered eligible, aligning with the proportion of smaller municipalities (those with populations under 5,000) within these rural locations. Finally, the one-off subsidy for recipient home-buyers consists of 10,800 euros, an amount that, in line with the policy requirements, is always higher than 20% of the local house prices.

The 2018 policy is not included in the baseline, which is estimated using price and wage data from 2010 to 2019. Rather, it is simulated in a counterfactual exercise. Since the focus of

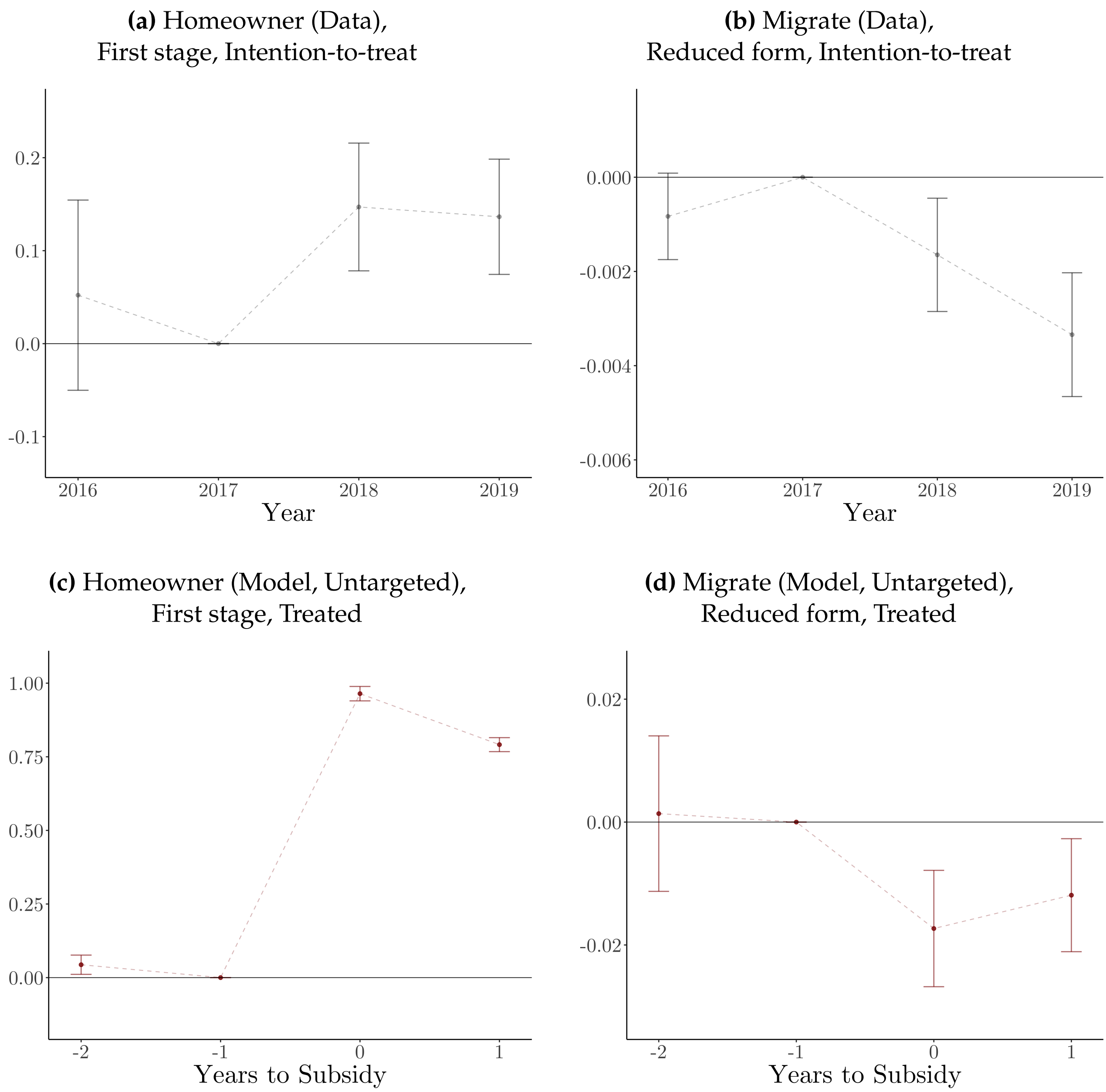


Figure 5: Treated in panels **(a)** and **(b)**: People aged less than 35 living in small cities (<10k inhabitants). Control group: same age living in slightly larger cities (10k-20k). Treatment year: 2018. Migration across regions (NUTS-1) and rural-urban areas (rural <10k, rural >10k or urban >40k). Treated in panels **(c)** and **(d)**: People who received the subsidy in the counterfactual model with the policy. Control group: same people as the treated, but in the baseline model without the policy. Other included controls and fixed-effects: gender (in the data), age, age squared, region, and region-year. Clustered (locations) standard errors. Data: EPF, EPC, EVR 2016-2019.

the diff-in-diff and event study analyses is on the short-term effect of the policy in the two subsequent years after it is put in place, I do not allow model prices and wages to adjust in general equilibrium. More details on the policy implementation in the model are given in Appendix F.1.

The treatment group comprises individuals receiving the subsidy in this counterfactual scenario, while the control group consists of these same individuals in the baseline model where the policy is absent. In order words, using the structure of the model, causal identification is achieved by directly comparing *potential outcomes*. I estimate the event study within the model using the same regression specification as its data counterpart, equation (17). However, since I am directly measuring the effect on the treated rather than the intention-to-treat, I use individual fixed-effects α_{i1} and α_{i2} instead of the small municipalities indicator functions α_{small1} and α_{small2}. Moreover, I don't control for gender (absent in the model) and I center the event studies around the year the individual receives the subsidy, either 2018 or 2019. As in the data, the sample is restricted to the years 2016-2019.

The evolution of the event studies for both the first-stage (Figure 5c) and the reduced-form (Figure 5d) is qualitatively similar to their data counterparts (Figures 5a and 5b). There are no pronounced pre-trends before the subsidy, and, mirroring the effect in the data, homeownership increases and migration decreases as a result of the policy. The corresponding difference-in-differences average effects are reported in columns (3) and (4) of Appendix Table F5. The magnitude of the effect on homeownership and migration in the model is, by construction, higher than in the data. This is because, in the model, I am measuring the impact on the treated rather than the intention-to-treat.[33]

However, the relative effect on migration with respect to homeownership is similar. When combining the diff-in-diff first-stage and reduced-form results, I obtain a migration elasticity with respect to changes in homeownership of -0.0211, which is close to the ones estimated in the data. This can be seen by comparing the model elasticity of column (3) in Table 4 with the data panel elasticity of columns (1) or the data policy elasticity of column (2). Notably, transaction costs – the key parameter driving homeowners' lower mobility in the model – are externally set and taken from the literature (Kaas et al. 2021), which makes the elasticity a fully untargeted moment.

Table 4: Estimated migration elasticity with respect to changes in homeownership.

	Migrate		
	Data Panel	Data Policy	Model Policy
	(1)	(2)	(3)
Homeowner	-0.0186*	-0.0183**	-0.0211***
	(0.0089)	(0.0099)	(0.0054)
Household FE	✓		
Individual FE			✓
Year-Region FE	✓	✓	✓
Region FE	✓	✓	✓
Observations	73,570	4,535,448	17,363

Note: Other included controls: age, age squared, and, in (1) and (2), gender. Clustered (location) std. errors in (1) and (3), bootstrap std. errors in (2), *p<0.1, **p<0.05, ***p<0.01. Data: EPF, EPC, EVR 2016-2019, EU-SILC 2004-2019.

[33] I can perform a back-of-the-envelope adjustment of the model estimates by multiplying them by the take-up rate in the model (among the eligible and non-eligible individuals aged less than 35), to obtain some approximate intention-to-treat estimates that can be more easily compared with the *absolute* changes in the data. Since the take-up rate in the model is 7.68%, back-of-the-envelope first stage and reduced form model estimates are $0.6697 \times 0.0768 = 0.0514$ and $-0.0141 \times 0.0768 = -0.0011$, respectively. These estimates are around two times lower than their (untargeted) data counterpart (0.1151 and -0.0021), as can be seen in Table F5.

As a final counterfactual experiment, I simulate the policy in an economy without transaction costs of selling the house ($\phi_s = 0$). As can be seen in the event studies of Figure F17, the policy increases homeownerhsip but has no significant reduced form effects on migration rates. Therefore, I conclude that the estimates from the quasi-experiment reflect the causal effects of homeownership on migration rates, as they are not explained by forces in the model other than transaction costs ϕ_s.

5.2 Natives Are More Likely to be Homeowners Despite Earning Less

An additional set of untargeted moments predicted by the model is illustrated in Figure 6. These figures delineate the lifecycle profiles of homeownership rates and income, distinguishing between natives and migrants. The model accurately predicts that natives have a higher propensity for homeownership compared to migrants (Figure 6a). The homeownership gap is higher at younger ages and shrinks as agents get older, although it remains persistent at around 10 percentage points.

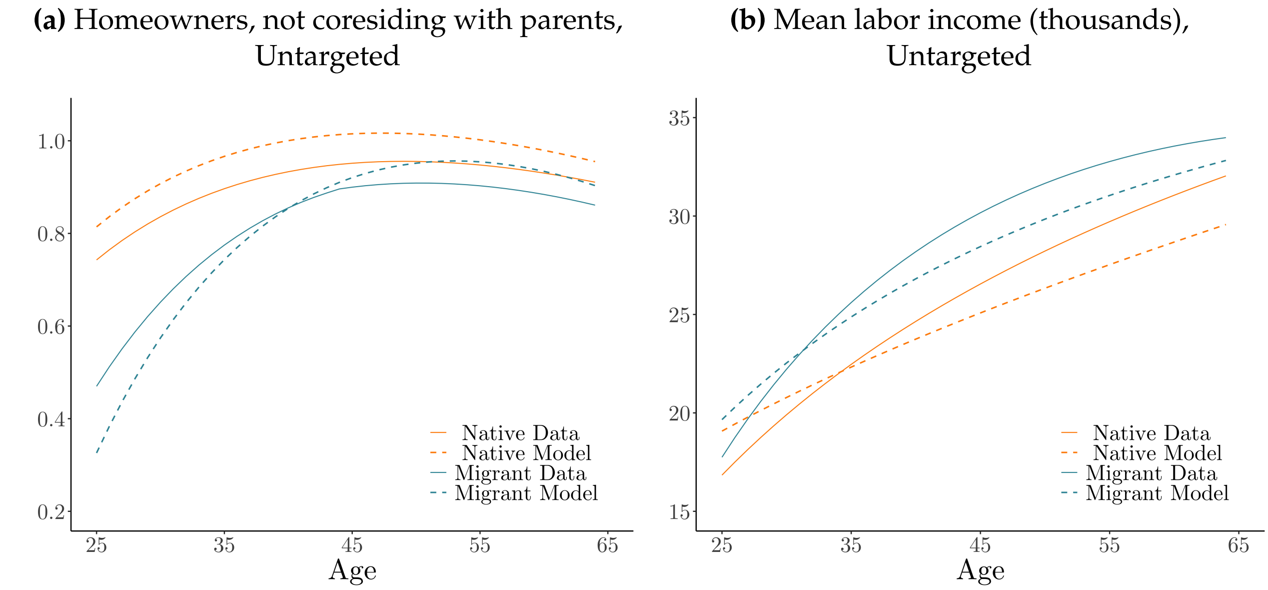


Figure 6: The figures plot the untargeted lifecycle profiles of homeownership rate and income, separately for natives and migrants. Data: Census 2011 (panel **a**), MCVL 2005-2019 (panel **b**).

Interestingly, natives are more likely to be homeowners even though they earn less over the lifecycle. This feature of the data is also matched in the model as an untargeted moment (Figure 6b). The higher income observed among migrants can be partially attributed to a larger proportion of college-educated individuals within this group. Additionally, this income advantage may serve as a compensating differential offsetting the inherent benefits enjoyed by natives, such as easiest access to bequests, the option for coresidence, and the home-bias utility. By delving into the mechanism, I conclude that the option to coreside with parents is the key element behind the gap in homeownership and income gap.

Mechanism To uncover the determinants of the homeownership and income gap between natives and internal migrants, I explore the effects of coresidence, housing bequests, and the home-bias exogenous utility parameter. By iteratively shutting down one of these three channels while maintaining the other two, I conclude the option for natives to coreside is the key driver of the gaps. If I keep the housing bequests and home-bias preference while eliminating the coresidence option, I find that both the homeownership and income gaps between natives and migrants vanish (Figure F18).[34]

Coresidence has a positive impact on savings and on (housing) wealth accumulation. This is different from Kaplan (2012), where the option to live with parents leads to overall *lower* saving rates. In his framework, this happens because coresidence reduces the precautionary savings motive by providing an insurance mechanism against negative income shocks. While this mechanism is also incorporated in my model, it is quantitatively less important than the direct effect coming from the absence of housing costs during coresidence. Moreover, differently from Kaplan (2012), my model incorporates homeownership paired with a down-payment constraint. Coresidence offers agents a way to overcome this credit friction. By saving while they are living with their parents, they can obtain sufficient funds for the down-payment, which leads to subsequent housing wealth accumulation.[35]

5.3 High Homeownership Locations Have Lower Wealth Inequality

The model also predicts the untargeted inverse relationship observed between the local homeownership rate and wealth inequality across locations. This relationship is shown in Figure 7, where net wealth inequality is measured using the Gini coefficient. It should be noted that, although the model closely mirrors the observed untargeted negative correlation (-0.8 in the model compared to -0.7 in the data), it underestimates the level of wealth inequality by approximately 40%. This discrepancy arises largely because the model omits much of the wealth heterogeneity among homeowners, given that housing prices in the model are constant within locations and education groups. Supporting this, a Gini decomposition exercise reveals that 66% of wealth inequality is driven by variation in wealth among homeowners, which in Spain is largely explained by differences in housing values.[36]

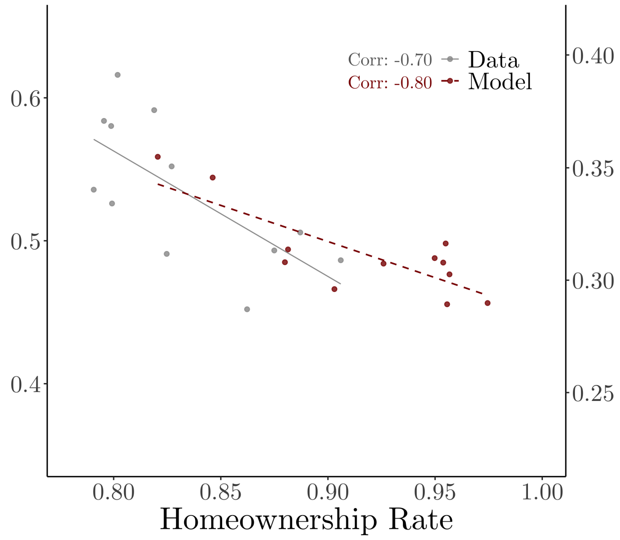
Mechanism A negative relationship between homeownership and wealth inequality has been observed across countries (Kaas, Kocharkov and Preugschat 2019, Kindermann and Kohls 2018). My analysis uncovers that a similar relationship also holds across locations within a single country. In particular, the -0.7 correlation between local homeownership rates and Gini of net wealth that I observe across Spanish locations (Figure 7) is similar to the -0.89

[34]Housing bequests do not significantly drive this gap because when migrants inherit property that they must sell due to their non-residence in their birthplace, they can still use the proceeds to purchase a new house if they choose. Furthermore, the exogenous home-bias preferences play virtually no role because they are estimated to be small (refer to Section 4.3.1).

[35]Additionally, the analysis in Kaplan (2012) focuses on low-income young agents, who experience particularly high income risk. In this population subgroup, the precautionary saving motive is likely strongest and the access to homeownership is low (see also the related discussion in Rosenzweig and Zhang 2019).

[36]The Gini decomposition exercise follows Mookherjee and Shorrocks (1982) and is performed using EFF 2005-2020 data. The R package `dineq` is used for the estimation. The main sources of variations for the Gini coefficient are wealth inequality within homeowners (66%) and between homeowners and renters (27%). The remaining variation comes from within renters inequality (1.5%) and the residual term (5.5%).

Figure 7: Gini of net wealth,
Untargeted



Note: The figure plots the untargeted relationship across locations between the local Gini of net wealth and the local homeownership rate among not coresidents. The left vertical axis refers to the data, whereas the right axis refers to the model. Data: EFF 2008-2020.

correlation that Kaas, Kocharkov and Preugschat (2019) find when comparing large European countries (Appendix Figure F19). This literature emphasizes that widespread access to homeownership lifts the wealth of the wealth poor relatively more, and tends to decrease wealth inequality. In Appendix F.3, I exploit the EFF panel dimension and find evidence that this mechanism is also at play across Spanish individuals and locations.

Using the unconditional quantile regression framework developed by Firpo, Fortin and Lemieux (2009), I find that homeownership increases net wealth along the entire distribution and, in relative terms, it does so especially among the wealth poor (Appendix Figure F20). As detailed in Appendix F.3, the regression accounts for household fixed-effects and other observables (including age, income, and education level), so that results are not simply driven by the selection of wealthier households into homeownership. Rather, the effect is identified from the variation in homeownership status occurring within households, keeping all other observables fixed. Buying the main residence is found to increase net wealth by a factor of 6 in the first decile and to more than double it in the second decile. As a comparison, the increase in net wealth for people in the top decile of the distribution is of just 4%. The estimated positive effect of homeownership on wealth accumulation reveals that Spanish households are not willing to fully substitute housing wealth with other types of financial wealth. This may be happening because, as in the model, people derive some direct utility from holding wealth in the form of housing, or because they value homeownership's insurance against rental price volatility.

Moreover, using the Recentered Influence Function (RIF) for the Gini coefficient (Firpo, Fortin and Lemieux 2009), a statistical tool that allows to compute the effect of individual observations on aggregate statistics, I show that wealth inequality tends to reduce when the share of wealth accounting to the bottom 20% increases and that of the top 20% reduces. Appendix Figure F21 reports the results, whereas Appendix F.3 provides details on the estimation procedure. This result, combined with the unconditional quantile effects of homeownership on net wealth, explains why higher homeownership rate is associated with lower wealth inequality: homeownership allows poorer households to accumulate relatively more wealth, which makes the wealth distribution more equal.

Accordingly, by estimating a regression that uses the RIF of the Gini of net wealth as outcome and controls for household fixed-effects and other observables, I find that homeownership tends to decrease wealth inequality (Appendix Table F6). Moreover, by interacting the homeownership treatment with the initial level of households' wealth, I find that this result is driven by households that start in the bottom 20% of the wealth distribution. In particular, the estimated negative effect of homeownership on the Gini of net wealth is highest in the bottom 10%, is still negative and significant for household with initial wealth between the first and second decile, and loses significance for richer households (Appendix Table F7).

A similar mechanism is at play in the model. Locations in the model with the highest homeownership rate have on average a 2% higher share of local net wealth accounting to the bottom 20% of the distribution, and around a 2% lower share accounting to the top 20% (Appendix Figure F22). Therefore, simularly to the data, the higher aggregate homeownership rate reduces wealth inequality to the extent that it contributes to the relative increase in net wealth in the bottom 20% of the distribution.

6 Should Governments Subsidize Homeownership?

Next, I use the model to analyze the welfare implications of housing policies. Mortgage interest deductions are found to increase welfare, whereas rent subsidies for young low-income individuals decrease it. Targeting policies to specific locations reduces the benefits of mortgage deductions but mitigates the welfare costs of rent subsidies. Since homeownership allows to insure against rental price volatility, the presence of aggregate shocks in the economy amplifies the welfare effects of policies affecting the homeownership rate.

6.1 Mortgage Interest Deductions

I study the welfare implications of mortgage interest tax deductions, by running in the model a policy of this kind that was in place in Spain until 2013. The policy allowed homeowners to annually deduct 1,300 euros from their labor income taxes while they were repaying their mortgage. I simulate three different versions of the policy. First, I simulate a version mirroring the actual policy in Spain, which applies across all locations. Then, I only target residents in the three highest-price urban locations. Finally, I simulate a version where only the three lowest-price rural locations residents are targeted.[37] I find that the untargeted version of the

[37] The three high-price urban locations belong to the Northeast, East, and Madrid regions. The low-price rural locations belong to the Northwest, Center, and South regions.

policy increases welfare by 1.64% in consumption-equivalent terms, whereas targeting high-price urban locations increases it by 0.74%. On the other hand, a policy that only targets low-price rural residents barely affects welfare.

To evaluate the effect of mortgage interest deductions, I compare the benchmark equilibrium with counterfactual equilibria where different policies are implemented. In the counterfactuals, I allow housing prices, wages, and income to adjust in response to policies. Housing prices and wages respond to changes in the spatial allocation of labor that, in turn, affect local housing demand and labor supply. The level of taxes ς_0 is also modified, keeping the tax progressivity parameter ς_1 fixed, to cover the additional revenue required by the policy. This takes into account changes in individuals' taxable income due to migration and general equilibrium effects. Comparisons with the counterfactual equilibrium are only made after prices, wages, and taxes have already converged, ignoring the transition paths between the stochastic steady-states.

Figures 8 and 9 plot the equilibrium outcomes of policies as colored dots, which are compared with the central black dot representing the benchmark equilibrium. In general, policies that increase homeownership tend to decrease internal migration, due to the transaction costs associated with selling the house (Figure 8a). Policy-induced increases in homeownership are also typically linked to lower levels of wealth inequality (Figure 8b), since homeownership tends to lift net wealth of households at the bottom of the distribution relatively more than the rest (see Section 5.3). Finally, policies that increase the urban population share are linked to lower income dispersion (Figure 9a) and higher price dispersion (Figure 9b) across locations. This happens because the influx of new migrants to high-price, high-wage urban locations tends to further increase urban prices and to reduce urban wages, due to the shifts in local housing demand and labor supply.

(a) Homeownership and Migration **(b)** Homeownership and Wealth Inequality

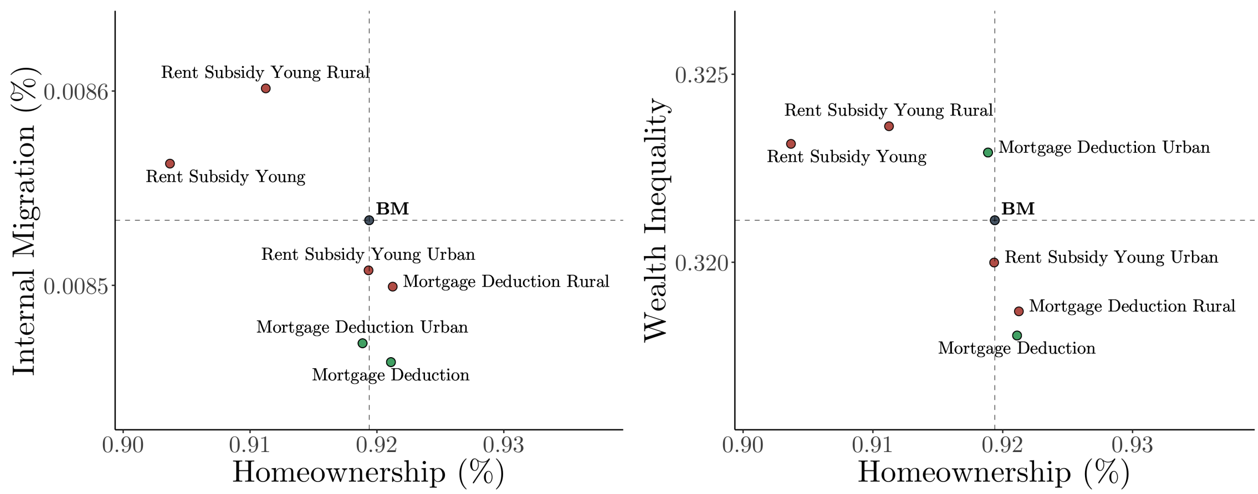


Figure 8: The figures plot the equilibrium outcomes of policies. Green dots correspond to welfare-improving policies, whereas red dots are used for policies that decrease welfare. The black *BM* dot represents the benchmark economy. Wealth inequality is measured as the Gini coefficient of net wealth. The homeownership rate is measured among agents not coresiding.

Welfare is measured as the percentage change in consumption that the average newborn agent would require, or give up, in order to be indifferent between the counterfactual and the benchmark equilibria. More details on how welfare is computed are given in Appendix G.1. As shown in Table 5, untargeted mortgage interests deduction policies increase welfare by 1.64% and are supported by a majority (83.1%), meaning that the lifetime utility of most newborn agents is higher in the counterfactual than in the benchmark.

Mortgage interest deductions increase homeownership by 0.2 percentage points among not coresidents and by 0.8 pp. at the individual level (the share of coresidents declines from 20.5% to 19.8%). As a result of the increase in the homeownership rate, both internal migration and wealth inequality decline (by -0.86% and -0.95%, respectively). The lower urban share following the introduction of the policy also translates into lower urban prices and spatial price dispersion. However, it leaves the spatial misallocation of labor roughly unchanged, as measured by the income dispersion across location (variance of log mean income by location). Overall, the average newborn is better after mortgage deductions are introduced, despite the 2 percentage points increase in the average tax rate needed to finance the policy.

Table 5: Welfare effects and share supporting housing policies.

	With Aggregate Shocks		Without Aggregate Shocks	
	Welfare Effect	Share Support	Welfare Effect	Share Support
Mortgage Interest Deduction				
All locations	0.0164	0.831	0.0027	0.684
High-price urban	0.0074	0.379	0.0034	0.418
Low-price rural	0.0009	0.324	-0.0078	0.337
Rent Subsidy to Young Low-Income				
All locations	-0.0134	0.149	-0.0064	0.195
High-price urban	-0.0055	0.086	-0.0030	0.120
Low-price rural	-0.0009	0.093	-0.0040	0.115

In the counterfactual exercise in which mortgage interest deductions are only targeted to the three highest-price urban locations, welfare increases by 0.74%. This policy, however, is not supported by a majority, as only 37.9% of agents are better off after its introduction. Interestingly, despite their pro-home buying nature, targeted mortgage interest deductions also cause a slight reduction in the homeownership rate. This happens because the policy leads to an increase in both urban prices and the urban population share. Despite the introduction of the mortgage interest deductions, marginal agents living in the targeted urban areas are unable to become homeowners due to higher housing prices. This increase in prices stems from the pressure on housing demand coming from the influx of (renter) migrants and the higher share of local residents who stop coresiding. Since the homeownership rate remains roughly constant and housing prices become more spatially dispersed, wealth inequality increases as a result of the policy.

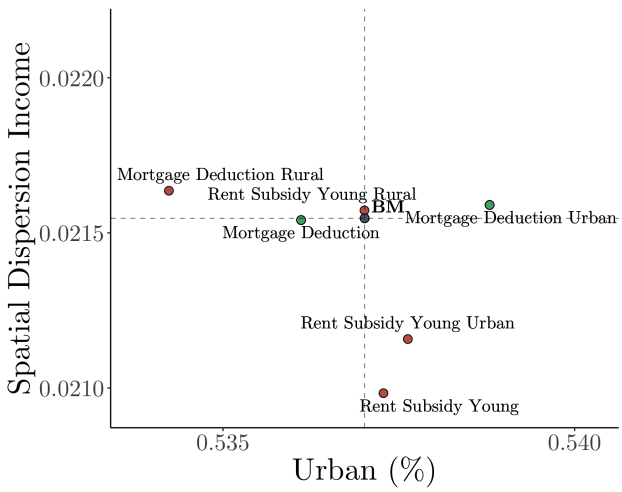
Finally, a mortgage interest deduction policy that only targets low-price rural residents barely affects welfare (Table 5). Similarly to its untargeted version, this policy increases homeownership and reduces internal migration (Figure 8a). However, it also increases the spatial misallocation of labor by 0.4% (Figure 9a). The resulting net effect of the policy on welfare is barely positive (0.1%), and the support among newborn agents is relatively low (32.4%).

The welfare effects of mortgage interest deductions are heterogeneous along the income distribution (Appendix Figure G23). Perhaps surprisingly, the policy tends to benefit more the income poor when it targets urban locations, and to harm them more when it targets rural locations. Welfare gains by income are instead roughly constant for the untargeted version of the policy. Figure G23 additionally shows the welfare effects of policies when price and taxes are fixed, and, in a different simulation, when income taxes are also not adjusted.

The tax increases needed to finance the policy offset most, though not all, of the partial equilibrium welfare benefits. When additionally allowing prices and wages to adjust in equilibrium, welfare gains further decrease for both the untargeted policy and the one targeted to urban locations. The losses are especially high in the targeted policy and for low-income agents, due to the increase in housing prices. Agents in this income group, indeed, are less likely to be homeowners and are more exposed to price fluctuations. Conversely, wage and price general equilibrium effects tend to benefit low-income agents in the policy targeted to rural location. However, these effects, which are driven by the decrease in housing prices, do not fully offset the partial equilibrium welfare losses.

Finally, a comparison of the welfare effects of the policy in a version of the model without aggregate price and wage shocks reveals that the existence of aggregate uncertainty makes mortgage deduction policies more valuable to agents (see Table 5). This is due to the pro-homeownership nature of the policy and to the fact that homeownership provides insurance against rental price volatility, which is valued by risk-averse agents. Absent aggregate uncertainty, welfare gains are around six times lower for the untargeted version of the policy and two times lower for the version that only targets high-price urban locations. Moreover, a mortgage interest deduction policy targeted at low-price rural locations would lead to welfare losses (-0.78%) in a model without aggregate shocks, whereas it leaves welfare mostly unaffected in the presence of aggregate uncertainty.

(a) Urban Share and Income Dispersion



(b) Urban Share and Price Dispersion

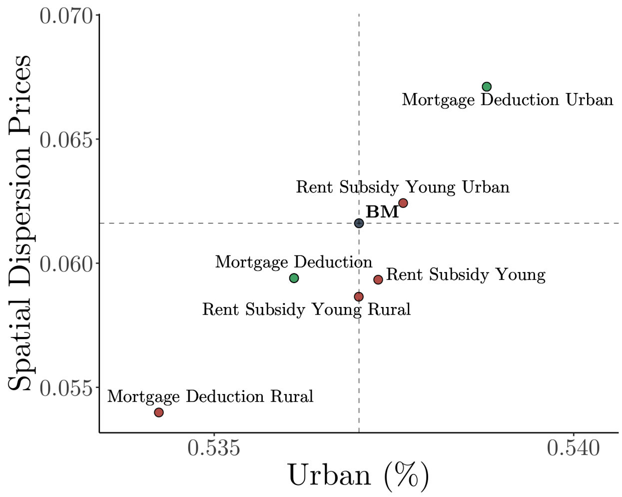


Figure 9: The figures plot the equilibrium outcomes of policies. Green dots correspond to welfare-improving policies, whereas red dots are used for policies that decrease welfare. The black *BM* dot represents the benchmark economy. Spatial dispersion is measured using variance of the log of the variable.

6.2 Subsidy to Young Low-Income Renters

I also study the welfare implications of a rent subsidy policy introduced in 2018 for young, low-income individuals. The eligibility criteria include a maximum gross annual income threshold of 19,500 euros and an age limit of 35 years.[38] The subsidy provides an annual benefit of 3,000 euros, a significant sum for the low-income recipients of the policy given that it amounts to around 30% of the average rent. As in the mortgage interest deductions counterfactual, I allow prices, wages, and taxes to adjust in general equilibrium in response to the subsidy, and study versions of the policy which are both untargeted and targeted by location.

As shown in Figure 8a, the untargeted policy decreases homeownership (-1.7%) and increases internal migration by 0.3% relative to the benchmark. It also attracts workers to urban locations, thus decreasing the misallocation of labor across space (-2.6%), as measured by the spatial dispersion of income (Figure 9a). Despite the redistributive nature of the policy, rent subsidies to low-income agents are found to increase wealth inequality by 0.6% (Figure 8b). This occurs because lower-income agents are more likely to rent to receive the subsidy, which reduces their incentives to accumulate housing wealth through homeownership.

Table 5 indicates that the rent subsidy diminishes welfare by 1.34% and is supported by only 14.9% of agents. Due to restrictiveness of the eligibility criteria, the benefits of rent subsidies are concentrated among few individuals. On the other hand, all employed workers need to bear the tax increase required finance the policy, although small (0.4 percentage points higher average tax rate). The take-up of the policy is low because few people find it optimal to rent, even with the subsidy: the majority of agents in the model are natives, who are better off coresiding, rather than renting, until they have enough funds to pay the down-payment and buy a house.

Finally, Table 5 reveals that targeting rent subsidies to high-price urban or low-price rural locations marginally mitigates the negative welfare effect of the policy. Support for the targeted policies, however, is even lower than for the untargeted rent subsidies, as only around 9% of newborn agents are better off with them than without.

7 Conclusion

Should governments promote homeownership? Although housing policies are widespread, subsidizing homeownership can reduce internal migration, drive up prices in productive locations, and increase the spatial misallocation of labor. To address this question, I build a spatial equilibrium model populated by finitely-lived agents making dynamic coresidence, homeownership, migration, and saving decisions.

Homeownership provides utility and insurance against aggregate rental price risk, but reduces migration as homeowners are forced to sell and pay the associated transaction costs

[38] The maximum permissible annual rent is set by Spanish law at 7,200 euros, or 10,800 euros in the most expensive ares. Rents in all model locations are lower than those thresholds.

before moving. The relationship between homeownership and migration, however, is not one-sided, as migration decisions themselves can impact future homeownership prospects. Non-migrant workers can live with their parents for a time, and coresidence can allow them to save and buy a house earlier than migrants. Additionally, by remaining in or returning to their birthplace, they have easier access to housing bequests.

I develop a new strategy to solve dynamic spatial models with aggregate uncertainty by modelling agents' expectations about local endogenous prices and wages with lower-rank factors. The model is calibrated for Spain, a country with high homeownership and low internal migration despite significant spatial differences in income and unemployment risk. I use quasi-experimental evidence from recent place-based policies that subsidized homeownership to validate the model.

Mortgage interest deductions increase welfare by 1.64%, have majority support, and reduce wealth inequality. However, they decrease internal migration and do not improve the spatial allocation of labor. Conversely, rent subsidies to young low-income individuals decrease welfare by 1.34%, despite increasing internal migration and reducing the spatial misallocation of labor. Targeting policies to specific locations reduces the benefits of mortgage deductions but mitigates the welfare costs of rent subsidies. Finally, the presence of aggregate shocks increases the welfare benefits of pro-homeownership policies.

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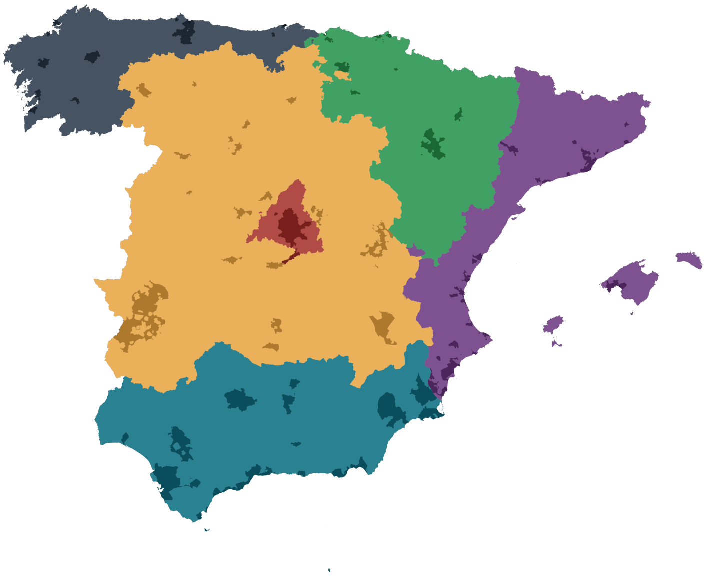
Appendix

This Appendix is organized as follows. Section A contains additional tables and figures referenced in the text. Section B provides details about the data. Section C presents further details on the model. Section D contains further information on the equilibrium. Section E provides details on the estimation strategy. Section F contains details on the validation. Finally, Section G provides additional information on the policy counterfactuals.

A Additional Figures and Tables

Figure A1: Locations: Combination of Regions and Urban-Rural Municipalities. [Back]



Note: This map shows the locations used in the data and model. Locations are defined as combinations of NUTS-1 regions in peninsular Spain and groups of municipalities classified as either urban or rural. The regions are represented by distinct colors, with darker shades used to indicate urban municipalities within each region. Peninsular Spain comprises six distinct NUTS-1 regions, resulting in a total of 12 locations when combined with urban and rural areas. The Canary Islands, which belong to the Atlantic Ocean northwest of Africa, and Ceuta and Melilla, Spanish enclaves lying in mainland Africa, are excluded. Urban municipalities are defined by the Spanish Ministry of Transport and Mobility (*áreas urbanas*) and have at least 40,000 residents.

Definition of Locations Locations in the data and model are combinations of NUTS-1 regions and urban and rural areas within each region. The NUTS classification is a hierarchical system developed by the European Union to divide its territory for statistical purposes. NUTS-1 regions refer to major socio-economic regions, with an average population size between 3 and 7 millions. There are six distinct NUTS-1 regions in peninsular Spain. I use official definitions of urban areas constructed by Spain's Ministry of Housing in 2008. Urban areas group municipalities linked by commuting and employment patterns. In order to identify urban areas in the MCVL data, which does not distinguish between cities with

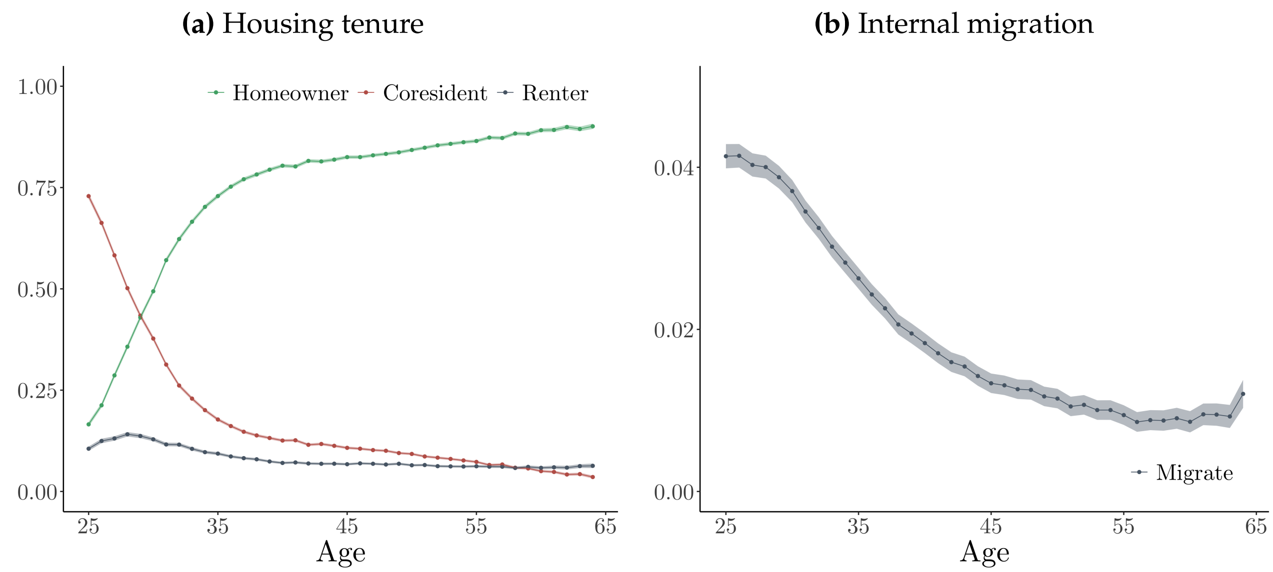


Figure A2: The figures plot age fixed-effects with 95% confidence intervals (heteroskedasticity-robust standard errors). Year fixed-effects are also included in panel **b**. Data: Census 2011 (panel **a**), MCVL 2005-2019 (panel **b**). [Back]

population below 40,000, I follow De la Roca and Puga (2017) and exclude from urban areas the municipalities with a population lower than 40k. The resulting 168 urban municipalities cover 80% of the urban population identified by the Spain's Ministry of Housing and 55% of the Spanish population. The remaining 7,968 municipalities are classified as rural.

Figure A1 shows the locations used in the data and model. The six NUTS-1 regions are represented by distinct colors, with darker shades used to indicate urban municipalities within each region. Locations group together different urban areas and rural areas within the same regions, and are thus 12 in total. The same urban location may encompass multiple non-adjacent urban areas. While it would be ideal to treat each urban area as a separate location, doing so would be computationally too costly. The high degree of heterogeneity in the model translates into a large state space. For a discussion of the computational challenges associated with increasing the number of locations, see footnote 21.

While it's essential to maintain a limited number of locations, differentiating between rural and urban areas is crucial for two main reasons. First, there is a marked difference in housing and labor markets in urban versus rural areas within the same region, leading to large difference in wages and prices (Figures D8, D9, and D10). Ignoring this distinction in the model, for instance by treating each region as a single location, would omit key sources of variations in the data. Second, the place-based policy used to validate the model is targeted to small rural locations. Therefore, the inclusion of rural locations is necessary to accurately simulate the policy in the model.

Lifecycle Housing Tenure and Migration Figure A2 plots the lifecycle evolution of housing tenure choices (panel a), i.e. homeownership, coresidence, and renting, and of internal migration rates (panel b). The age fixed-effects predicting internal migration (panel b) are estimated using the MCVL for precision. Nonetheless, the convex and decreasing lifecycle pattern is similar when estimated with the EU-SILC.

Migration Regressions Table A1 reports the estimated coefficients of a regression that takes the form:

$$\text{Migrate}_{it} = \alpha_i + \alpha_r + \alpha_{rt} + \tau\text{Homeowner}_{it} + \alpha X_{it} + \epsilon_{it}$$

The outcome variable is the migration event, which occurs when the following year's location of residence is different from the current one. The specification includes region (NUTS-1) and region-year fixed effects α_r and α_{rt} (column 1 of Table A1), and, in column (2), additionally includes household fixed-effects α_i. Additional controls X_{it} include age, age squared, income level, and indicators for college-educated, married, parent, employed, and gender. The regressions are estimated with the EU-SILC 2004-2019 panel.

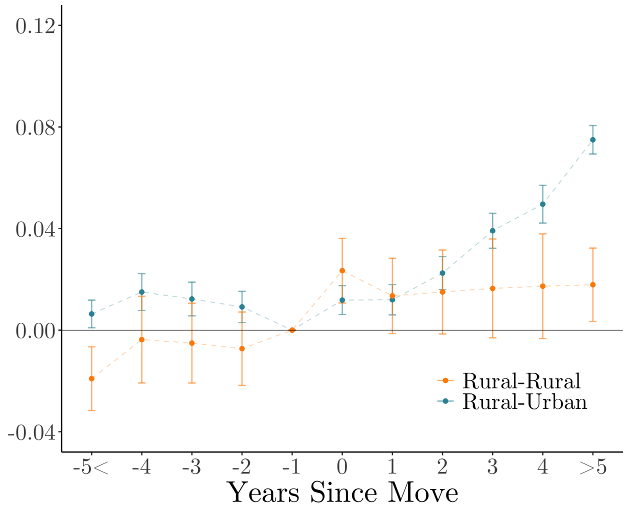
In the specification of column (1), I find that homeowners are less likely to migrate than renters after controlling for age and other observables. It should be noted that the only significant predictors of migration behavior include homeownership status, age, and college education. Each of these characteristics is specifically modeled as migration cost shifters within the theoretical framework, as detailed in Section 3.2.

Table A1: Migration occurs when the following year's location of residence is different from the current one. Region fixed-effects refer to NUTS-1 regions. Standard errors are clustered at the location level, *p<0.1, **p<0.05, ***p<0.01. Data: EU-SILC 2004-2019. [Back]

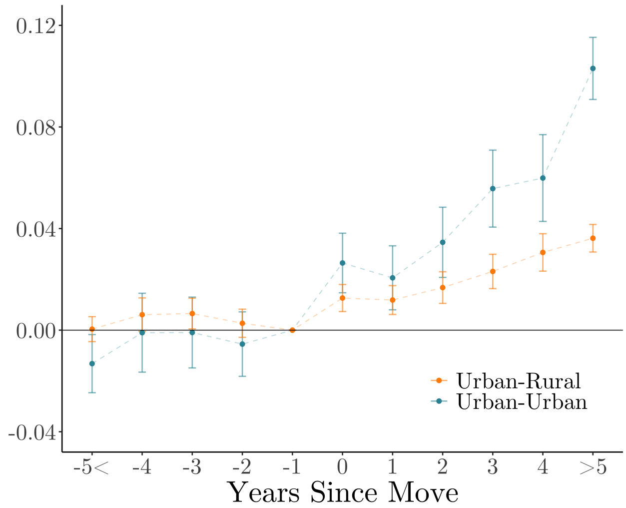
	Migrate	
	(1)	(2)
Homeowner	-0.0045**	-0.0192**
	(0.0019)	(0.0089)
Age	-0.0012**	-0.0049*
	(0.0005)	(0.0023)
Age^2	0.0000*	0.0000*
	(0.0000)	(0.0000)
College	0.0024*	-0.0008
	(0.0013)	(0.0069)
Married	-0.0007	-0.0048
	(0.0012)	(0.0076)
Parent	-0.0023	-0.0039
	(0.0016)	(0.0065)
Employed	0.0006	-0.0003
	(0.0010)	(0.0031)
Income	0.0003	-0.0006
	(0.0002)	(0.0004)
Male	-0.0012	-0.0049
	(0.0020)	(0.0077)
Household FE		✓
Region FE	✓	✓
Year-Region FE	✓	✓
Observations	72,593	72,593
R^2	0.0527	0.3882
Migration Rate	0.0082	0.0082

When I additionally include household fixed-effects (column 2), the coefficients associated with homeownership status and age keep their significance. The effect of college education becomes insignificant, likely due to the limited within-household variation in educational attainment that can be exploited in a 4-year panel. Looking at the magnitude of the effects, homeownership is the single most important predictor of migration rates: the probability of moving reduces by around 1.92 percentage points for household heads who become homeowners.

(a) Log income, migration event from urban locations



(b) Log income, migration event from rural locations



(c) Log income, migration event by education group

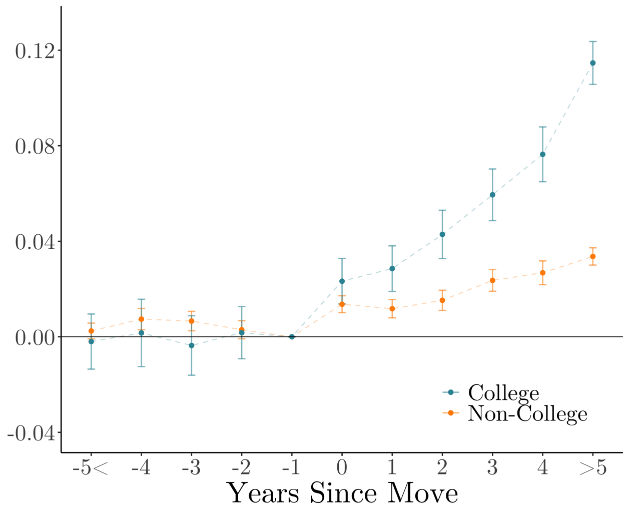


Figure A3: The figures plot the fixed-effects corresponding to the years from the migration event, with 95% confidence intervals (heteroskedasticity-robust standard errors). Other included fixed-effects are: year, gender, college-educated, sector (3-digits NACE), permanent contract, part-time contract, public employee, occupational skills (five groups from low-skilled to very high-skilled, as in De la Roca and Puga (2017)). Data: MCVL 2005-2019. [Back]

Migration Event Studies and Income In Figure A3 I plot three event studies centered around migration events. Specifically, I plot the τ_j coefficients in a a series of regressions that take the form:

$$\log y_{it} = \alpha_t + \sum_{\substack{j=-4 \\ j\neq -1}}^{4} \tau_j \mathbb{1}\left\{(t-t_0)=j\right\} + \tau_{-5}\mathbb{1}\left\{(t-t_0)\leq -5\right\} + \tau_5 \mathbb{1}\left\{(t-t_0)\geq 5\right\} + \alpha X_{it} + \epsilon_{it},$$

where the outcome y_{it} is annual labor income, α_t are year fixed-effects, τ_j are the event study fixed effects relative to the migration event occurring at t_0, and τ_{-5} and τ_5 are the average effects before and after five years from the event, which are included to avoid collinearity between the year fixed-effects and the τ_j yearly coefficients. Finally, X_{it} contains additional controls, which include indicators for gender, college-educated, sector (3-digits NACE), permanent contract, part-time contract, public employee, and occupational skills (five groups from low-skilled to very high-skilled, as in De la Roca and Puga (2017)). The regressions are estimated with MCVL 2005-2019 data.

The event studies are estimated using different sample restrictions and migration events. In the regression plotted in panel A3a, the sample is restricted to migration events from rural locations, and an interaction is added to differentiate between moves to urban vs. rural locations. The same is done for the regression of panel A3b, with the difference that the sample is restricted to migration events that originate from urban locations. Finally, panel A3c plots the event study coefficient estimated from the full sample, but adding an interaction with a college identifier to the τ_j coefficients.

The event studies reveal that internal migrants experience persistent income gains after moving. This is especially true when moving to urban locations (panels A3a and A3b) and for the college-educated workers (panel A3c).

Table A2: Standard errors are heteroskedasticity-robust, *p<0.1, **p<0.05, ***p<0.01. Data: MCVL 2005-2019. [Back]

	Log Labor Income		Coresident	
	(1)	(2)	(3)	(4)
Age	0.0282***	-0.1865***	-0.0397***	-0.0143***
	(0.0001)	(0.0021)	(0.0000)	(0.0007)
Age^2	-0.0004***	-0.0004***	0.0007***	0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
College	0.4552***	0.1080***	-0.0087***	-0.1415***
	(0.0009)	(0.0015)	(0.0006)	(0.0011)
Native	-0.0314***	-0.0169***		
	(0.0007)	(0.0017)		
Log Labor Income			-0.0258***	-0.0042***
			(0.0003)	(0.0003)
Individual FE		✓		✓
Location FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R^2	0.1250	0.7154	0.1476	0.7117
Observations	5,253,926	5,253,926	5,253,926	5,253,926

Income and Coresidence Regressions Table A2 reports the estimated coefficients of a regression that takes the form:

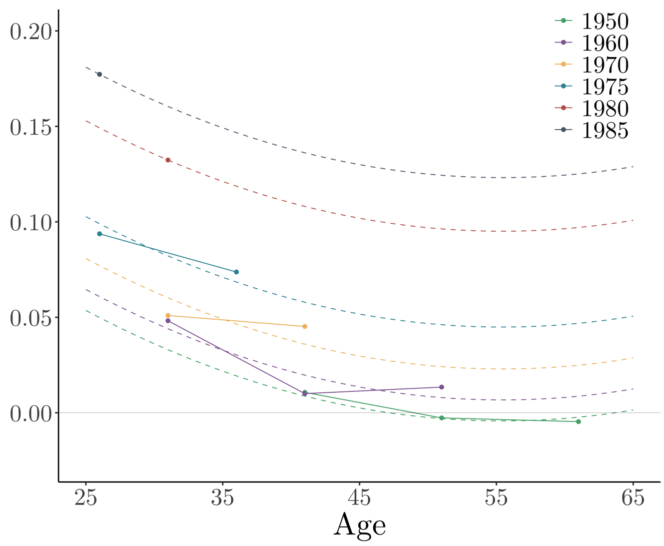
$$y_{it} = \alpha_i + \alpha_d + \alpha_t + \alpha X_{it} + \epsilon_{it}.$$

The outcome y_{it} is either log labor income (columns 1 and 2) or a coresident dummy (columns 3 and 4). The regression includes location and year fixed effects α_d and α_t, and, in columns (2) and (4), additionally includes individual fixed-effects α_i. Controls X_{it} include age, age squared, college, and indicators for natives (in columns 1 and 2) or log labor income levels (in columns 3 and 4). The regressions are estimated with the MCVL 2005-2019 data.

The first two columns of Table A2 reveal that natives, all else equal, gain less than internal migrants. This earnings gap might arise partly from compensating differentials – for instance, natives might have a home-bias, making them more willing to forego some income to remain in their birthplace. Another contributing factor could be selection, which may play a role if migrants, on average, have higher unobservable ability. Even after accounting for individual fixed-effects (as shown in column 2), the wage premium for migrants remains, although reduced to roughly half, 1.7% as opposed to 3.2%. This suggests that selection on fixed unobservables alone does not explain the entirety of the gap, and that compensating differentials are likely to also play a role.

Column (3) of Table A2 shows that coresidents are, all else equal, negatively selected in terms of labor income. Interestingly, even after accounting for individual fixed-effects, the association between income and coresidence remains negative and significant (column 4). This suggests that the option to live with parents can be used as insurance against negative income shocks occuring during the lifecycle.

Figure A4: Natives-migrants homeownership gap by cohort



Note: The dashed line in the figure depicts, for different cohorts, age polynomial functions estimated in a regression where the dependent variable is the partialled-out homeownership gap by age between natives and migrants. The fixed-effects used to partial-out homeownership are: location, gender, college-educated, married, parent, employed (reference group: male, non-college, single, not parent, employed). Data: Census 1991, 2001, 2011. [Back]

Natives-Migrants Homeownership Gap by Cohort When computing the homeownership gap between natives and migrants (Figure 2a), accounting for cohort effects is crucial. Over the past 60 years, Spain has moved from a dictatorship to a democratic system and completed the structural transformation process. These changes have had profound impacts on both the price-to-income ratio and internal migration rates (Budí-Ors and Pijoan-Mas 2022).

To adjust for cohort effects, I first separately estimate with 1991, 2001, and 2011 Census data three regressions of the form:

$$\text{Homeowner}_{itq} = \alpha_{jnq} + \beta X_{itq} + \epsilon_{itq}.$$

The dependent variable is a homeownership dummy, α_{jnq} is an age-native fixed-effects for cohort (i.e. birth year) q, and X_{itq} contains indicators for location, gender, college-educated, married, parent, and employed.

I then obtain the partialled-out homeownership rates by age and native status, $\widehat{\alpha}_{j0q}$ (migrants at age j) and $\widehat{\alpha}_{j1q}$ (natives at age j), for three different cohorts at each age. Then, after defining the partialled-out homeownership gap between natives and migrants by age and cohort, $\text{Gap}_{jq} = \widehat{\alpha}_{j1q} - \widehat{\alpha}_{j0q}$, I separately estimate the regression

$$\text{Gap}_{jq} = \alpha_{q0} + \alpha_{q1}\text{Age}_j + \alpha_{q2}\text{Age}_j^2 + \epsilon_{jq} \tag{18}$$

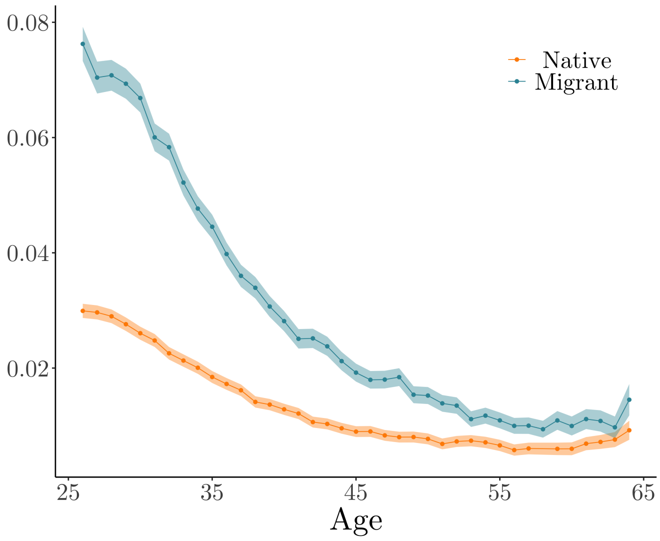
by fitting the homeownership gaps with a cohort specific polynomial in age. The dashed lines in Figure A4 represent the fitted polynomial functions for different cohorts, whereas the dots linked by solid lines depict Gap_{jq}.

As can be seen in Figure A4, the homeownership gap between natives and migrants has been increasing with every new cohort. A naive cross-sectional analysis that ignored cohort effects would conclude that the gap is at around 20 percentage points at age 25 and disappears by age 64. However, when we account for cohort effects, it becomes clear that this gap persists throughout the lifecycle for the most recent cohorts.

The baseline Figure 2a uses Census 2011 data. I don't adjust for cohort effects for ages ranging from 25 to 35; instead, I rely on cross-sectional data to determine the homeownership gap between migrants and natives. It's likely that cohort effects during the initial 10-year age period aren't as pronounced. Conversely, the large changes in the coresidence rates observed among young people, which evolve very differently between natives and migrants before age 35 (see 2c), have a large effect on the homeownership gap due to the selected type of people that stop coresiding each year. The cohort analysis of regression (18) is unable to account for these trends, since the age polynomial function is constant across the lifecycle, which is why I choose not to use those estimates for ages 25-35. However, starting at age 36, I do adjust for cohort effects, applying the homeownership gap derived from regression (18) for the 1975 cohort (who turned 36 in 2011).

Migration Rates Among Natives and Migrants Figure A5 plots age fixed-effects of a regression where the dependent variable is the migration event. Other included fixed-effects are location, gender, college-educated, married, parent, and employed. Migrants are more likely to change residence again in the future, especially at younger ages.

Figure A5: Share migrating



Note: The figure plots age fixed-effects of a regression where the dependent variable is the migration event. Other included fixed-effects are: location, gender, college-educated, married, parent, employed (reference group: male, non-college, single, not parent, employed). Confidence intervals at 95% level with heteroskedasticity-robust standard errors. Data: MCVL 2005-2019. [Back]

Housing Expenditure Among Natives and Migrants Figure A6 plots age fixed-effects of two regressions where the dependent variable is the imputed housing expenditure for natives and migrants. The regressions, that also control for location, gender, college education, and employment status fixed-effects, are estimated using the Household Budget Survey (*Encuesta de Presupuestos Familiares*, or EPF). The limitation of the EPF is that it only contains household-level expenditure data, which cannot be readily attributed to household members. As a result, we must make assumptions about how much coresidents contribute to their parents' housing expenses.

In the left panel (Figure A6a), I make the assumption that coresidents do not contribute to the overall household consumption. Conversely, in the right panel (Figure A6b), I make the opposite extreme assumption: coresidents cover their entire OECD equivalence share of expenses. This share ranges between 11.1% to 16.7%, depending on the number of siblings. The expenses taken into account cover housing, maintenance, and utilities costs for the main residence.

The EPF does not include birthplace information, and thus does not allow to differentiate between natives and migrants directly. To navigate this, I estimate overall expenditure by age and assume that the consumption behavior of natives and migrants is observationally equivalent *within* the group of people who are coresiding and *within* those who are not coresiding. Then, I impose the lifecycle coresidence shares by native status, computed using the 2011 Census, and obtain the plots of Figure A6.

Regardless of the assumptions made in panels A6a and A6b, a substantial expenditure gap exists between natives and migrants. Depending on how much coresidents pay for household expenditure, natives under the age of 35 save, on average, between 2,300 and 3,000 euros more in annual housing costs than their migrant counterparts. This higher saving rate can be attributed to the economies of scale associated with coresidence and to the fact that natives are more likely to coreside than migrants.

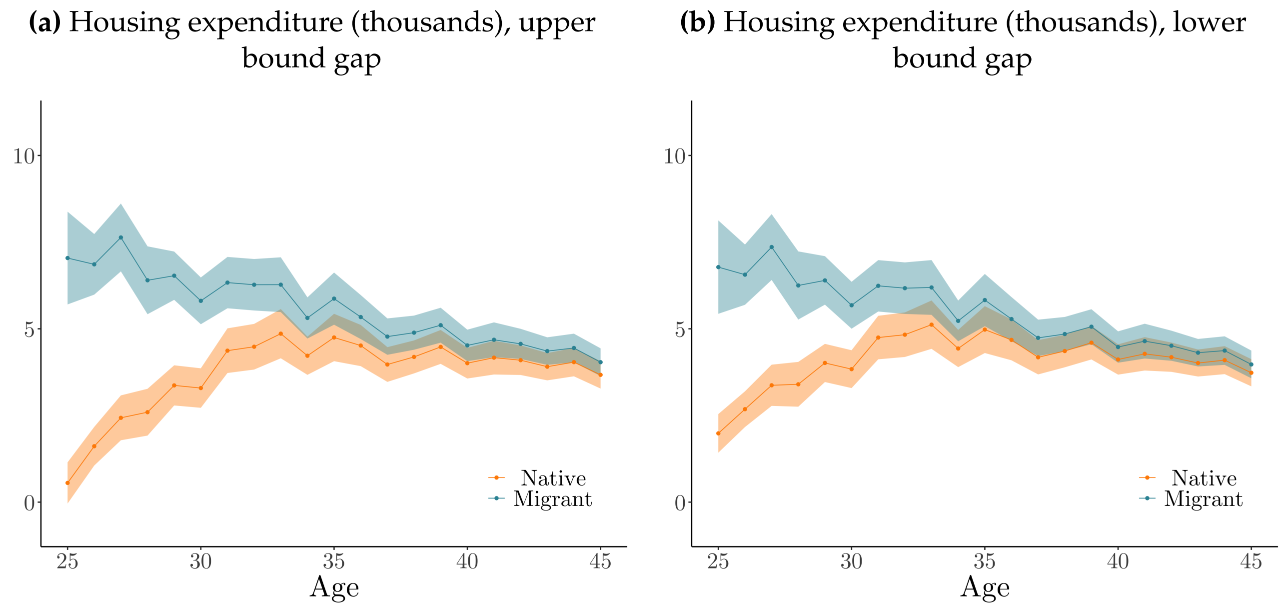
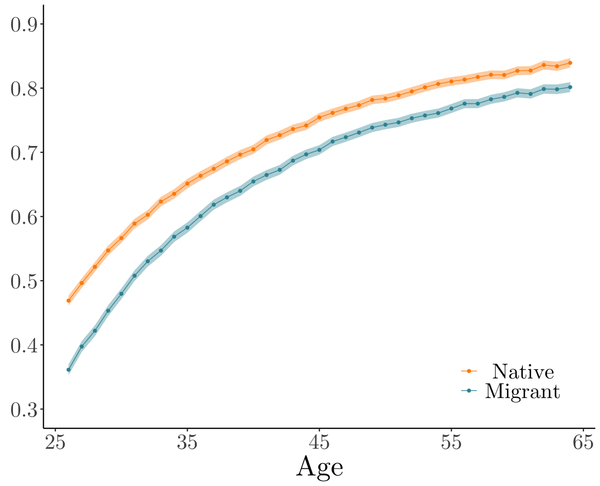


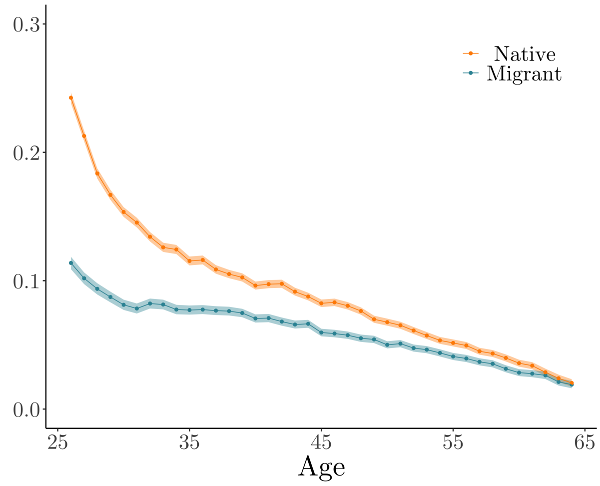
Figure A6: Age fixed-effects are plotted. Other included fixed-effects: location, gender, college, employed. Assumptions: 1. Native coresidents pay either no share of household consumption (left panel) or 11.1-16.7% of it, based on number of siblings and OECD equivalence scale (right panel); 2. When not living with parents, natives and migrants' expenditure is assumed to be observationally equivalent. Categories: housing, maintanance, utilities (no second houses). Confidence intervals at 95% level with heteroskedasticity-robust standard errors. Data: EPF 2016-2019. [Back]

Rosenzweig and Zhang (2019) use unique individual-level expenditure data for China and find that parents' saving rates reduce by 12 percentage points when their children coreside with them. This is consistent with the assumption of panel A6a that children pay no share of housing costs when coresiding, since parents expenditure goes down by an amount that is roughly equal to the children's OECD equivalence share. Accordingly, agents in the model pay no housing rent when living with parents. Nonetheless, it's important to highlight that the results from Rosenzweig and Zhang (2019) are not precisely estimated. This leaves open the possibility that children might be contributing to some part of the household expenditure, as assumed in panel A6b.

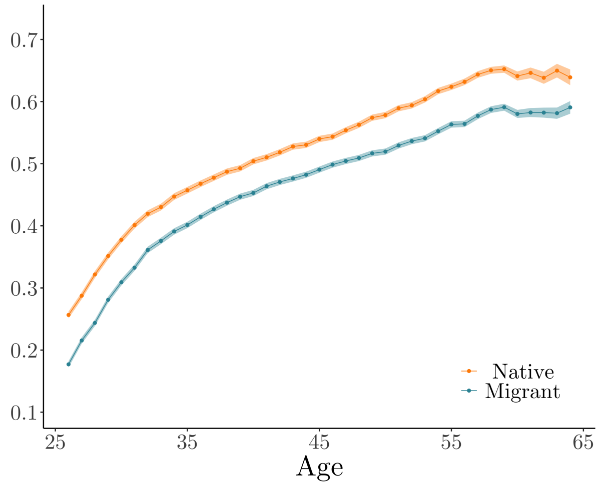
(a) Homeowners, not coresiding with parents, United States



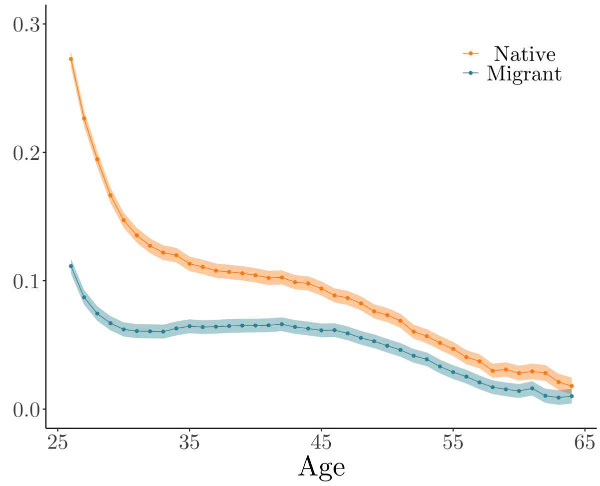
(b) Coresidents with parents, United States



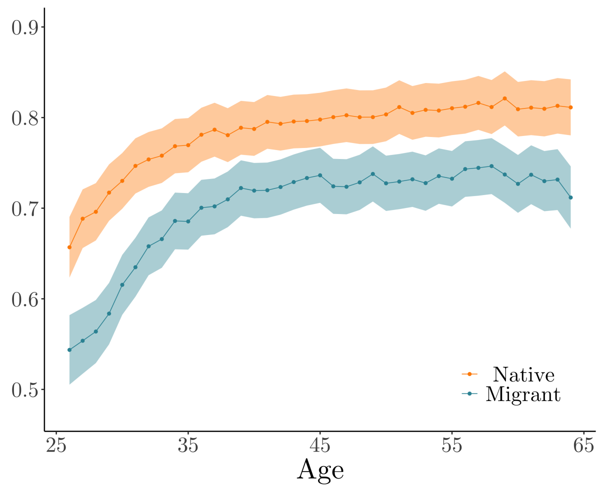
(c) Homeowners, not coresiding with parents, France



(d) Coresidents with parents, France



(e) Homeowners, not coresiding with parents, Italy



(f) Coresidents with parents, Italy

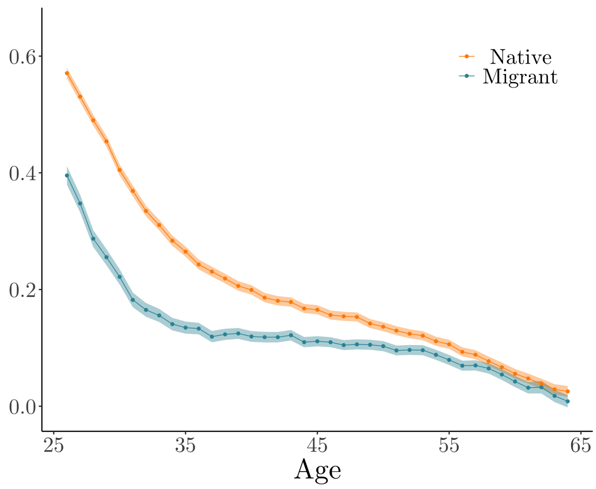


Figure A7: The figures plot age fixed-effects. Other included fixed-effects are: location, gender, college-educated, married, parent, employed, and, in the U.S. sample, race (reference group: male, non-college, single, not parent, employed, white). Location: MSA (United States), NUTS-3/*Département* (France), NUTS-2/*Regione* (Italy); Native: living in State of birth (United States), living in NUTS-3 of birth (France, Italy). Confidence intervals at 95% level with heteroskedasticity-robust standard errors are plotted. Data: ACS 5-years 2007-2011, 2011 Census (France, Italy). [Back]

International Comparison: Natives-Migrants Homeownership and Coresidence Gaps The homeownership gap between observationally equivalent natives and internal migrants is also observed in France, Italy, and the United States, as shown in Figures A7a, A7c, and A7e. The choice of these countries is driven by the availability of ACS and Census data on coresidence, homeownership, and both current and birthplace locations within OECD countries, together with data on the observables used as controls: indicators for location, gender, college-educated, married, parent, employed, and, in the U.S. sample, race.

Current and birthplace locations in each country are defined by using the smallest available geographical units that can be assimilated to cities. The chosen definitions for current locations are Metropolitan Statistical Areas in the United States, NUTS-3 regions (*Départements*) in France and NUTS-2 regions (*Regioni*) in Italy. Furthermore, natives are defined as people living in the state of birth (in the United States), or in the NUTS-3 region of birth (in France or Italy).

Figures A7b, A7d, and A7f illustrate that in each of these countries, natives have a higher tendency to coreside with parents compared to migrants. This pattern, also observed in the Spanish context (Figure 2c), suggests that coresidence can be a key factor influencing the homeownership gap between natives and migrants. The unavailability of data on the share of people living in inherited houses does not allow me to compare across countries the importance of housing bequests in generating the homeownership gap between natives and migrants (Figure 2b).

B Data Appendix

[Back]

Several cross-sectional and panel datasets are used in the analysis, encompassing Census, survey, administrative, and online sources. All samples are restricted to individuals aged between 25 and 64 who are Spanish-born citizens and currently active, i.e. employed or unemployed. Detailed descriptions of these data sources are provided below.

MCVL The continuous Work History Sample (*Muestra Continua de Vidas Laborales*, or MCVL) is a 4% non-stratified sample of individuals affiliated to the Spanish social security. This panel records job changes and contractual modifications within the same firm. Information on wages is provided for the entire working life of the sampled individuals, when available. I focus on 2005–2019, the period in which job spells are matched with tax record data that provide uncensored earnings, and compute yearly full-time equivalent wages using the available information on working hours. For a small number of cases, the computed wages are much higher than workers' contributions to social security. To prevent these outliers from affecting the results, I remove the observations corresponding to the top 1% of the wage distribution. Labor income is deflated using the 2014 Consumer Price Index.

Furthermore, the MCVL provides information on workers' gender and age, which are contained in social security records. The sample is also matched with Spain's Continuous Register Statistics (*Estadística del Padrón Continuo*), so that individual characteristics such as province of birth and residence, educational attainment, and an indicator for those coresiding with parents can be recovered.[39] Data on municipalities of birth and residence are also provided when these municipalities have population over 40,000. This information is used in combinations with the province data (mappable to NUTS-1 regions) to retrieve birthplace and current location, as explained in Appendix A.

Employers assign workers to different social security contribution groups that are highly related to the level of education required to perform the job. Following De la Roca and Puga (2017), I organize these groups into five skill categories: very high-skilled, high-skilled, medium-high-skilled, medium-low-skilled, and low-skilled occupations. For example, the upper contribution group, which includes very high-skilled occupations, is reserved for jobs that require an engineering or bachelor's degree and for top managerial positions. Finally, the NACE 3-digit sector of the establishment and its location are also reported. The final dataset consists of 5.25 million observations.

EU-SILC The European Union Statistics on Income and Living Conditions (EU-SILC) is a survey that spans the years 2004-2019 and contains 74,000 Spanish households. It is a household-level panel with a 4-year rotating structure. It includes information on homeownership, coresidence, household-level income, transfers, unemployment benefits, and household members' employment status. It also includes information on NUTS-1 regions of residence and on the size of the municipality of residence (indicator for municipalities with population larger than 50,000). By approximating the 40,000 cutoff with the 50,000 one, urban and rural locations of residence can be defined accordingly.

The household-level annual migration rate matched in the model comes from the EU-SILC rather than the MCVL. A number of reasons motivate this choice. First, the EU-SILC provides representative information on employed and unemployed household heads, while the MCVL only contains information on the unemployed receiving unemployment benefits. Second, the migration behavior of individuals in the EU-SILC can be compared with changes in homeownership, a piece of information that is missing in the MCVL. The elasticity between migration and homeownership is an important moment that is compared to the model counterpart. Lastly, while the EU-SILC regularly surveys the municipality of residence, this data is reliant on individuals' self-reporting in the MCVL, in line with Spanish bureaucratic procedures (*Empadronamiento*). This can introduce time lags in updates and potentially bias the migration information coming from the administrative data.

EFF The Survey of Household Finances (*Encuesta Financiera de las Familias*, or EFF) is a household-level panel that covers the years 2005-2020 and comprises 15,000 households. The Bank of Spain conducts this survey triennally. However, since each wave contains data from two successive years, only one year out of three contains no data. The dataset covers all the important variables that are relevant for the analysis: these include location (current and birthplace), homeownership, coresidence, and income (only at the household-level).

[39] The Continuous Register Statistics contains information on the household composition (date of birth and gender of each individual living in the household). I count a person as coresiding with parents if they are living with someone that is at least 18 years older than them.

The EFF is also the only dataset with wealth information. The net wealth information used for the analysis comprises all household wealth, including financial assets, real estate, businesses shares, private pension plans, and other real valuables minus total debt. Finally, the data contains information on housing bequests received at some point in life (not necessarily during the sample period), which is needed to estimate the probability to inherit a dwelling in the model.

The Bank of Spain, as the EFF data provider, has authorized remote access to restricted geographic information (current and birthplace) in compliance with privacy guidelines. The 2005-2006 wave lacks data on birthplace. Whenever this piece of data is needed for the analysis, I use the 2008-2020 version of the panel. Urban and rural locations are classified within NUTS-1 regions following the 40,000 population threshold rule for municipalities in urban areas.

Census The 2011 Census of Population and Housing includes 1.3 million observations. It contains cross-sectional information on location (province of birth, municipality of residence), homeownership (whether the current dwelling has been paid, inherited, or is still mortgaged), and coresidence. The municipalities of residence can be directly mapped to rural and urban locations. The 1991 and 2001 Censuses contain similar data and can be used to account for cohort effects.

EVR, EPC The combined Residential Variation Statistics (*Estadística de Variaciones Residenciales*, or EVR) and the Continuous Register Statistics (*Estadística del Padrón Continuo*, or EVR) provide data on the universe of Spanish movers and stayers, respectively. They include an indicator for residents in cities with population lower than 10,000 and between 10,000 and 20,000 - among other population thresholds. The granualarity and precision of these data sources allows me to study the migration effect of place-based policy introduced in small municipalities.

EPF The Household Budget Survey (*Encuesta de Presupuestos Familiares*, or EPF) provides expenditure data and additional variables, including homeownership status, on a yearly sample of approximately 24,000 households. It also has indicators for residents in small municipalities, which enables me to examine the impact of place-based policy on homeownership. Average housing sizes are also measured with this data source.

Idealista *Idealista* is the leading real estate web portal in Spain. Its database covers the quasi-universe of dwellings that have been listed on the internet. Their website offers publicly available reports with housing prices and rents times series for both NUTS-3 and NUTS-2 regions, as well as for a selection of municipalities, encompassing all urban municipalities used in the analysis.[40] I use this data source focusing on the period between 2010 and 2019, to avoid missing data in some locations before 2010.

Price and rent series for urban locations are computed using population-weighted averages of time series at the urban municipality level. For rural locations series, a two-step approach is used. First, I compute prices and rents at the *rural* NUTS-2 levels as the residual

[40]The data can be accessed at https://www.idealista.com/sala-de-prensa/informes-precio-vivienda/.

series that would yield the *aggregate* observed NUTS-2 series, when combined in a population weighted-average with the observed *urban* NUTS-2 prices and rents. Then, I aggregate the rural NUTS-2 series at the rural location level using population weighted averages.

C Model Appendix

[Back]

C.1 Labor Markets

[Back]

Firms Output in location d produced by the representative firm is given by

$$Y_{dt} = X_{dt}(\zeta_{dt} L_{Ndt}^{\rho} + (1 - \zeta_{dt}) L_{Edt}^{\rho})^{1/\rho},$$

where X_{dt} is the location-specific productivity and L_{edt} is total efficiency units supplied in location d by education group e. Local labor markets are competitive. The first-order conditions determine wage per skill $\widehat{w}_{edt} = w_{edt}^{\vartheta_{ed}}$ of college and non-college labor

$$\widehat{w}_{edt} = X_{dt}(\zeta_{dt} \mathbb{1}_N + (1 - \zeta_{dt}) \mathbb{1}_E)(\zeta_{dt} L_{Ndt}^{\rho} + (1 - \zeta_{dt}) L_{Edt}^{\rho})^{\frac{1-\rho}{\rho}} L_{edt}^{\rho-1}, \tag{19}$$

where $\mathbb{1}_E$ and $\mathbb{1}_N$ are indicator functions for the college and non-college first-order conditions, respectively. The firms' output consists of the freely tradable consumption good, which acts as the numeraire.

Individuals The supply of efficiency-units of labor, given population shares μ_{edjt}, employment shares $\widehat{l}_{edjt} = \mathbb{E}[\mathbb{1}\{l_{edjt} = 2\}]$, age income profiles Υ_{edj} and distribution function $\varphi_{edjt}(\theta_e, z_{ej})$, is given by

$$L_{edt}^{S} = \sum_{j=1}^{J} \mu_{edjt} \widehat{l}_{edjt} \int \exp(\theta_e + z_{ej} + \Upsilon_{edj}) \varphi_{edjt}(\theta_e, z_{ej}) \, d\theta_e \, dz_{ej}. \tag{20}$$

Gross labor income is given by

$$\tilde{y}_{edjt} = \widehat{w}_{edt} \exp(\theta_e + z_{ej} + \Upsilon_{edj}).$$

Estimation To identify parameters in the benchmark, divide the first-order conditions and manipulate to obtain:

$$\zeta_{dt} = \frac{\frac{\widehat{w}_{Ndt}}{\widehat{w}_{Edt}} \left(\frac{L_{Ndt}}{L_{Edt}} \right)^{1-\rho}}{1 + \frac{\widehat{w}_{Ndt}}{\widehat{w}_{Edt}} \left(\frac{L_{Ndt}}{L_{Edt}} \right)^{1-\rho}}.$$

Given the substitution parameter ρ and benchmark equilibrium quantities

$$L_{edt} = L_{edt}^{S}, \tag{21}$$

derive ζ_{dt} by perfectly matching wages within locations and in all years (i.e. under all realizations of the aggregate shocks, as described in Section 4.2.3). Finally, use any of the two location-specific first-order conditions to derive X_{dt} in all years and locations.

C.2 Housing Markets [Back]

Firms The representative construction firm operating in location d sells houses at price p_{dt} (per square meters) and has a convex technology cost of production

$$C(H_{dt}) = k_{dt}\frac{H_{dt}^{\psi+1}}{\psi+1},$$

where H_{dt} is the total housing stock supplied, measured in square meters, and $k_{dt} > 0$, $\psi > 0$. The convexity of the cost function is a reduced-form way to capture the scarcity of buildable land and possible inputs and regulation constraints, while intercept k_{dt} captures construction costs that may vary across location and periods.

Profit maximization in competitive housing markets leads to the first-order condition

$$p_{dt} = k_{dt}H_{dt}^{\psi}, \tag{22}$$

which is the inverse housing supply function. The inverse housing supply elasticity ψ reflects the responsiveness of housing prices to changes in the housing stock.

Finally, there is a representative real-estate firm operating in each location that rents out housing units at price q_{dt}. Assuming that the outside-option investment has returns r and that operating costs of real-estate firms (e.g. monitoring costs, depreciation of the housing unit) are a fixed, location-dependent proportion $\overline{q}_d$ of the housing price, the zero-profit conditions is given by

$$q_{dt} - \overline{q}_d p_{dt} = rp_{dt}.$$

Therefore, denoting $\kappa_d = \overline{q}_d + r$, housing rents (per square meter) are given by

$$q_{dt} = \kappa_d p_{dt}, \tag{23}$$

where κ_d is the price-to-rent ratio.

Individuals Renters and homeowners demand housing sizes of $\overline{h}_{1ed}$ and $\overline{h}_{2ed}$ square meters, respectively. These quantities are fixed choices but are allowed to vary by education group and location.

Given population shares μ_{edjt}, renter shares $\widehat{h}_{1edjt} = \mathbb{E}[\mathbb{1}\{h_{edjt} = 1\}]$, and homeowner shares $\widehat{h}_{2edjt} = \mathbb{E}[\mathbb{1}\{h_{edjt} = 2\}]$, housing demand is given by

$$H_{dt}^{D} = \sum_{j=1}^{J}\sum_{e=1}^{2}\mu_{edjt}(\widehat{h}_{1edjt}\overline{h}_{1ed} + \widehat{h}_{2edjt}\overline{h}_{2ed}). \tag{24}$$

Estimation Given the inverse housing supply elasticity ψ and benchmark equilibrium quantities

$$H_{dt} = H_{dt}^{D}, \tag{25}$$

derive k_{dt} by perfectly matching prices (per square meter) under all realizations of the aggregate shocks (Section 4.2.3). Finally, κ_d is estimated by computing the ratio between average housing prices and rents by location.

C.3 Government [Back]

Budget Constraint The government budget balances in each year, i.e. expenditure on policies, transfers and unemployment benefits, and other public goods (denoted by G_t^p, G_t^g and $\overline{G}_t$ respectively) equals revenues from income taxes (T_t). Expenditure on public goods $\overline{G}_t$ does not affect individuals' utility.

Given the distributions of transfer recipients and taxpayers by gross labor income and given the shares of workers that receive transfers and pay taxes, $\varphi^g_{edjt}(\tilde{y}_{edjt})$, $\varphi^{\varsigma}_{edjt}(\tilde{y}_{edjt})$, $\widehat{l}^g_{edjt}$ and $\widehat{l}^{\varsigma}_{edjt}$ respectively, and given mean gross income levels $\overline{y}$ and the overall share of unemployed $\bar{l}_1$, the government budget constraint is given by

$$T_t = \overline{G}_t + G_t^g + G_t^p, \tag{26}$$

where

$$G_t^g = \int \widehat{l}^g_{edjt}\left(g_1 - g_2\left(\frac{\tilde{y}_{edjt}}{\overline{y}}\right)\right)\varphi^g_{edjt}(\tilde{y}_{edjt})\, d\tilde{y}_{edjt} + \bar{l}_1 b,$$

$$T_t = \int \tilde{y}_{edjt}\widehat{l}^{\varsigma}_{edjt}\left(1 - \varsigma_0\left(\frac{\tilde{y}_{edjt}}{\overline{y}}\right)^{-\varsigma_1}\right)\varphi^{\varsigma}_{edjt}(\tilde{y}_{edjt})\, d\tilde{y}_{edjt}.$$

Estimation Given benchmark tax revenues and transfers, $\overline{G}_t$ is chosen to balance the budget when $G_t^g = 0$ (benchmark equilibrium under all realizations of the aggregate shocks, as described in Section 4.2.3). In counterfactual exercises, only G_t^p, G_t^g and T_t change, and the level of labor income taxes ς_0 is adjusted to balance the budget. Given the benchmark tax progressivity, this corresponds to a proportional change in taxes along the income distribution.

C.4 Budget Constraint For Movers [Back]

Homeowners who want to move are forced to sell, which may limit mobility. Homesellers need to bear transaction costs $\phi_s p_{dt}\overline{h}_{deh}$, and buying again in the new location requires paying transaction costs $\phi_b p_{d't}\overline{h}_{d'eh}$. Renters and coresidents don't pay such costs when moving, which, all else equal, makes them more likely to migrate.

The budget constraint of a homeowner living in location d and migrating to d', in case they rent in the new location, is given by

$$a_{j+1} = (1+r)(a_j + y_{edtj} - c_j + (1-\phi_s)p_{dt}\overline{h}_{deh} - \kappa_{d'}p_{d't}\overline{h}_{d'eh}) \geq \mathbf{0}.$$

If instead they coreside in the new location d', the budget constraint is given by

$$a_{j+1} = (1+r)(a_j + y_{edtj} - c_j + (1-\phi_s)p_{dt}\overline{h}_{deh}) \geq \mathbf{0}.$$

Finally, in case they decide to buy in d', it is given by

$$\begin{aligned}
&a_{j+1} = (1 + r\mathbb{1}_{a_j \geq 0} + r^h \mathbb{1}_{a_j<0})(a_j + y_{edjt} - c_j + (1-\phi_s)p_{dt}\overline{h}_{deh} - (1+\phi_b)p_{d't}\overline{h}_{d'eh}) \\
&a_{j+1} \geq a_j \left(\frac{(J-1)-j}{J-j}\right) \mathbb{1}_{a_j<0} \text{ for } j<J, \\
&a_{J+1} \geq 0.
\end{aligned}$$

For homeowners or coresidents living in location d, instead, there are no transaction costs of selling to pay after moving to location d'. Their budget constraint if they decide to rent in d' is given by

$$a_{j+1} = (1+r)(a_j + y_{edtj} - c_j - \kappa_{d'}p_{d't}\overline{h}_{d'eh}) \geq \mathbf{0}$$

if they decide to coreside by

$$a_{j+1} = (1+r)(a_j + y_{edtj} - c_j) \geq \mathbf{0}$$

and if buying by

$$\begin{aligned}
&a_{j+1} = (1 + r\mathbb{1}_{a_j \geq 0} + r^h \mathbb{1}_{a_j<0})(a_j + y_{edjt} - c_j - (1+\phi_b)p_{d't}\overline{h}_{d'eh}) \\
&a_{j+1} \geq a_j \left(\frac{(J-1)-j}{J-j}\right) \mathbb{1}_{a_j<0} \text{ for } j<J, \\
&a_{J+1} \geq 0.
\end{aligned}$$

C.5 Housing Bequests [Back]

The formulation of the maximization problem reported below makes the role of housing bequests explicit. Let b_{j+1} be a variable that takes value 1 if the agent receives a housing bequest in the following period and is 0 otherwise, and let $\boldsymbol{x^b_{j+1}}$ be the resulting state vector whenever $b_{j+1} = 1$. Then, we have

$$\begin{aligned}
v_j(\boldsymbol{x_j}, b_j = 0, d') = \max_{c_j>0, h_j} \; & u(c_j, h_j, d'; \boldsymbol{x_j}) + \beta\pi^b_{edoj}\mathbb{E}_{z,\boldsymbol{p_{t+1}},\boldsymbol{q_{t+1}}}\left[\overline{v}_{j+1}(\boldsymbol{x^b_{j+1}}, b_{j+1} = 1)|z_j, j, \boldsymbol{p_t}, \boldsymbol{q_t}\right] \\
& + \beta(1-\pi^b_{edoj})\mathbb{E}_{z,\boldsymbol{p_{t+1}},\boldsymbol{q_{t+1}}}\left[\overline{v}_{j+1}(\boldsymbol{x_{j+1}}, b_{j+1} = 0)|z_j, j, \boldsymbol{p_t}, \boldsymbol{q_t}\right]
\end{aligned}$$

with

$$\begin{cases} h_j^b = 1 \\ a_{j+1}^b = a_{j+1} \end{cases} \quad \text{if } h_j \neq 2 \text{ and } d' = d_{j_0}$$

$$\begin{cases} h_j^b = h_j \\ a_{j+1}^b = a_{j+1} + \frac{p_{d_0 t}\overline{h}_{d_0 eh}}{\kappa^b}(1-\phi^s) \end{cases} \quad \text{otherwise}$$

D Estimation Strategy With Aggregate Shocks [Back]

D.1 Solution Algorithm for the Benchmark Equilibrium [Back]

Below, I present an algorithm to compute the benchmark equilibrium:

1. Estimate the exogenous parameters, including forecast rule (16) and the aggregate factors' laws of motion (14) and (15).
2. Guess the internally calibrated parameters.
3. Given the model's parameters, solve and simulate the model by:
   i. Imposing prices and wages $\boldsymbol{q}$ observed in the data
   ii. Using the estimated forecast rule for $\boldsymbol{q'}$
4. Given the simulated equilibrium objects (H_d, L_{Nd}, L_{Ed}), use equations (7), (8), and (9) to find parameters $\boldsymbol{\mathcal{Z}}$ that are consistent with the observed prices and wages.[41]
5. If the fit of the targeted moments is good, stop. Otherwise, update the guesses for the internally calibrated parameters and repeat steps 3, 4, and 5 until the data moments are fitted well.

D.2 Solution Algorithm for the Counterfactual Equilibrium [Back]

Below, I present an algorithm to compute the counterfactual equilibrium:

1. Start with the benchmark parameters, which include parameters $\boldsymbol{\mathcal{Z}}$. These parameters are kept fixed in the counterfactual.
2. Given the model's parameters, solve and simulate the model *with the counterfactual* by initially imposing prices, wages, and forecast rule as in the benchmark.
3. Given counterfactual equilibrium objects ($\widehat{H}_d$, $\widehat{L}_{Nd}$, $\widehat{L}_{Ed}$) and the benchmark parameters $\boldsymbol{\mathcal{Z}}$, use equations (7), (8), and (9) to update local prices and wages, $\widehat{\boldsymbol{q}}$. A dampening parameter $k \in [0, 1]$ can be used for the update.

[41] The price-to-rent ratio κ_d of equation (23), is estimated by computing the ratio between average housing prices and rents by location, as explained in Appendix C.2.

4. Given the updated counterfactual prices and wages $\widehat{\boldsymbol{q}}$, use equation (16) to update ($\widehat{\boldsymbol{\lambda}}_{\mathbf{1}}$, $\widehat{\boldsymbol{\lambda}}_{\mathbf{2}}$), keeping f_1' and f_2' to their counterfactual values and assuming that $\boldsymbol{v}_{\boldsymbol{q}} = 0$.

5. Solve and simulate the model *with the counterfactual* by imposing the *updated* prices, wages, and forecast rule.

6. Repeat steps 3., 4., and 5. until the new ($\widehat{\boldsymbol{\lambda}}_{\mathbf{1}}$, $\widehat{\boldsymbol{\lambda}}_2$) guesses are close to the guesses in the previous iteration.

D.3 Connection With Krusell and Smith (1998) [Back]

In this section, I show how my low-rank forecast rule relates to typical forecast rules in the Krusell and Smith (1998) tradition. To keep the problem general, I initially assume away the existence of the two aggregate factors (f_1, f_2). Instead, I assume that each of the $\boldsymbol{\mathcal{Z}}$ location-specific parameters is an aggregate shock.

I assume a Krusell and Smith-type linear forecast rule that uses two moments from the distribution of current prices and wages $\boldsymbol{q}$, $m_1(\boldsymbol{q})$ and $m_2(\boldsymbol{q})$:

$$\boldsymbol{q}' = a_1(\boldsymbol{\mathcal{Z}}, \boldsymbol{\mathcal{Z}}')m_1(\boldsymbol{q}) + a_2(\boldsymbol{\mathcal{Z}}, \boldsymbol{\mathcal{Z}}')m_2(\boldsymbol{q}), \tag{27}$$

where $a_1(\boldsymbol{\mathcal{Z}}, \boldsymbol{\mathcal{Z}}')$ and $a_2(\boldsymbol{\mathcal{Z}}, \boldsymbol{\mathcal{Z}}')$ are the time-varying coefficients mapping moments to predictions, which depend on the realizations of the exogenous aggregate shocks $\boldsymbol{\mathcal{Z}}$ and on their known laws of motion.[42]

In my model, I assume that $\boldsymbol{\mathcal{Z}}$ are parameters that vary in response to aggregate shocks f_1 and f_2. My forecast rule (16) is equal to the one in equation (27) if $m_1(\boldsymbol{q}) = \boldsymbol{\lambda}_{\mathbf{1}}$, $m_2(\boldsymbol{q}) = \boldsymbol{\lambda}_{\mathbf{2}}$, $a_1(\boldsymbol{\mathcal{Z}}, \boldsymbol{\mathcal{Z}}') = f_1'$, and $a_2(\boldsymbol{\mathcal{Z}}, \boldsymbol{\mathcal{Z}}') = f_2'$, where expectations over future f_1' and f_2' are based on factors' laws of motions (14) and (15).[43]

In addition to the computational benefits described in Section 4.2.3, my strategy has the added advantage of greatly reducing the problem's dimensionality, while still accurately matching the data. If each of the $\boldsymbol{\mathcal{Z}}$ location-specific parameters were an aggregate shock, then the integration problem needed to compute expectations over $\boldsymbol{\mathcal{Z}}'$ would be too high-dimensional to be computationally feasible.[44]

D.4 Accuracy of the Forecast Rule [Back]

[42]For example, this equation is analogous to equation (14) in Kaplan, Mitman and Violante (2020). In the paper, they use a strategy based on Krusell and Smith (1998) to estimate a dynamic model with homeownership and aggregate price fluctuations.

[43]It is sufficient for agents to know (f_1,f_2), rather than $\boldsymbol{\mathcal{Z}}$, to form predictions about future prices and wages. Moreover, the moments that agents use in their forecast rule are the $\boldsymbol{\lambda}$ parameters, which indicate how much aggregate shocks to factors load into prices and wages in each location. For instance, if they know that aggregate shocks to the country-level factors tend to have a muted impact on rural prices, they may expect low future rural price increases if they observe a positive aggregate shock in the current period.

[44]Agents of education e would need to integrate their expectations over 24 dimensions (12 prices and 12 wages). Assuming 3 grid points for each Markovian process, the state space would increase by a factor of 3^{24}, i.e. by almost 300 billion points.

I have assumed that the infinitely-dimensional $\mathcal{Q}(\cdot)$ function in equation (12) can be approximated by a factor model of rank 2, i.e.,

$$\begin{aligned}\boldsymbol{q} &= \mathcal{Q}(f_1, f_2)\\ &= \boldsymbol{\lambda_1} f_1 + \boldsymbol{\lambda_2} f_2\end{aligned}$$

However, the correct model may also be

$$\boldsymbol{q} = \boldsymbol{\lambda_1} f_1 + \boldsymbol{\lambda_2} f_2 + \boldsymbol{\lambda_3} f_1 f_2, \tag{28}$$

or

$$\boldsymbol{q} = \boldsymbol{\lambda_1} f_1 + \boldsymbol{\lambda_2} f_2 + \boldsymbol{\lambda_3} f_1 f_2 + \boldsymbol{\lambda_4} f_1^2 + \boldsymbol{\lambda_5} f_2^2,$$

or a different function with higher-order interactions between the factors. I show that the prediction properties of the forecast rule (16) do not improve if I use the mildest possible relaxation (28) as an alternative specifications for the $\mathcal{Q}(\cdot)$ function:

$$\boldsymbol{q'} = \boldsymbol{\lambda_1} f_1' + \boldsymbol{\lambda_2} f_2' + \boldsymbol{\lambda_3} f_1' f_2' + \boldsymbol{\upsilon_q}. \tag{29}$$

To do so, I compute the prediction errors and R^2 of the forecast rules (16) and (29), both in the benchmark and in the counterfactual equilibria.

In the benchmark, both forecast rules exhibit high R^2 values, although the relaxed forecast rule (29) has a marginally higher R^2 of 0.996 compared to 0.991 in (16). The R^2, however, is not a sufficient statistic to measure the accuracy of forecast rules and can sometimes be misleading (Den Haan 2010). When examining the mean and median forecasting errors, the baseline forecast rule (16) performs marginally worse in terms of the former but better in the latter, with errors of 4.8% (mean) and 2.3% (median). In contrast, the errors for (29) are 4.3% and 3.3%, respectively. Therefore, the overall prediction properties are not unambiguously improved when relaxing the forecast rule.

As pointed out by Den Haan (2010), the accuracy of Krusell and Smith (1998)-type forecast rules over longer horizons may be poor, even if 1-year ahead prediction properties are good. Therefore, I repeat the same exercise for 25-year ahead prediction errors and R^2. To simplify the exercise, I check the accuracy of the forecast rule based on *average* guesses about future prices and wages, while still allowing $\boldsymbol{q'}$ in the left-hand side to evolve following the actual (f_1', f_2') realizations.

In particular, using the laws of motion (14) and (15), I impose $f_1' = \varrho_1 f_1$ and $f_2' = \varrho_2 f_2$ for 1-year ahead average predictions, and $f_1' = \varrho_1^{25} f_1$ and $f_2' = \varrho_2^{25} f_2$ for 25-year ahead average predictions. The prediction properties of the baseline forecast rule do not worsen significantly over longer time horizon. The mean and median prediction errors go from 5.7% and 4.4% to 6.6% and 5.2%, respectively, whereas the R^2 increases when predicting 25-year ahead data, from 0.991 to 0.993.[45]

[45]Prediction errors are higher in this exercise because I am restricting agents to only use ϱ_1 and ϱ_2 to predict

Finally, the exercise is repeated in the counterfactual equilibrium where housing policies are introduced.[46] The forecasting properties of the baseline rule (16) and relaxed rule (29) in the counterfactual remain very similar to the benchmark equilibrium: the R^2 are 0.992 and 0.996, the mean prediction errors are 4% and 4%, and the median prediction errors are 1.8% and 2.9%, respectively. Again, the overall prediction properties are not unambiguously improved when relaxing the forecast rule. Therefore, I use the baseline forecast rule (16) to solve for the benchmark and counterfactual equilibria.

D.5 Fit of the Factor Model

[Back]

Using subscript t for convenience, prices and wages can be written as function of the two aggregate (country-level) factors f_{1t} and f_{2t}, which are orthogonal and time-varying, and the set of fixed loading parameters $\boldsymbol{\lambda_d}$:

$$\begin{aligned} p_{dt} &= \lambda^p_{1d} \times f_{1t} + \lambda^p_{2d} \times f_{2t}, \\ w_{edt} &= \lambda^{w_e}_{1d} \times f_{1t} + \lambda^{w_e}_{2d} \times f_{2t}. \end{aligned}$$

The factors and loading parameters are estimated outside of the model using the interactive fixed effects strategy developed in Bai (2009).[47] Data cover the period 2010-2019, and come from Idealista (housing prices) and the MCVL (hourly wages).

As can be seen in Figures D8, D9, and D10, the factor model fits the data very well. The prediction captures in a parsimonious way the evolution of local prices and wages between 2010 and 2019. Aggregate price and wage shocks are correlated between themselves, across locations, and over time. These realistic features of the data are well captured by the factor model structure.

The estimated factor f_{1t} increases, whereas factor f_{2t} decreases over the 2010-2019 period. Since loading parameter $\lambda^{w_e}_{1d}$ is estimated to be positive for all locations and education types and $\lambda^{w_e}_{2d}$ is estimated to be close to zero, predicted wages increase over time across all location and education groups (Figures D8 and D9).

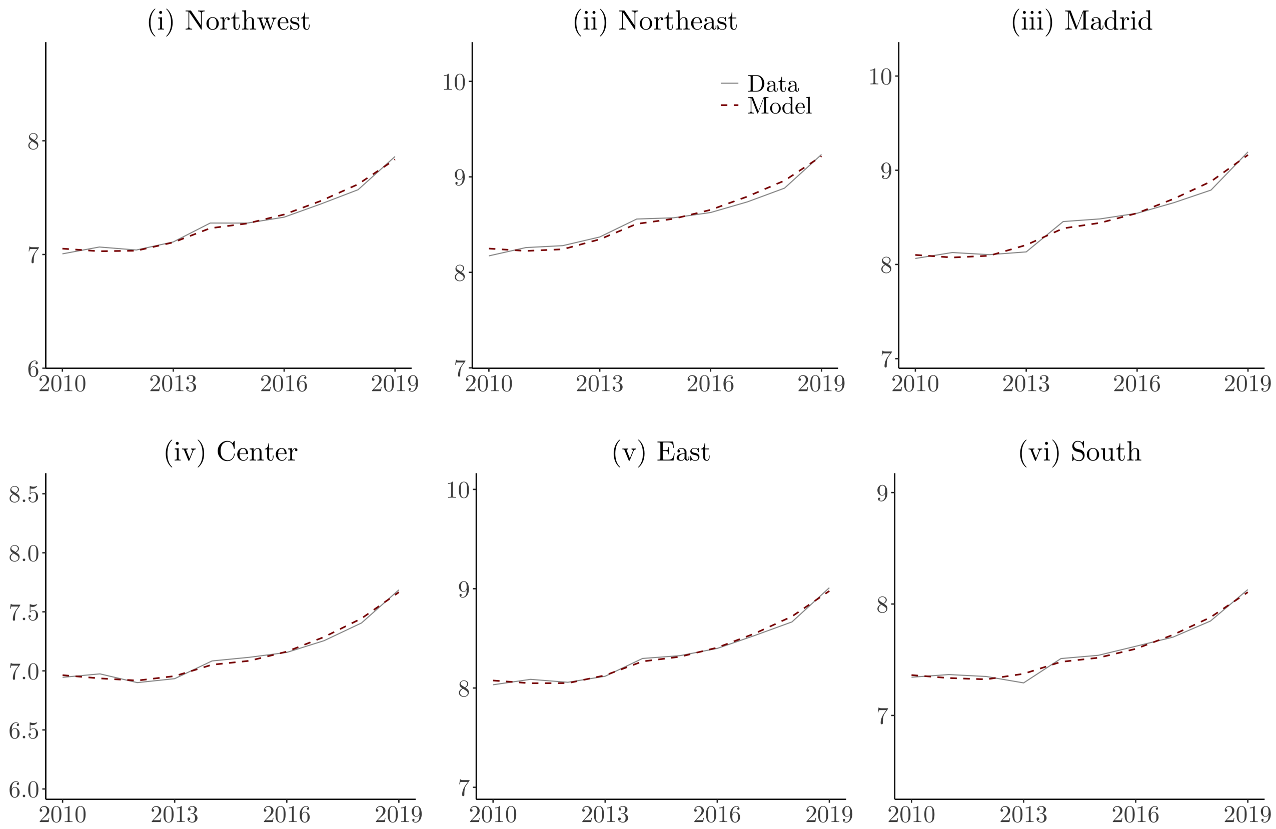
The evolution of housing prices, however, is more heterogenous across locations. Loading parameters λ^p_{2d} are positive everywhere, which, together with the decreasing evolution of the f_{2t} factor, tends to push prices down over the 2010-2019 period. Meanwhile, λ^p_{1d} is positive in high-productivity areas like Madrid and the East Regions, but negative in less productive areas like the Northwest and Central regions. In places where λ^p_{1d} is positive, the f_{1t} factor drives housing prices upwards. Consequently, by 2019, prices in these areas return to their 2010 levels, as shown in Figure D10.

future $\boldsymbol{q}$, instead of taking into account the full exogenous laws of motion for f_1 and f_2 as when solving for the equilibrium. Therefore, a large part of these deviations comes from the underlying volatility of the exogenous stochastic factor processes, rather than from errors in the baseline forecast rule.

[46] I report here the results following the introduction of the untargeted mortgage interest deduction policy. Results are similar for the rent subsidy to low-income young agents.

[47] Estimation is carried out with the R package `phtt` (Bada and Liebl 2014).

(a) Non-college wages, urban locations



(b) Non-college wages, rural locations

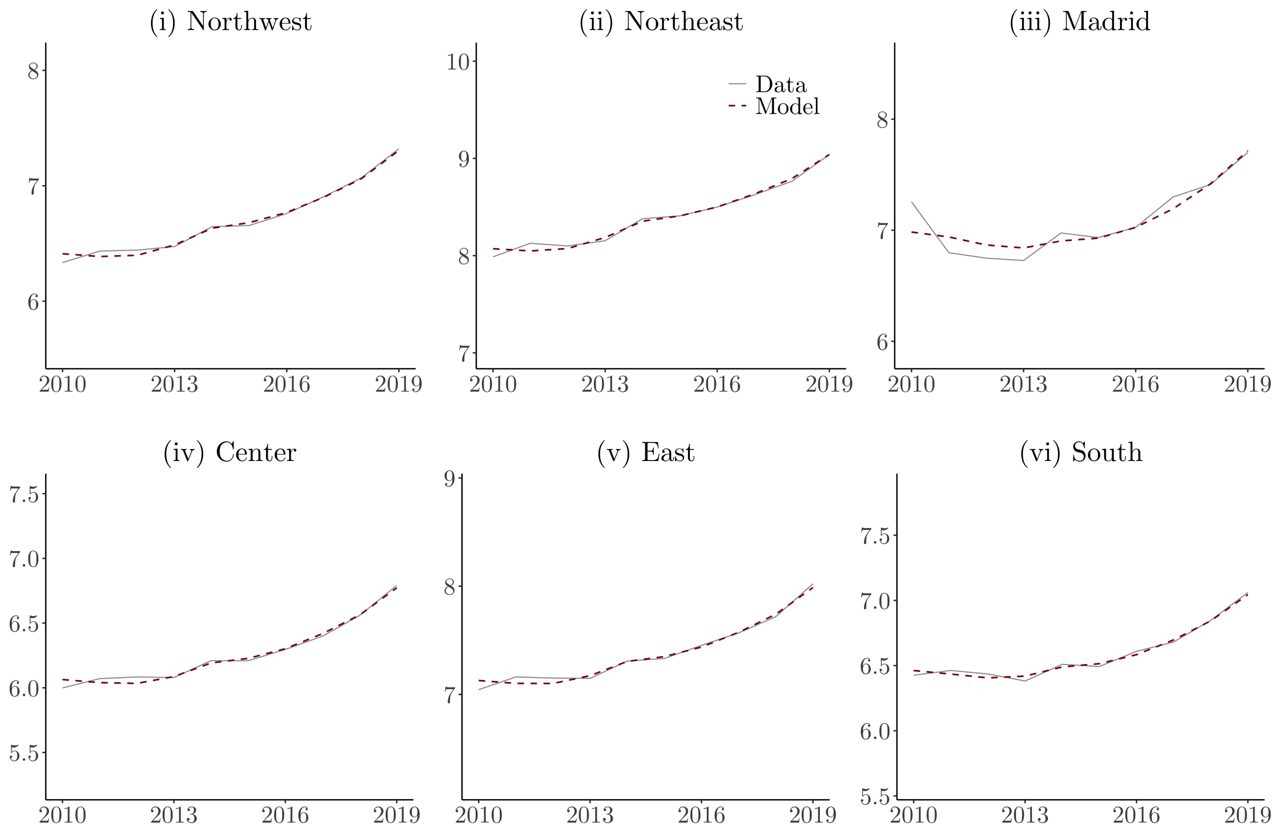
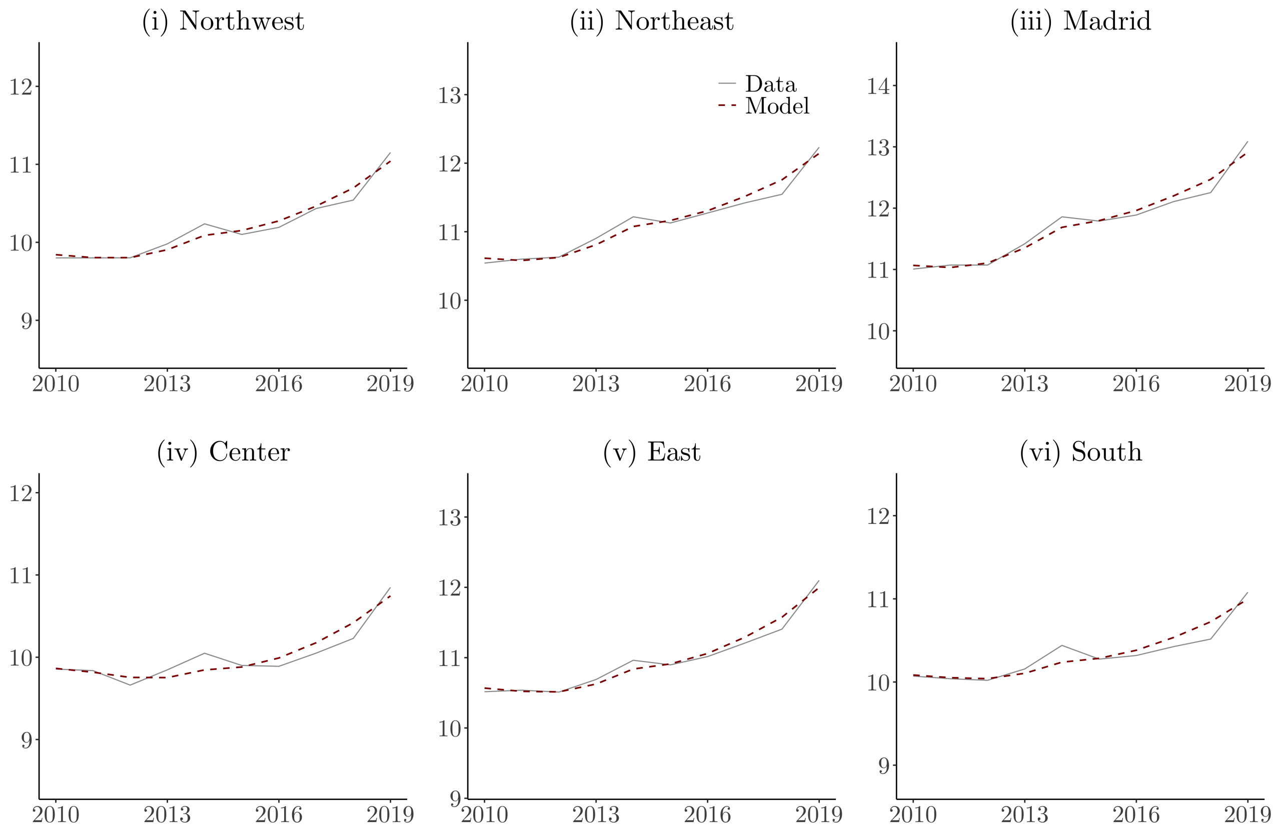


Figure D8: The figures plot mean non-college annual gross hourly wages (in thousands). Data: MCVL. [Back]

(a) College wages, urban locations



(b) College wages, rural locations

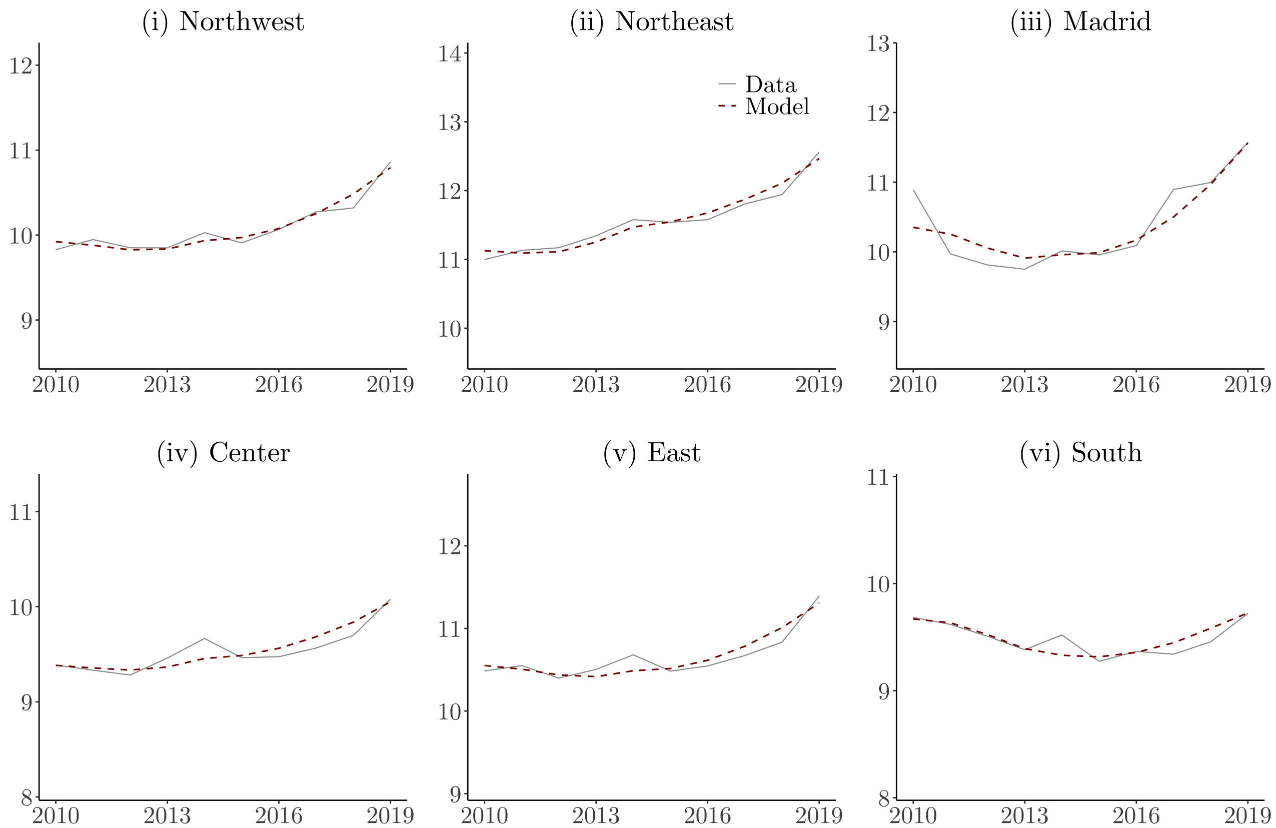
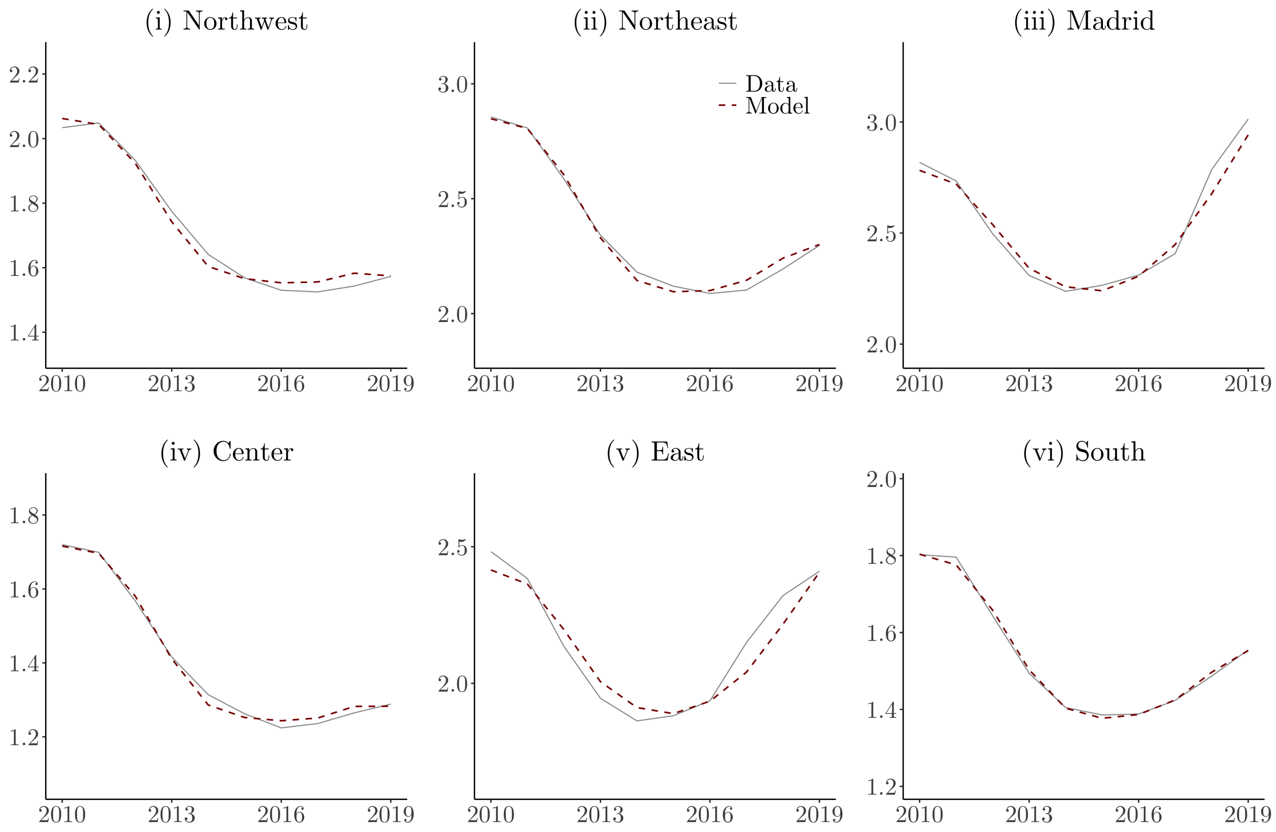


Figure D9: The figures plot mean college annual gross hourly wages (in thousands). Data: MCVL. [Back]

(a) Housing prices, urban locations



(b) Housing prices, rural locations

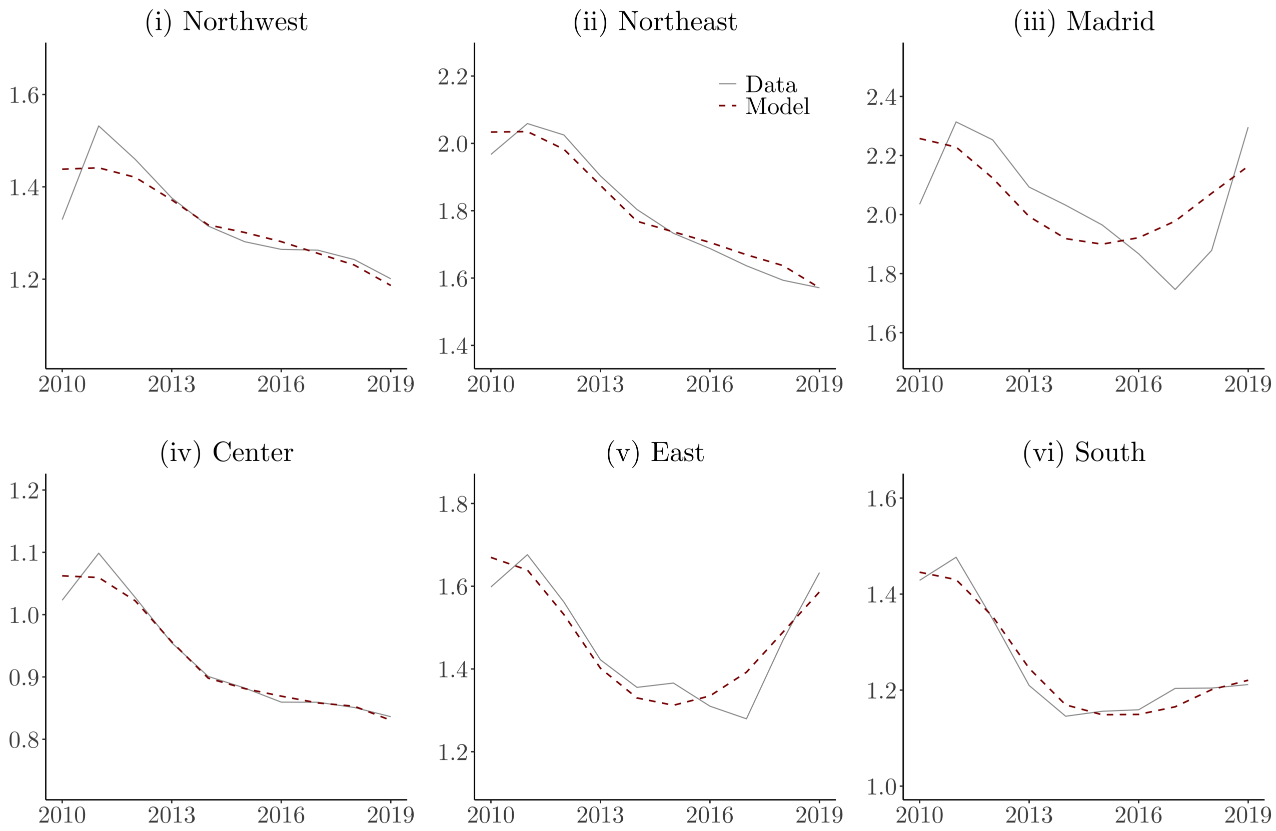


Figure D10: The figures plot mean housing prices per square meter (in thousands). Data: Idealista.
[Back]

D.6 Further Remarks [Back]

The large degree of heterogeneity in terms of agents' types and aggregate states makes the model computationally expensive to solve. Moreover, the discrete choice nature of the decision problem and the existence of income thresholds for the amount of taxes paid and transfers or subsidies received – whose eligibility depends on local wages and hence on the migration choice – introduce non-linearities in the value function. Therefore, the endogenous grid method developed by Carroll (2006) cannot be directly applied to speed up the estimation strategy. Hence, the model is solved using value function iteration.

For efficient model estimation, it's crucial to minimize the number of state variables. As detailed in Appendix E.3, there is no need to incorporate a housing bequest indicator. Moreover, my formulation of the mortgage repayment schedule only requires current age j and current assets a_j (see Section 3.2). Even without including additional state variables, the model yields realistic repayment patterns, with cross-sectional mortgage debt declining smoothly over the lifecycle. Additionally, in large parts of the value function iteration procedure, tracking the birthplace d_0 is not necessary. By knowing the agents' current location (state) and future location (decision), I can determine their status as natives or migrants in the subsequent period, which is enough to compute current utility.

D.7 Definition of Equilibrium [Back]

For a given interest rate r, government expenditure $\overline{G}_t$ and G^p_t, tax function $T_t(\cdot)$, and transfer function $G^g(\cdot)$, an equilibrium in period t consists of a set of wages w_{dt}, housing prices p_{dt}, housing rents q_{dt}, consumption, housing tenure, and migration decision rules $c^*_j(\boldsymbol{x_j})$, $h^*_j(\boldsymbol{x_j})$, and $d^*_j(\boldsymbol{x_j})$, population shares μ_{edjt}, renters and homeowners shares, $\widehat{h}_{1edjt}$ and $\widehat{h}_{2edjt}$, employment shares $\widehat{l}_{edjt}$, population shares receiving transfers and paying taxes, $\widehat{l}^g_{edjt}$ and $\widehat{l}^\varsigma_{edjt}$, and distribution functions $\varphi_{edjt}(\theta_e, z_{ej})$, $\varphi^g_{edjt}(\tilde{y}_{edjt})$, and $\varphi^\varsigma_{edjt}(\tilde{y}_{edjt})$ such that:

1. Individual decisions are optimal, i.e. solve equations (1) and (2).

2. Wages w_{edt} clear local labor markets according to equations (19), (20), and (21) in Appendix C.1.

3. Housing prices p_{dt} and housing rents q_{dt} clear local housing markets according to equations (22), (23), (24), and (25) in Appendix C.2.

4. The government budget is balanced, i.e. equation (26) in Appendix C.3 holds.

5. Population shares μ_{edjt}, $\widehat{h}_{1edjt}$, $\widehat{h}_{2edjt}$, $\widehat{l}_{edjt}$, $\widehat{l}^g_{edjt}$, and $\widehat{l}^\varsigma_{edjt}$, and distribution functions $\varphi_{edjt}(\theta_e, z_{ej})$, $\varphi^g_{edjt}(\tilde{y}_{edjt})$, and $\varphi^\varsigma_{edjt}(\tilde{y}_{edjt})$ are consistent with individual decisions.

6. Total population is normalized to one, i.e. $\sum_{d=1}^{D}\sum_{e=1}^{2}\sum_{j=1}^{J}\mu_{edjt} = 1$.

The equilibrium changes in each period due to aggregate shocks to prices and wages, given by aggregate factors (f_1, f_2). The stochastic process that governs the aggregate shocks, however, is stationary – as detailed in Section 4.2.2. The laws of motion for the aggregate shocks are given by (14) and (15), and the agents' forecast rule (16) is consistent with equilibrium prices and wages under all realizations of (f_1, f_2).

E Estimation of Model Inputs

[Back]

E.1 Probability of Being Unemployed

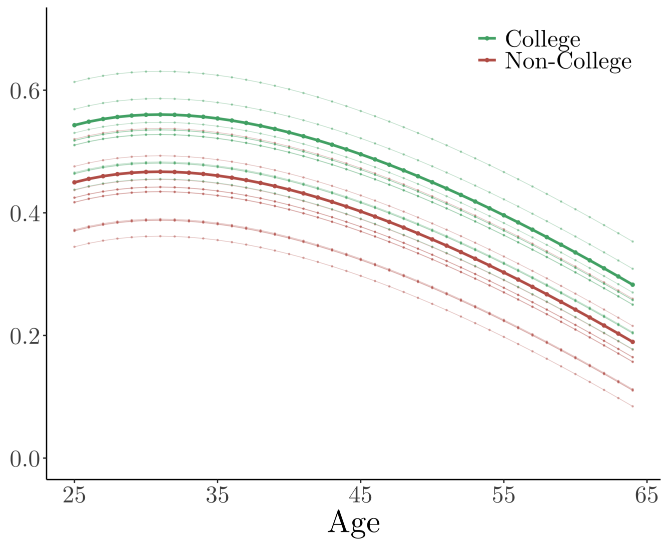
[Back]

The probability of transitioning from employment to unemployment by education and location is plotted in Figure E11. These probabilities are estimated using the EU-SILC 2004-2019 panel following the procedure described in Section 4.1.1, i.e. by running the linear probability regression models:

$$\begin{aligned} \overbrace{\mathbb{1}_{l_{edj+1}=1}}^{\text{Unemployed next period}} &= \alpha_t + \alpha_e + \alpha_d + \alpha_1 j + \alpha_2 \log(j) \\ \underbrace{\mathbb{1}_{l_{edj+1}=2}}_{\text{Employed next period}} &= \beta_t + \beta_e + \beta_d + \beta_1 j + \beta_2 \log(j). \end{aligned}$$

Re-employment probabilities decrease sharply at older ages, so that the unemployment state becomes more persistent over the lifecycle. Similarly to the probability of becoming unemployed (Figure 3a), there is substantial variation across locations and educational groups. Re-employment probabilities are higher for the college-educated and for urban residents.

Figure E11: Employed → Unemployed
(East urban location emphasized)



Note: The figure plots age polynomial functions for different locations and education groups (East urban location is emphasized). Data: EU-SILC 2004-2019. [Back]

E.2 Income Process [Back]

The parameters of the income process are estimated using the generalized method of moments. Following a standard choice in the literature, I use the cross-sectional variance of log income by age as moment conditions (Storesletten, Telmer and Yaron 2004).

From equation (3), residualized log income is given by

$$\begin{aligned}\tilde{u}_{ej} &= \ln \tilde{y}_{edjt} - \Upsilon_{edj} - \vartheta_{ed} \ln w_{edt} \\ &= \theta_e + z_{ej}\end{aligned}$$

Given education type e, the variance of $\tilde{u}_{ej}$ for $j \in \{1, ..., J\}$ is

$$Var(\tilde{u}_{ej}) = \sigma^2_{\theta e} + \sigma^2_{ve} \sum_{j'=0}^{j-1} \varrho_e^{2j'}.$$

Accordingly, the J moment conditions for education e are given by:

$$\begin{aligned} g_1(\tilde{\boldsymbol{u}}_{\boldsymbol{e}}, \sigma_{\theta e}, \sigma_{ve}, \varrho_e) &= \tilde{u}^2_{e1} - \sigma^2_{\theta e} + \sigma^2_{ve}, \\ g_2(\tilde{\boldsymbol{u}}_{\boldsymbol{e}}, \sigma_{\theta e}, \sigma_{ve}, \varrho_e) &= \tilde{u}^2_{e2} - \sigma^2_{\theta e} + \sigma^2_{ve}(1 + \varrho_e^2), \\ &\vdots \\ g_J(\tilde{\boldsymbol{u}}_{\boldsymbol{e}}, \sigma_{\theta e}, \sigma_{ve}, \varrho_e) &= \tilde{u}^2_{eJ} - \sigma^2_{\theta e} + \sigma^2_{ve} \sum_{j'=0}^{J-1} \varrho_e^{2j'}, \end{aligned}$$

with $\mathbb{E}\left[g(\tilde{\boldsymbol{u}}_{\boldsymbol{e}}, \sigma_{\theta e}, \sigma_{ve}, \varrho_e)\right] = 0$.

The GMM uses these moments conditions and the variance of log residual income coming from the data. The grey solid lines of Figures E12c and E12d depict these empirical variances for the non-college and college educated, respectively. Residualized income in the data is given by equation (6), and can be computed by regressing out observables from regression (5), which is estimated with the MCVL. As described in Appendix B, I remove outlier observations corresponding to the top 1% of the wage distribution. I also exclude workers whose annual income is lower than the level of unemployment benefits (3,300 in the benchmark economy). Such low income levels can be observed in the data when workers are only employed for some months of the year and are unemployed (or out of the labor force) in the rest of the year. This status is treated as unemployment in the model, and, accordingly, it does not affect the estimated income process of employed workers.

The variance of log income tends to increase with age for both college and non-college workers. However, especially for non-college workers (Figure E12c), the lifecycle pattern becomes non-monotonic from age 55 through 64. This is likely due to the pre-retirement choices of workers, which happen at different points in life for different individuals. Given this idyosincratic behavior of the last 10 ages in the model, I estimate the income process by restricting the sample to workers aged 25-54 ($J = 30$), both for the non-college and for the college educated.

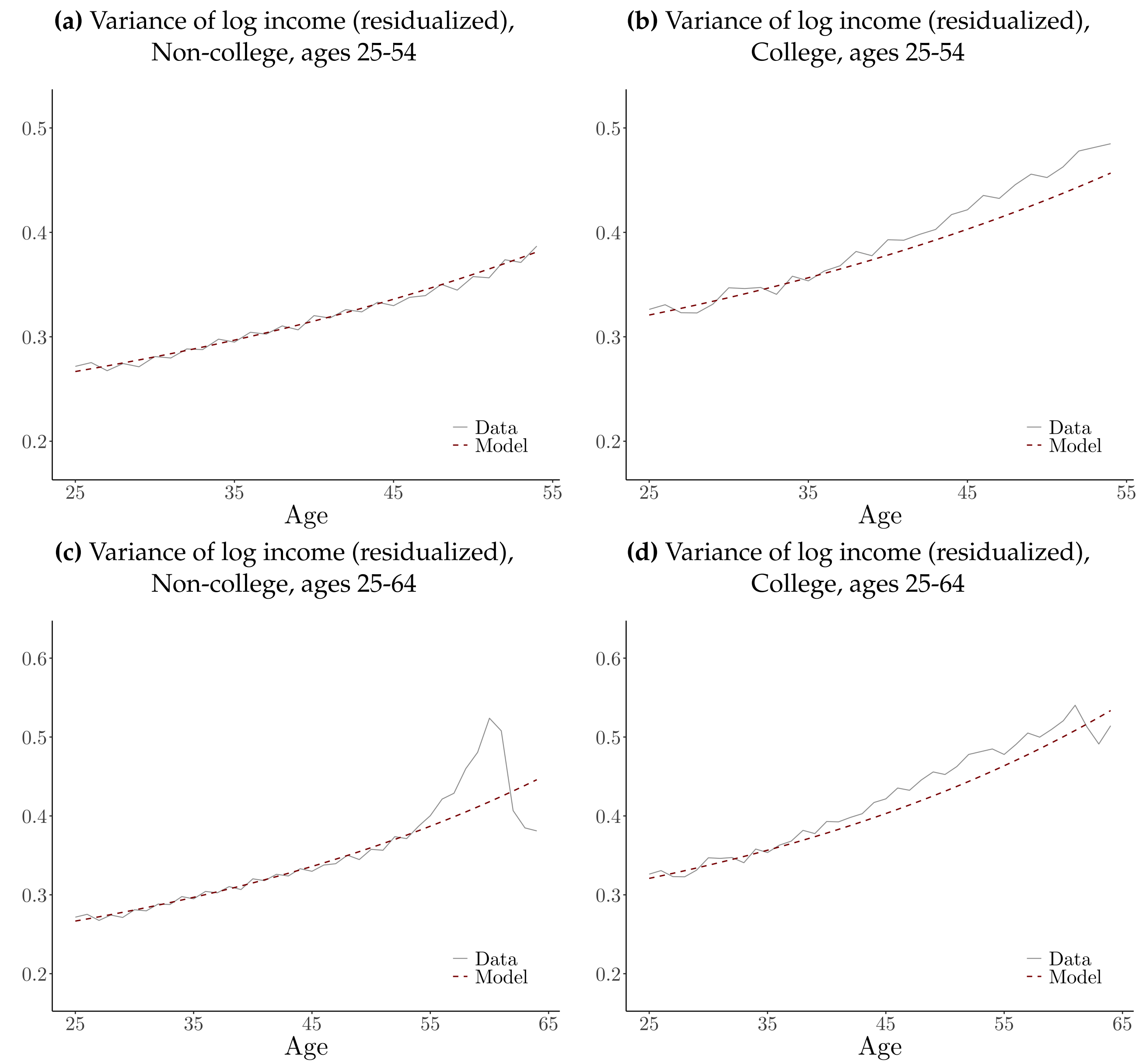


Figure E12: The figures plot the variance of log residualized income over the lifecycle for non-college and college educated workers and for different age groups (25-54 and 25-64). The solid grey line depicts the data, whereas the red dashed line represents the lifecycle variance profiles predicted by the GMM model used to estimate the income process. The model is estimated by restricting the sample to workers aged between 25 and 54. Data: MCVL 2005-2019. [Back]

The resulting lifecycle variance profile predicted by the GMM model is plotted with red dashed lines in Figures E12a and E12b (non-college and college workers), as well as in Figures E12c and E12d. The model fits the data well, both for the 25-54 age groups and for the full 25-64 group. For comparison, in Figure E13 I plot with red dashed lines the predicted lifecycle income variances that I obtain by estimating the GMM with the unrestricted 25-64 sample. Due to the non-monotonic behavior observed in the data at ages 55-64, the model overpredicts earnings uncertainty at ages 35-54 for non-college workers. Overall, the estimation that uses the restricted 25-54 version of the sample appears to fit better the lifecycle evolution of the variance of log income.

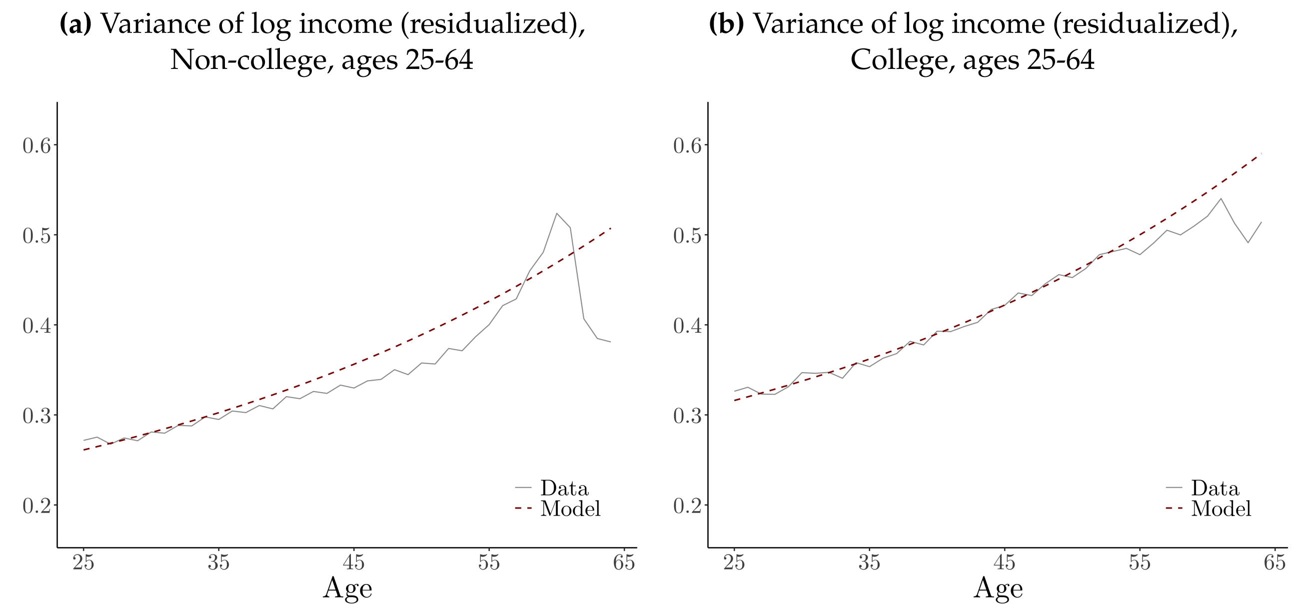


Figure E13: The figures plot the variance of log residualized income over the lifecycle for non-college and college educated workers aged 25-64. The solid grey line depicts the data, whereas the red dashed line represents the lifecycle variance profiles predicted by the GMM model used to estimate the income process. The model is estimated by restricting the sample to workers aged between 25 and 64. Data: MCVL 2005-2019. [Back]

E.3 Probability of Receiving Housing Bequests [Back]

The share of individuals who have ever inherited a house at different ages throughout their lives is plotted in panel (a) of Figure 4 for those without a college degree, and in Figure E14 for those with a college education. This data, sourced from the EFF 2008-2020 and grouped by birthplace (rural vs. urban), needs to be transformed into an annual probability, $\pi^b_{ed_0 j}$, of receiving a housing bequest. This probability varies by types and serves as input for the model.

This conversion would be straightforward if one were to add an additional state variable, indicating that the agent has received a housing bequest in the past. In that case, calling $\pi^{b,\text{cum}}_{ed_0 j}$ the share of people who have ever inherited a house at age j, the probability of receiving a housing bequest would be

$$\widehat{\pi}^b_{ed_0 j} = \pi^{b,\text{cum}}_{ed_0 j+1} - \pi^{b,\text{cum}}_{ed_0 j} \tag{30}$$

for those who have not received a housing bequest in the past, and $\widehat{\pi}^b_{ed_0 j} = 0$ for those who have already received a housing bequest.

Introducing an extra state variable to the benchmark is computationally taxing. Specifically, it would require solving the model at 650 million points instead of the current 325 million. Below, I outline an approach to compute the annual probability of receiving a housing bequest, ensuring its consistency with the lifecycle profile depicted in Figure E14a, without adding an extra state variable. This method only works by allowing agents the possibility of inheriting a house multiple times over their lives, which might be viewed as receiving a significant inheritance. While comparing both options, I observed that the results remain almost identical whether or not a state variable for housing bequests is included.

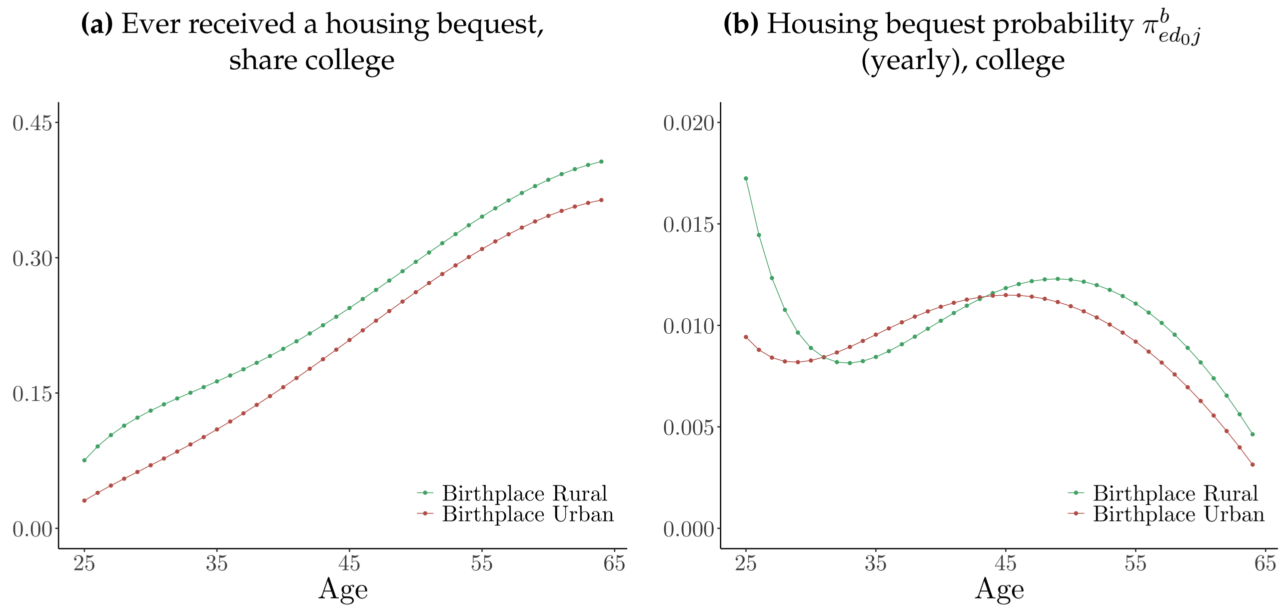


Figure E14: The figures plot the share of college-educated individuals who have ever inherited a house during their lifetime (panel a), computed age by age, and the annual probability of receiving a housing bequest (panel b). The equivalent figures for workers without a college decree are plotted in Appendix Figure 4. Data: EFF 2008-2020. [Back]

To adjust equation (30) to determine the annual probability of inheriting a house in a model without bequest state variables, I use:

$$\pi^b_{ed_0j} = \frac{\pi^{b,\text{cum}}_{ed_0j+1} - \pi^{b,\text{cum}}_{ed_0j}}{1 - \pi^{b,\text{cum}}_{ed_0j}}. \tag{31}$$

It's easy to see that this probability mirrors the cumulative patterns shown in Figure E14a when all agents have the opportunity to inherit a house multiple times. The rise in the cumulative share of people receiving a bequest by age, indeed, is driven by the fraction $(1 - \pi^{b,\text{cum}}_{ed_0j})$ that has yet to receive one, i.e.

$$0 \times \frac{\pi^{b,\text{cum}}_{ed_0j+1} - \pi^{b,\text{cum}}_{ed_0j}}{1 - \pi^{b,\text{cum}}_{ed_0j}} \times \pi^{b,\text{cum}}_{ed_0j} + 1 \times \frac{\pi^{b,\text{cum}}_{ed_0j+1} - \pi^{b,\text{cum}}_{ed_0j}}{1 - \pi^{b,\text{cum}}_{ed_0j}} \times (1 - \pi^{b,\text{cum}}_{ed_0j}),$$

which aligns with the cumulative rise $\pi^{b,\text{cum}}_{ed_0j+1} - \pi^{b,\text{cum}}_{ed_0j}$ observed in the data.

The share $\pi^{b,\text{cum}}_{ed_0j}$ is estimated from the EFF data. In this dataset, the heads of surveyed households report if they have ever inherited one or more properties. Being a household-level survey, the probability must be adjusted for coresidents. Specifically, in the EFF data we can only estimate the probability of receiving a housing bequest conditional on not coresiding, denoted by $\pi^{b,h_{j+1}>0}_{ed_0j+1}$. Yet, our goal is the unconditional probability, $\pi^b_{ed_0j+1}$. However, note that:

$$\begin{aligned}\pi^{b}_{ed_0 j+1} &= \mathbb{E}(\mathbb{1}\{h_{j+1} = 0\}) \times \pi^{b,h_{j+1}=0}_{ed_0 j+1} + \mathbb{E}(\mathbb{1}\{h_{j+1} > 0\}) \times \pi^{b,h_{j+1}>0}_{ed_0 j+1} \\ &= \mathbb{E}(\mathbb{1}\{h_{j+1} > 0\}) \times \pi^{b,h_{j+1}>0}_{ed_0 j+1}\end{aligned}$$

since $\pi^{b,h_{j+1}=0}_{ed_0 j+1} = 0$, i.e. people who are currently coresiding with their parents cannot have received a housing bequest from them in the previous period. $\mathbb{E}(\mathbb{1}\{h_{j+1} > 0\})$ is measured in the 2011 Census using the share of people coresiding by age. Thus, converting the conditional housing inheritance probability to the unconditional one is straightforward.

As a concluding step, the final probability of receiving a housing bequest is achieved by evenly distributing the housing inheritance probability for newborns, $\pi^{b}_{ed_0 1}$, throughout the lifecycle. This strategy prevents abrupt shifts in the lifecycle probability patterns due to starting conditions. The resulting lifecycle probability $\pi^{b}_{ed_0 j}$ is depicted in Figure 4b for people without a college education and in Figure E14b for the college-educated.

E.4 Other Inputs and Moments

[Back]

E.4.1 Migration Shares by Destination

[Back]

Migration shares by destination are computed using the MCVL. This administrative dataset is preferred over the EU-SILC due to its greater number of observations. Migration events to certain Spanish locations are relatively infrequent, and using a dataset with millions of observations reduces sampling error.

Table E3: Amenity estimates and targeted migration shares by destination. [Back]

	Parameter	Estimate
Amenities		
Northwest Rural	A_{Nwr}	-0.124
Northwest Urban	A_{Nwu}	-0.121
Northeast Rural	A_{Ner}	-0.172
Northeast Urban	A_{Neu}	-0.322
Madrid Rural	A_{Mr}	-0.029
Madrid Urban	A_{Mu}	0.009
Center Rural	A_{Cr}	-0.070
Center Urban	A_{Cu}	-0.152
East Rural	A_{Er}	0.000
East Urban	A_{Eu}	-0.007
South Rural	A_{Sr}	-0.046
South Urban	A_{Su}	-0.029

	Data	Model
Migration shares		
Northwest Rural	0.043	0.043
Northwest Urban	0.040	0.056
Northeast Rural	0.030	0.029
Northeast Urban	0.024	0.018
Madrid Rural	0.057	0.058
Madrid Urban	0.157	0.150
Center Rural	0.106	0.114
Center Urban	0.061	0.060
East Rural	0.174	0.158
East Urban	0.166	0.151
South Rural	0.059	0.061
South Urban	0.085	0.100

E.4.2 Share of Never-Movers

[Back]

This section outlines the procedure used to infer the share of never-movers from EU-SILC and MCVL data. The procedure combines information on the annual migration rate from the EU-SILC with the lifecycle migration patterns inferred from the longer MCVL panel.

Let $\widehat{\text{moved}}_0$, $\widehat{\text{moved}}_1, ..., \widehat{\text{moved}}_{\overline{k}}$ be the share of people that have migrated a total of $k = 0, 1, ..., \overline{k}$ times, respectively, over the period of K years observed in the data. By construction, in the context of yearly migration events, $\overline{k} \leq K$. Since one extra year is needed to compute migration episodes, the EU-SILC (a 4-years rotating panel) has $K = 3$ whereas the MCVL (a 14-years panel) has $K = 13$.

The ideal dataset for computing $\widehat{\text{moved}}_0$, the share of people that never moved over the lifecycle, would have $K = J = 40$. I leverage the extended panel dimension of the MCVL panel to approximate this ideal dataset. Define the ratio between the number of individuals migrating more than once ($k > 1$) and those migrating just once as

$$\overline{m}_k = \frac{\widehat{\text{moved}}_k}{\widehat{\text{moved}}_1}.$$

Then, the annual migration rate can be computed as

$$\begin{aligned} \text{Annual Migration Rate} &= \frac{\widehat{\text{moved}}_1 + 2 \times \widehat{\text{moved}}_2 + ... + \overline{k} \times \widehat{\text{moved}}_{\overline{k}}}{K} \\ &= \widehat{\text{moved}}_1 \left(\frac{1 + 2 \times \overline{m}_2 + ... + \overline{k} \times \overline{m}_{\overline{k}}}{K} \right) \end{aligned}$$

The share of people moving only once, $\widehat{\text{moved}}_1$, that is consistent with the EU-SILC annual migration rate of 0.0082 and the MCVL lifecycle migration quantities $\overline{m}_2, ..., \overline{m}_{\overline{k}}$, and K is then given by

$$\widehat{\text{moved}}_1 = K \times \frac{\text{Annual Migration Rate}}{(1 + 2 \times \overline{m}_2 + ... + \overline{k} \times \overline{m}_{\overline{k}})} = 0.0569.$$

Finally, the share of never-movers can be computed as

$$\widehat{\text{moved}}_0 = 1 - \widehat{\text{moved}}_1(1 + 2 \times \overline{m}_2 + ... + \overline{k} \times \overline{m}_{\overline{k}}) = 0.8938.$$

E.4.3 Housing Sizes

[Back]

Fixed housing sizes by housing tenure, education, and location (urban vs. rural) are estimated using simple conditional averages from EPF 2016-2019. As can be seen in Table E4, house sizes tend to be larger for homeonwers, the college-educated, and rural residents.

Table E4: Housing sizes (in square meters) by tenure, education, and location. Data: EPF 2016-2019. [Back]

	Homeowner		Renter	
	College	Non-College	College	Non-College
Rural	129	116	92	84
Urban	106	93	83	76

E.4.4 Initial Conditions [Back]

Agents are born with four fixed types: birthplace location d_0, education level e, migration type τ, and individual-level fixed productivity θ_e, allowed to vary by education. Birthplace and education types are drawn from two empirical categorical distributions estimated with Census 2011 data. Migration types are drawn from a Bernoully distribution with calibrated parameter π_τ, the probability of drawing a "stayer" type. Finally, θ_e is drawn from from two education-specific normal distributions with standard deviations σ_{θ_N} and σ_{θ_E}, estimated with the income process using MCVL 2005-2019 data.

In the first period of the model, individuals also draw initial assets a_{j-1}, location d_{j-1} and housing status h_{j-1}. Initial assets follow a log normal distribution estimated using non-housing net wealth data from the EFF 2005-2020. The categorical distributions for locations and housing status are instead estimated with the 2011 Census. The initial housing tenure shares (coresidents, renters, and homeonwers) are separately estimated by native status, as natives are more likely to coreside than migrants. Agents are born with some mortgage debt in case they enter the model as homeowners. Debt is computed using EFF 2005-2020 data, separately by education level. Initial mortgage debt is a fixed share of housing wealth.

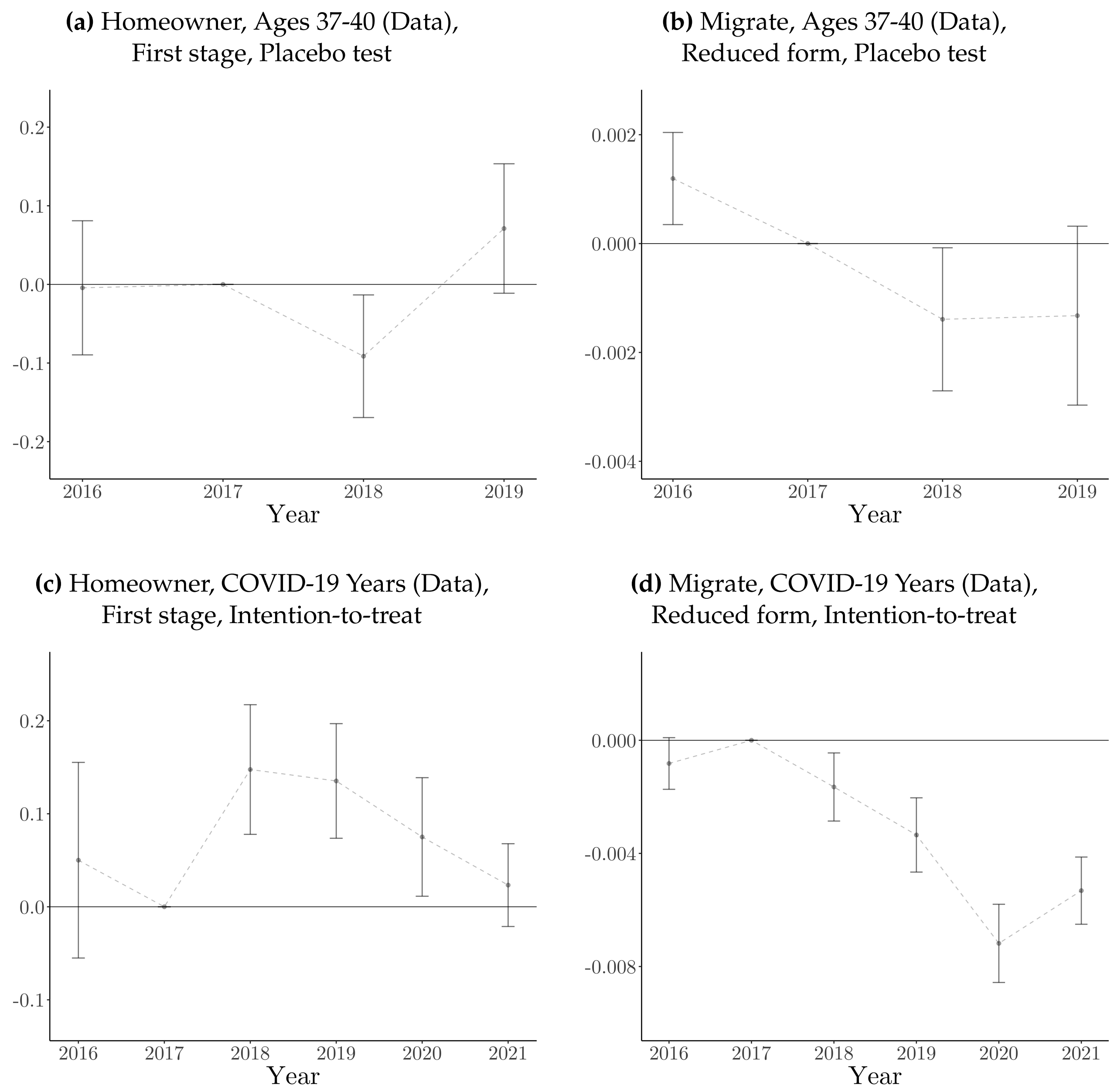
A fraction of migrants effectively behave as natives: they derive home-bias utility from living in the initial location and, as long as they stay in that location, can coreside with parents.[48] The probability of belonging to this group of migrants is given by the ratio of the share of migrant coresidents at age 25 over the share of native coresidents at age 25. Finally, initial employment status by education and location is drawn from a categorical distribution estimated using EU-SILC 2004-2019 data.

F Validation [Back]

[48] This is needed to match the fact that some migrants coreside in the data (see Figure 2c). An alternative strategy would be to classify as natives all migrants that were coresiding at 25 (the first age in the model), since these people are likely able to also coreside in the future by staying in the same city (e.g., because their parents migrated with them before they turned 25). Yet, due to the constraints in available data, this method cannot be adopted. The census data is cross-sectional, lacking information about, for example, whether a 45-year-old migrant who is currently a non-coresident had previously coresided in the same city at the age of 25.

F.1 Place-Based Subsidy for Young Homebuyers [Back]

Policy in The Data As a robustness exercise, I estimate two placebo event analyses on individuals aged 37-40, just beyond the age eligibility for the subsidy. Treatment and control definitions remain consistent with the main regressions. As expected, these placebo treatments don't significantly impact the outcomes (see Figures F15a and F15b).



(a) Homeowner, Ages 37-40 (Data), First stage, Placebo test

(b) Migrate, Ages 37-40 (Data), Reduced form, Placebo test

(c) Homeowner, COVID-19 Years (Data), First stage, Intention-to-treat

(d) Migrate, COVID-19 Years (Data), Reduced form, Intention-to-treat

Figure F15: Treated: People living in small cities (<10k inhabitants), aged between 37 and 40 (panels **(a)** and **(b)**) or less than 35 (panels **(c)** and **(d)**). Control group: same age living in slightly larger cities (10k-20k). Treatment year: 2018. Migration across regions (NUTS-1) and rural-urban areas (rural <10k, rural >10k or urban >40k). Other included controls and fixed-effects: gender (in the data), age, age squared, region, and region-year. Clustered (locations) standard errors. Data: EPF, EPC, EVR 2016-2019. [Back]

Additionally, I restrict the sample to only include people *born* in municipalities with populations under 20,000, and treat people who were born in locations with less than 10,000 inhabitants. Results are similar to the baseline event studies (Figure F16). Event-study versions including COVID-19 years up to 2021 are in Figures F15c and F15d.

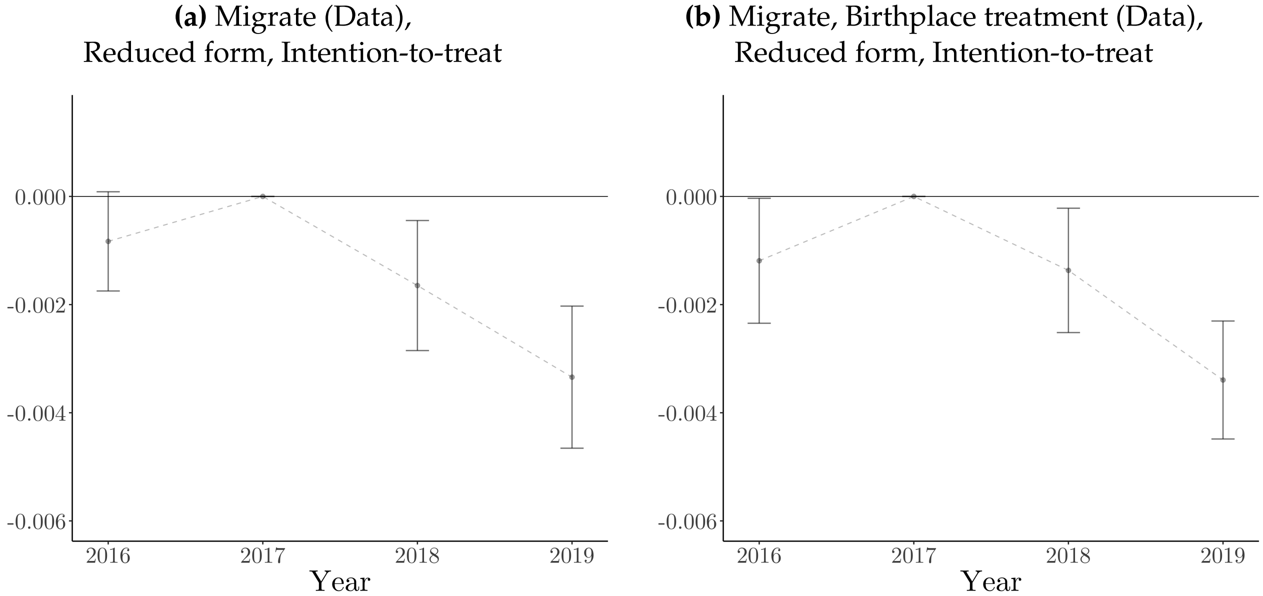


Figure F16: Treated: People aged less than 35 living (panel **(a)**) in small cities (<10k inhabitants) or born (panel **(b)**) in small cities. Control group: same age living, or born, in slightly larger cities (10k-20k). Treatment year: 2018. Migration across regions (NUTS-1) and rural-urban areas (rural <10k, rural >10k or urban >40k). Other included controls and fixed-effects: gender (in the data), age, age squared, region, and region-year. Clustered (locations) standard errors. Data: EPF, EPC, EVR 2016-2019. [Back]

The difference-in-differences regression takes the form:

$$y_{it} = \alpha_{\text{small}} + \tau \text{Treated}_{it} + \alpha_r + \alpha_{rt} + \alpha X_{it} + \epsilon_{it}, \tag{32}$$

where y_{it} is the outcome, which is either the homeownership status (first-stage) or the individual migration event (reduced form), α_{small} is an indicator function for the set of treated cities (municipalities with less than 10,000 inhabitants), τ is the coefficient associated to the treatment, an indicator equal to one for years 2018-2019 and small municipality residents, and zero otherwise, whereas α_r and α_{rt} are region and region-year fixed-effects, respectively. In the baseline specification, additional controls X_{it} include gender, age and age squared. The sample restriction is the same as in the event studies (regression (17)): individuals younger than 35 living in cities with less than 20,000 inhabitants, so that the control group is composed of people living in cities with size just above the policy population threshold. The data covers the years 2016 to 2019, encompassing two years before and after the implementation of the policy in early 2018.

Policy in The Model After buying a house with the subsidy, the policy allows the homebuyer to resell the property under certain circumstances: if they are relocating for work, if they are buying a new house in the same or a different area, or once five years have passed since receiving the subsidy. Conversely, if the individual chooses to migrate before this five-year period without satisfying one of these conditions, they are obligated to pay back a pro-

Table F5: Regressions (1) and (2) also include a control for gender. Standard errors are clustered at the location level, *p<0.1, **p<0.05, ***p<0.01. Data: EPF, EPC, EVR 2016-2019. [Back]

	Data, Treated Locations:		Model, Treated Individuals:	
	Homeowner	Migrate	Homeowner	Migrate
	(1)	(2)	(3)	(4)
Treated	0.1151**	-0.0021***	0.6697***	-0.0141***
	(0.0502)	(0.0006)	(0.0156)	(0.0034)
Age	0.0150	0.0206***	0.2736***	-0.0004
	(0.0645)	(0.0018)	(0.0193)	(0.0055)
Age^2	0.0003	-0.0004***	-0.0154***	-0.0002
	(0.0011)	(0.0000)	(0.0011)	(0.0003)
Treated Locations FE	✓	✓		
Individual FE			✓	✓
Year-Region FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
R^2	0.09850	0.00314	0.68957	0.36216
Observations	2,056	4,533,392	17,363	17,363

portionate amount of the subsidy. For example, migrating after just two years without meeting any of the exceptions would require a 5,400 euro repayment of the subsidy.

There repayment rules and exceptions are reproduced when simulating the policy in the model. First, I add an additional state variable that takes on three values: not eligible for the policy, eligible and not recipient, and recipient. This differentiation is required as individuals who have already received the subsidy stop being eligible. Additionally, while subsidy recipients might need to reimburse a part of the subsidy if they migrate, non-recipients don't face this constraint.

Keeping track of the years since the policy was received, to ensure the five-year threshold is met, would be computationally too costly. However, I can use the mortgage repayment schedule, the agents' age, and the current level of assets to infer the years since the property's purchase. In particular, I compute the level of negative assets realized in equilibrium for people with a mortgage, averaged by location, education, age, and years since the house was bought. These averages define the thresholds above which I classify individuals with the corresponding types (location, education, and age) as having been homeowners for a certain amount of years.

Recipients of the policy who move before the five-year mark and don't buy a house in the new location, are forced to make a proportional repayment of the policy. In the model, I cannot distinguish between work and non-work related moves, whereas the policy allows recipients to migrate if the reason is job-related. Non-work related moves among homeowners aged 25-40 that do not buy a house elsewhere in the following year are 71% of the total in the U.S. (CPS 2009-2019).[49] Thus, in the model, when repayments arise, they are adjusted down by 29%. Finally, I simulate the subsidy exclusively during the years it was implemented in Spain (2018-2021). This is done to estimate the short-term effects of the policy and mimic the event study design estimated in the data.

[49]No similar survey data is available for Spain.

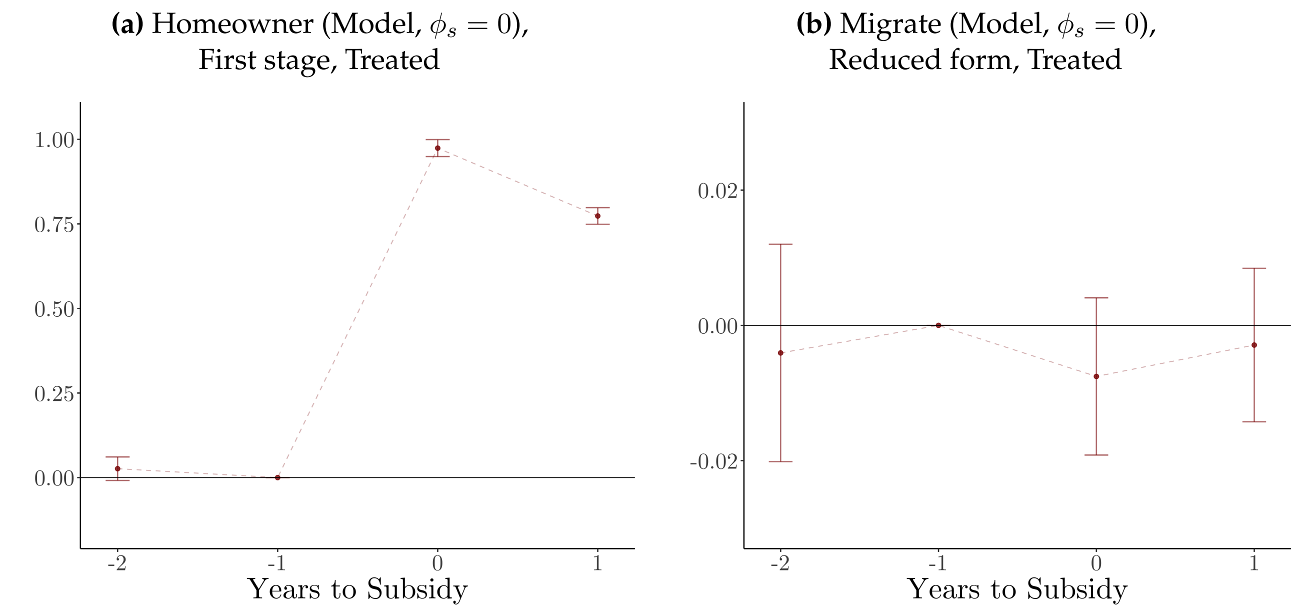


Figure F17: Treated: People who received the subsidy in the counterfactual model with the policy and $\phi_s = 0$. Control group: same people as the treated, but in the baseline model without the policy. Included controls and fixed-effects: age, age squared, region, and region-year. Clustered (locations) standard errors. [Back]

Figure F17 plots the simulated effects of the policy in a counterfactual exercise without transaction costs of selling houses ($\phi_s = 0$). The policy increases homeownership without significantly influencing migration rates in the reduced form. Therefore, I conclude that transaction costs ϕ_s are the key driver of reduced migration among homeowners.

F.2 Coresidence Explains Higher Homeownership Among Natives [Back]

Figure F18 plots the untargeted lifecycle profiles of homeownership rate and income, separately for natives and migrants, in the counterfactual economy where the is no coresidence option. When I take away this option, I find that both the homeownership and income gaps between natives and migrants vanish.

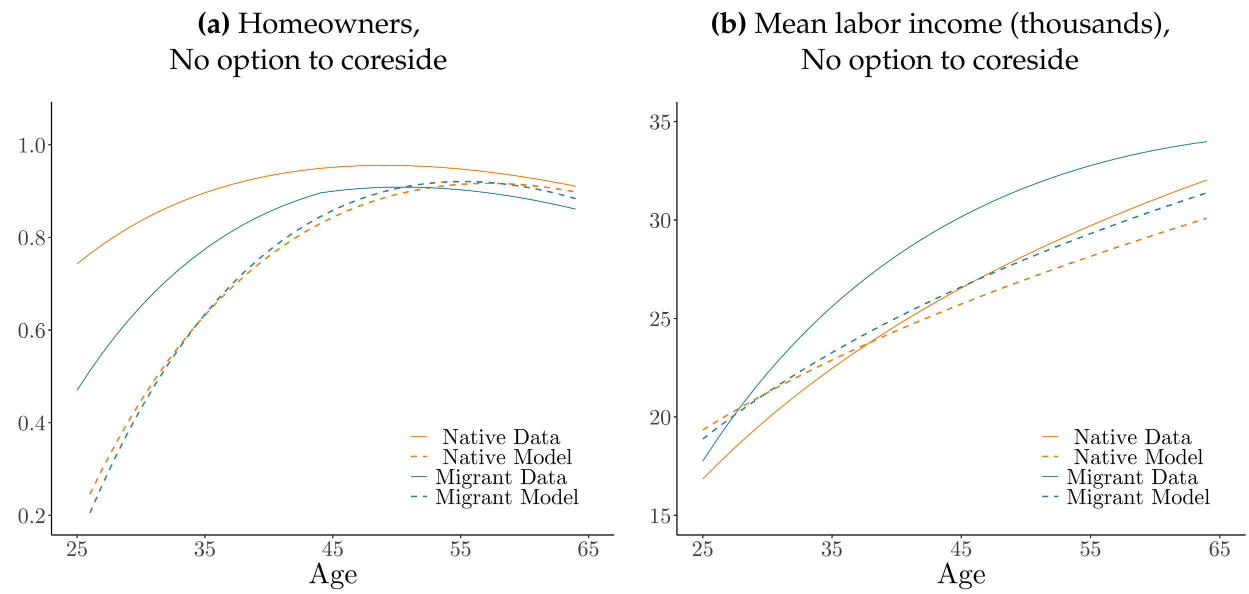
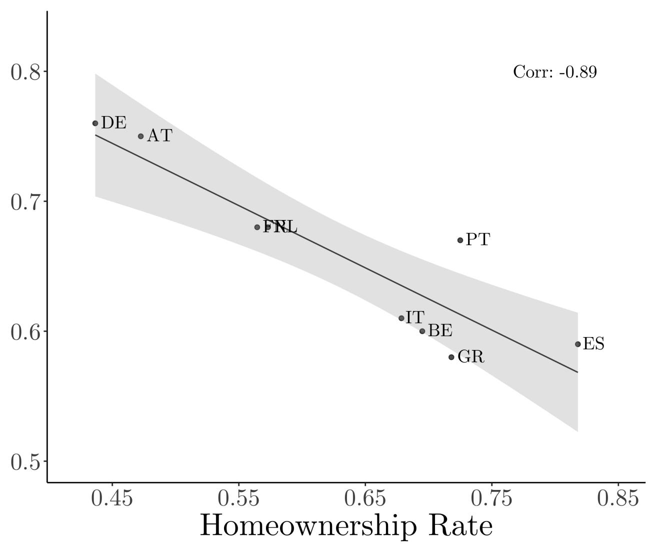


Figure F18: The figures plot the lifecycle profiles of homeownership rate and income, separately for natives and migrants, in the counterfactual economy where the is no coresidence option. Data: Census 2011 (panel **a**), MCVL 2005-2019 (panel **b**).

F.3 Why Does Homeownership Reduce Wealth Inequality? [Back]

Figure F19 plots the relationship between the local Gini of net wealth and the local homeownership rate across large European countries. The source is Figure 1 in Kaas, Kocharkov and Preugschat (2019). They use data coming from the Household Finance and Consumption Survey (HFCS), which is the European equivalent of the EFF data I use to compute the same relationship across Spanish locations (Figure 7).

Figure F19: Gini of net wealth



Note: The figure plots the relationship between the local Gini of net wealth and the local homeownership rate among not coresidents across large European countries. Source: Kaas, Kocharkov and Preugschat (2019), using HFCS 2013-2016 data. [Back]

Figure F20 plots the unconditional quantile effects of homeownership on net wealth along the wealth distribution (Firpo, Fortin and Lemieux 2009). Figure F20a plots the estimates for the entire distribution, whereas Figure F20b focuses on the top 50%. The estimated unconditional quantile regression takes the form:

$$\text{RIF}\left\{y_{it}, \text{Quantile}_k(F_{y_{it}})\right\} = \alpha_i + \alpha_t + \tau\text{Homeowner}_{it} + \alpha\text{X}_{it} + \epsilon_{it}$$

for quantiles $k \in \{10, 20, ..., 90\}$. The outcome variable $\text{RIF}\left\{y_{it}, \text{Quantile}_k(F_{y_{it}})\right\}$ measures the influence of the individual observation indexed by i and t on the unconditional quantile k of the net wealth distribution. We are interested in parameter τ, the effect of homeownership on the recentered influence function. The regression includes household and year fixed-effects, α_i and α_t, and individual controls X_{it}: household income and number of members, household head's age and age squared, and indicators for self-employed, college-educated, married, and parent. The data used to estimate the regression comes from EFF 2005-2020.

As in Kaas, Kocharkov and Preugschat (2019), unconditional quantile effects are reported in terms of semi-elasticities, by dividing them by each corresponding quantile value. Household fixed-effects are included. As can be seen in Figure F20, homeownership is found to increase net wealth along the entire distribution and, in relative terms, it does so especially among the wealth poor. Becoming homeowners increases the net wealth by a factor of 6 in the first decile and more than doubles it in the second decile. The increase in net wealth for people in the top decile of the distribution is comparatively much lower, amounting to about 4%.

(a) RIF quantile effect homeowner on wealth (%)

(b) RIF quantile effect homeowner on wealth (%), top five deciles

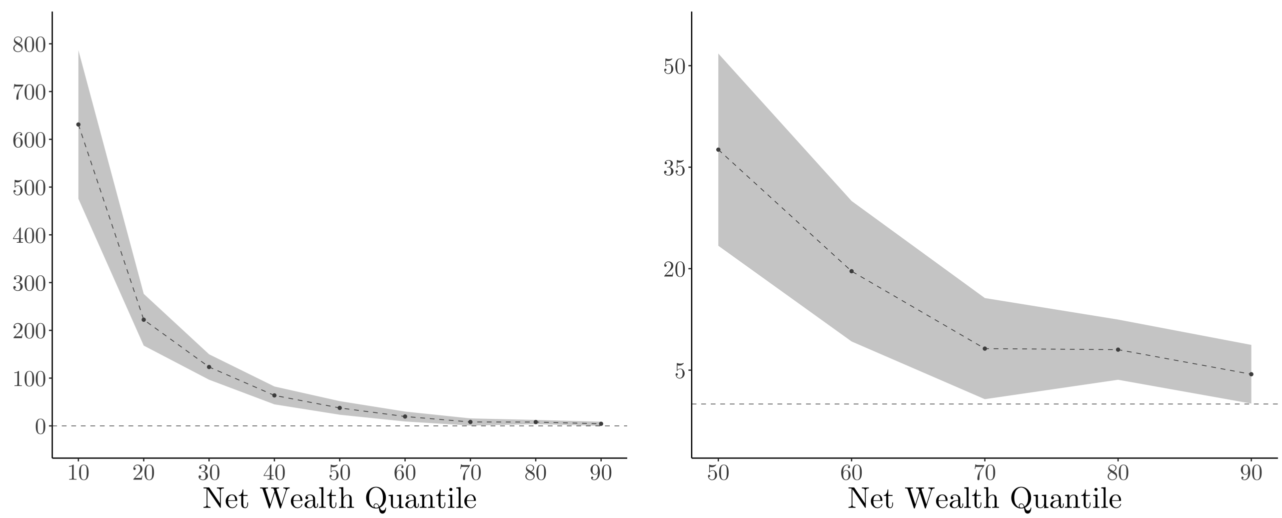
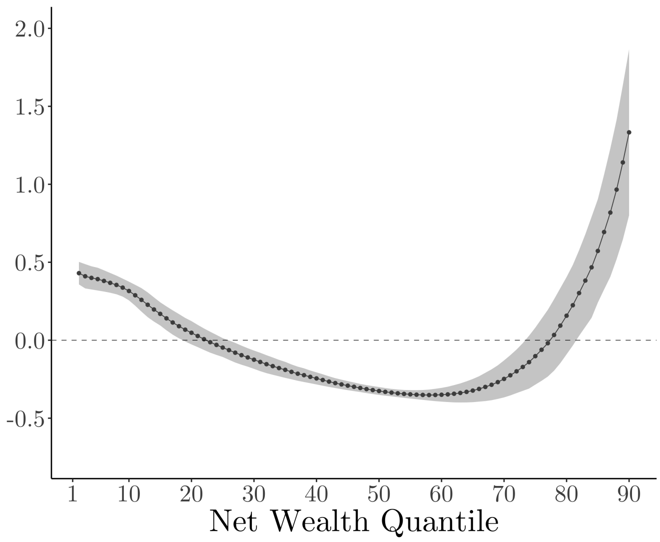


Figure F20: The figures plot the unconditional quantile effects of homeownership on net wealth along the wealth distribution (Firpo, Fortin and Lemieux 2009). Quantile effects are reported in terms of semi-elasticities, by dividing them by each corresponding quantile value (Kaas, Kocharkov and Preugschat 2019). Household and year fixed-effects are included. The other included controls are household income and number of members, household head's age and age squared, and indicators for self-employed, college-educated, married, and parent. Data: EFF 2005-2020. [Back]

Figure F21 plots the Recentered Influence Function (RIF) of the net wealth Gini coefficient by quantile (Firpo, Fortin and Lemieux 2009), computed using EFF 2005-2020 data. The recentered influence function measures the predicted effect of each individual observation on the overall Gini of net wealth. Positive values in the bottom and top two deciles of the wealth ditribution reveal that increasing the mass of households in the bottom or top 20% increases inequality. Conversely, the negative RIF values from quantile 20 to 80 tell us that moving households towards the middle 60% of the distribution reduces the net wealth Gini coefficient.

Figure F21: Recentered Influence Function of Gini net wealth



Note: The figure plots the Recentered Influence Function of the net wealth Gini coefficient by quantile (Firpo, Fortin and Lemieux 2009). Data: EFF 2005-2020. [Back]

To estimate the effect of homeownership on wealth inequality, I run the following regression:

$$\text{RIF}\left\{y_{it}, \text{Gini}(F_{y_{it}})\right\} = \alpha_i + \alpha_t + \tau\text{Homeowner}_{it} + \alpha X_{it} + \epsilon_{it}, \tag{33}$$

where RIF $\{y_{it}, \text{Gini}(F_{y_{it}})\}$ measures the influence of the individual observation indexed by i and t on the overall Gini of net wealth, α_i and α_t are household and year fixed-effects, and controls X_{it} include household income and number of members, household head's age and age squared, and indicators for self-employed, college-educated, married, and parent. The data used to estimate the regression comes from EFF 2005-2020.

Results are reported in Table F6. Homeownership is estimated to reduce wealth inequality, both when household fixed-effects are not included (column 1) and when they are included (column 2). In the baseline specification with household fixed-effects, a 10 percentage points increase in the homeownership rate is estimated to reduce the Gini of net wealth by around -0.019 points.

In column (2) of Table F7, I report results for a regression that is analogous to (33), with the only difference that the homeownership treatment is interacted with a categorical variable measuring the level of households' wealth in the first available panel period: bottom

Table F6: Year fixed-effects are always included, whereas household fixed-effects are only included in column (2). Other included controls are: household income level, indicators for college-educated and married, and other demographic variables (age, age squared, number of household members, indicators for parent and self-employed). Heteroskedasticity-robust standard errors, *p<0.1, **p<0.05, ***p<0.01. Data: EFF 2005-2020. [Back]

	RIF of Gini net wealth	
	(1)	(2)
Homeowner	-0.4273***	-0.1938***
	(0.0600)	(0.0521)
Income	0.0165**	0.0151
	(0.0081)	(0.0114)
College	-0.4530*	0.0020
	(0.2569)	(0.0616)
Married	-0.1340*	0.0100
	(0.0730)	(0.0431)
Demographic Variables	✓	✓
Household FE		✓
Year FE	✓	✓
R^2	0.11	0.77
Observations	20,783	20,783

10%, between 10% and 20%, or above the bottom 20% of the wealth distribution. This specification reveals that the average negative effect of homeownership on the Gini of net wealth, reported in column (1) for comparison, is fully driven by the bottom of the distribution. In particular, the estimated impact is highest in the bottom 10%, is still negative and significant for household with initial wealth between the first and second decile, and loses significance for richer households.

Table F7: Year and household fixed-effects are included. Other included controls are: household income level, indicators for college-educated and married, and other demographic variables (age, age squared, number of household members, indicators for parent and self-employed). Heteroskedasticity-robust standard errors, *p<0.1, **p<0.05, ***p<0.01. Data: EFF 2005-2020. [Back]

	RIF of Gini net wealth	
	(1)	(2)
Homeowner	-0.1938***	
	(0.0521)	
Homeowner, Wealth$_{t=1}$ < p10		-0.3978***
		(0.1129)
Homeowner, Wealth$_{t=1}$ $\in$ [p10, p20]		-0.2179***
		(0.0625)
Homeowner, Wealth$_{t=1}$ > p20		-0.0184
		(0.1231)
Demographic Variables	✓	✓
Household FE	✓	✓
Year FE	✓	✓
R^2	0.77	0.77
Observations	20,783	20,783

Figure F22 plot the share of local net wealth accounting to the top and bottom 20% by location, as simulated in the benchmark model. The horizzontal axis measures the simulated local homeownership rate. Locations in the model with the highest homeownership rate have on average a 2 pp. higher share of local net wealth accounting to the bottom 20% of the distribution, and around a 2 pp. lower share accounting to the top 20%.

(a) Local share of net wealth in bottom 20% by location (Model)

(b) Local share of net wealth in top 20% by location (Model)

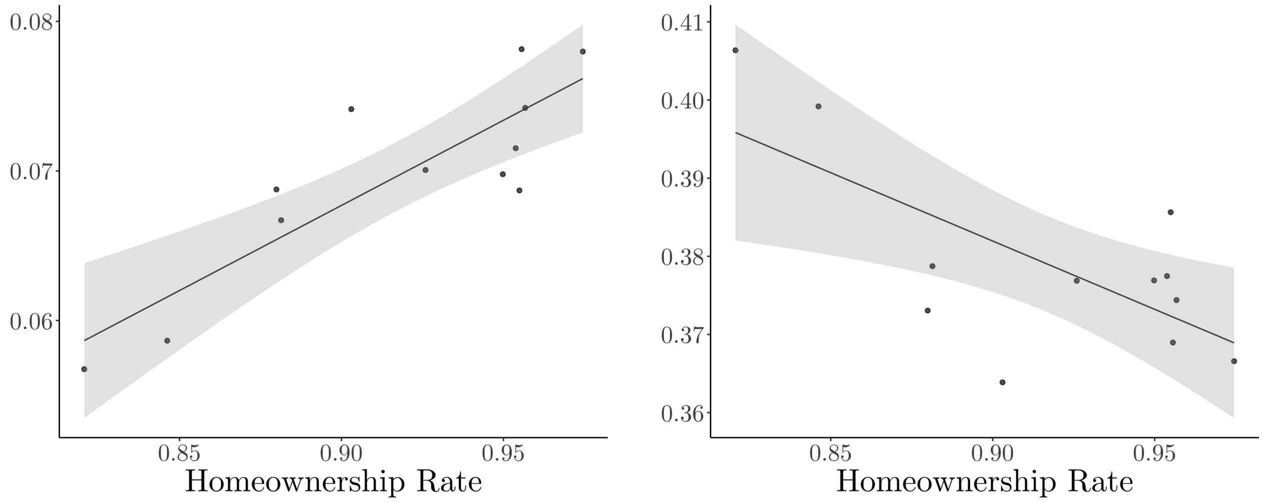


Figure F22: The figures plot the share of local net wealth accounting to the top and bottom 20% by location. This is a simulated outcome from the benchmark model. The horizzontal axis measures the simulated local homeownership rate. [Back]

G Policy Counterfactuals [Back]

G.1 Welfare Measure [Back]

Let lifetime utility of newborns ($j = 1$) in the benchmark and in the policy counterfactual with consumption tax Δc be denoted by V and $\hat{V}(\Delta c)$, respectively. The consumption-equivalent tax Δc is defined such that

$$V - \hat{V}(\Delta c) = 0$$

$$V = \frac{1}{N}\sum_{i=1}^{N}\left\{u(c^*_{ij}, h^*_{ij}, d^*_{ij}, \boldsymbol{x_{ij}}) + \beta\mathbb{E}_{l_{iedj}, z_{iej+1}, \pi^b_{ied_0 j+1}, \boldsymbol{p_{t+1}}, \boldsymbol{w_{et+1}}}\left[\overline{v}_{j+1}(\boldsymbol{x_{ij+1}})|l_{iedj}, z_{iej}, \boldsymbol{p_t}, \boldsymbol{w_{et}}\right]\right\}$$

$$\hat{V}(\Delta c) = \frac{1}{N}\sum_{i=1}^{N}\left\{u((\Delta c)\hat{c}_{ij}, \hat{h}_{ij}, \hat{d}_{ij}, \boldsymbol{x_{ij}}) + \beta\mathbb{E}_{l_{iedj}, z_{iej+1}, \pi^b_{ied_0 j+1}, \boldsymbol{p_{t+1}}, \boldsymbol{w_{et+1}}}\left[\overline{v}_{j+1}(\boldsymbol{x_{ij+1}})|l_{iedj}, z_{iej}, \boldsymbol{p_t}, \boldsymbol{w_{et}}\right]\right\}$$

where $(c^*_{ij}, h^*_{ij}, d^*_{ij})$ and $(\hat{c}_{ij}, \hat{h}_{ij}, \hat{d}_{ij})$ denote optimal choices in the benchmark and counterfactual equilibria, and N is the number of simulated individuals.

The consumption tax parameter Δc adjusts all agents' consumption uniformly either upwards or downwards. A value of $\Delta c > 1$ suggests that, following the policy implementation, agents require a higher level of consumption to be indifferent with the benchmark. Conversely, $\Delta c < 1$ indicates that agents would give up part of their consumption to keep the policy.

My measure of welfare is given $1 - \Delta c$. In other words, welfare measures the percentage change in consumption that the average newborn agent would require, or give up, in order to be indifferent between the counterfactual and the benchmark. I don't analyze welfare along the transition path between the stochastic steady-states. In particular, I compare newborn agents who are either born in the benchmark equilibrium or in the counterfactual equilibrium after prices, wages, and taxes have already converged.

G.2 Mortgage Interest Deductions [Back]

The welfare effects of mortgage interest deductions change depending on the average lifecycle income of newborns by quintile, as shown in Figure G23. Interestingly, the policy favors the lower-income brackets more when targeted to urban locations, but adversely affects them when targeted to rural locations. For the version of the policy that does not target specific locations, welfare gains across income levels remain roughly stable.

Figure G23: Mortgage interest deduction: welfare effects by lifecycle income [Back]

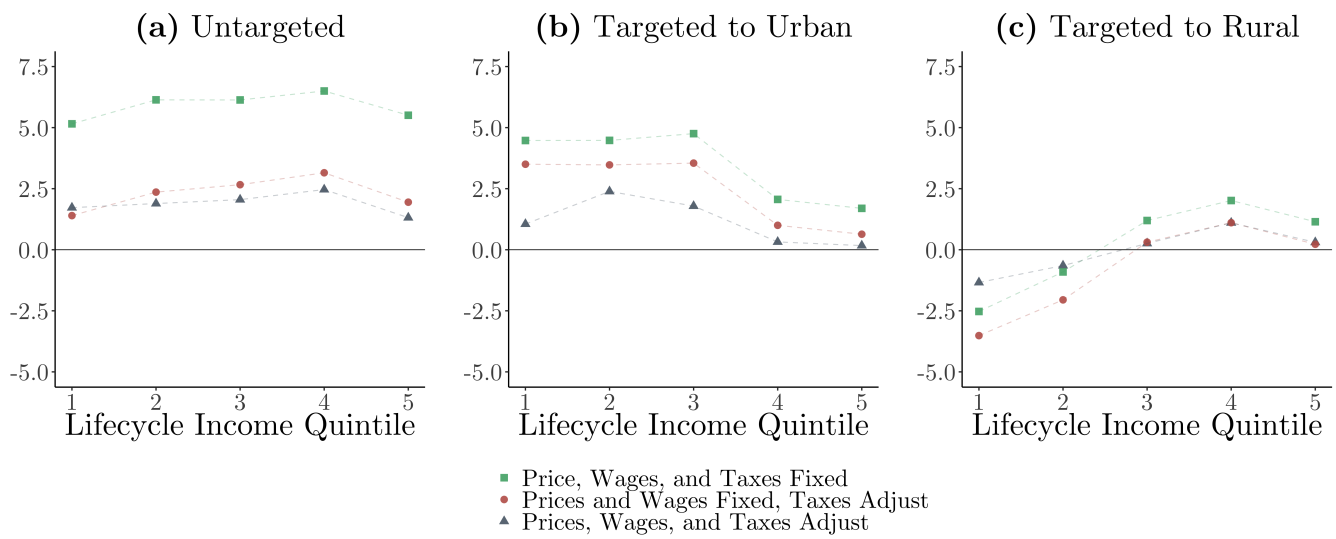


Figure G23 further plots the welfare effects when prices and taxes remain fixed to their counterfactual values, and in a different simulation where income taxes are also fixed. The welfare gains in partial equilibrium are generally higher. However, the tax increases needed to finance the policy offset most, though not all, of the welfare gains of untargeted mortgage interest deductions, and substantially reduce the gains from a policy targeted to urban locations.

When allowing prices and wages to adjust in equilibrium, welfare gains further decrease for the untargeted policy and for the policy targeted to urban locations. The losses are especially high in the targeted policy and for low-income agents, due to the increase in housing prices. Agents in this income group, indeed, are less likely to be homeowners and are more exposed to price shocks. On the other hand, wage and price general equilibrium effects tend to benefit low-income agents in the policy targeted to rural location. However, these effects, which are driven by the decrease in housing prices, do not fully offset the negative partial equilibrium welfare effect of this targeted policy on lower-income agents.

Tax increases also depend on the realizations of aggregate shocks. With positive aggregate shocks, higher wages reduce the need to raise taxes. However, the take-up of the policy also increases, as more agents stop coresiding and become homeowners. Therefore, the policy's impact on the Government's budget depending on factors' realizations is ambiguous. I find that tax increases are hump-shaped with respect to the sign and magnitude of aggregate shocks. Tax increases are lowest when shocks are negative, become larger as shocks turn positive, and then slightly reduce again for extremely positive shocks.