# Online Appendix

## Homeownership and Portfolio Choice over the Generations

Gonzalo Paz-Pardo

# A Data

The data used in this paper is taken mostly from the Panel Study of Income Dynamics (PSID) and the Survey of Consumer Finances (SCF). The former is particularly valuable because it allows to follow several cohorts of households over a very long period of time (1968-2013), and it is the base for the estimation of the earnings process and most of the housing-related measures. However, it contains, particularly in its earlier periods, very limited information about stock market participation, wealth, and financial asset allocation of households. For these measures I rely on the Survey of Consumer Finances, which contains very detailed information about households' balance sheets. However, with limited exceptions, it lacks a panel dimension.

I now briefly describe the characteristics of each of the surveys, the sample selection criteria, and the estimation of the several targets and profiles used in the paper.

## A.1 PSID

The Panel Study of Income Dynamics (PSID) follows a large number of U.S. households and their qualifying spinoffs since 1968 and provides information about demographic characteristics, sources of income, housing status, and, since more recently, their wealth and consumption. When it started, the PSID was composed of two main subsamples: the SRC (Survey Research Center), which was designed to be representative of the U.S. population at the time and which is a random sample itself, and the SEO (Survey of Economic Opportunity), which oversampled the poor. Later, the PSID was augmented with the Immigrant and Latino subsamples.

The survey was yearly from 1968 to 1997, and started being biennial since then. Wealth information was available in the 1984, 1989, 1994 waves, and from 1999 onwards, and has become progressively richer and improved in quality. Since 1999 it broadly replicates the wealth inequality patterns present in the SCF without oversampling the richest.

For my main results, I drop the SEO, Latino and Immigrant samples and am therefore left with a random sample, which makes computations simpler given that weights are not needed Haider (2001). However, the weighting of the final dataset can be affected by attrition and the sample selection requirements. In Appendix C.1 I report how different sample selection and deflation procedures affect some key features of the earnings process.

### A.1.1 Measures and sample selection

In the PSID data, I define cohorts as follows:

- The **1940s cohort** are the households whose head was born between 1940 and 1950. For the estimation of the income process, I increase the sample size and consider households between 1930 and 1950. For simulation purposes, I consider they were born in 1942.
- The **1960s cohort** are households whose head was born between 1960 and 1970 (1950-1970 for the income process). For simulation purposes, I consider they were born in 1962.
- The **1980s cohort** are households whose head was born between 1980 and 1990 (1970-1990 for the income process). For simulation purposes, I consider they were born in 1982.

Naturally, the changes in earnings dynamics, homeownership, etc. have happened progressively over time and do not necessarily correspond with the admittedly arbitraty boundaries set. To some extent, the features of the 1940s earnings process are a weighted average of the earnings process of people born between 1930 and 1950. However, including those allows me to increase the sample sizes, and to obtain more observations of people going through a recession at different ages.

For the earnings process, I assume that all business cycle effects are absorbed by the business-cycle dependent process, so I do not extract year effects. For the representation of changes in earnings risk and the computation of age-efficiency profiles, I extract a linear yearly trend from earnings data.

The estimation of the household income process requires eliminating households that display very low attachment to the labor market (whose labor income in a given year is below a minimum level of $1500 in 2013 prices). This assumption is standard in the earnings processes literature (see De Nardi, Fella and Paz-Pardo (2020) for details) and avoids issues related with taking logs of very small numbers. Furthermore, I also drop those households for whom there are no two consecutive observations available.

For the older ages of the younger cohorts, there are some cases in which there are very few observations for a particular combination of the labor market aggregate state, which are not sufficient for the estimation of the flexible parameters. In those cases I replace the missing cohort-age-states with their correspondent levels of the previous cohort. This affects the 1960s cohort after age 50 for the states of recovery and staying in a recession, and the 1980s cohort for all states related to a recession after age 30. I follow a similar procedure for years which are not yet observable (1980s cohort from ages 35-40), and provide some robustness checks with respect to this assumption in Section V.D.

For all of the other measures reported in the paper (homeownerhip, etc.) none of these restrictions are imposed. In particular, I do not require the sample to be composed of the same households in every year. This allows me to keep a bigger sample, but implies the assumption that any attrition or nonresponse happens randomly and does not affect the evolution of the measures reported.

With respect to the two types of housing, "detached houses" are those defined in the PSID as "detached single family houses" and "non-detached houses" are all other types of structures (including 2-family houses, apartments, etc.).

From 1968 to the end of the sample, housing PTI ratios are computed as the ratio of the median house price reported by PSID homeowners to median household income in the PSID.

### A.1.2 Tax progressivity

As explained in Section III.D, the model explicitly includes the choice between taking the standard deduction or itemized deductions. However, this implies that the tax progressivity coefficient $\tau$ in Equaton 16 needs to be reestimated, because in previous studies, such as Heathcote, Storesletten and Violante (2014), it was computed taking into account the existence of itemization and the standard deduction. Removing the standard deduction from disposable income implies a reduction of the progressivity coefficient, as it is an important driver of progressivity in the US and other tax codes Blackburn (1967).

To perform this estimation, I need to compute the counterfactual disposable income or, alternatively, the counterfactual level of taxes paid $T^*_{it}$ by a household with pre-tax income $y_{it}$ in the absence of standard deduction or HMID. To do so, I first estimate the following equation in my PSID sample:

$$\log \hat{y}_{it} = \lambda_1 + (1 - \tau_1) \log y_{it} \tag{A.1}$$

where $\hat{y}_{it}$ is post-tax pre-benefit household income. I use the estimated parameters from this equation to predict $T^*_{it}$, assuming that $T^*_{it} = \log \tilde{y}^*_{it} - \lambda_1 + (1 - \tau_1) \log y^*_{it}$, where $y^*_{it} = y_{it} + max(sd, HM)$, $sd$ stands for the standard deduction, and $HM$ for the HMID that corresponds to a given household. The basic assumption here is that the taxes paid by a household with a certain level of income in the counterfactual world with no standard deduction are the same as those paid by a household with that level of income plus the deduction in the observed world. As for the mortgage deductions, I define them to be the product of the average mortgage interest rate in a certain year and the outstanding mortgage the household claims to have in the PSID, as long as they are smaller than the total mortgage payments the household has made in the previous year.

Once I have counterfactual taxes $T^*_{it}$, I construct counterfactual disposable income (post-tax, post-benefit) $\tilde{y}^*_{it} = \tilde{y}_{it} + T_{it} - T^*_{it}$, run the following regression:

$$\log \tilde{y}^*_{it} = \lambda + (1 - \tau) \log y_{it} \tag{A.2}$$

and obtain $\tau = 0.085$. In models where itemization and the standard deduction are not explicit, this value is frequently around 0.15-0.18 (0.151 in Heathcote, Storesletten and Violante (2014)).

## A.2 SCF

The Survey of Consumer Finances (SCF), conducted every three years since 1983, provides information about the financial situation of US households. It contains detailed data on household balance sheets, income, and other demographic characteristics. Given the focus on wealth, the survey oversamples the rich, who hold most of the assets in the economy. To do so, it combines an area-probability sample (geographical stratification) with a list sample that guarantees that a sufficient amount of wealthy individuals are included.

Apart from the 1983-2007 waves, I also consider the older historical waves of the Survey of Consumer Finances made available by the University of Michigan. Namely, I consider the 1963, 1968, 1969, 1970, 1971, and 1977 waves to construct, where relevant, statistics like wealth to income ratios or shares of stock market participants. While this data is less exhaustive than the recent waves of the SCF, it is the only source to provide reliable information about household wealth and its composition for the cohorts I am interested in before 1980. For a longer discussion, analysis and harmonization procedures of these waves of the SCF, see Kuhn, Schularick and Steins (2017).

I use the SCF to obtain stock market participation data. I consider a household to be participating in the stock market if any of its members hold stocks directly or indirectly via an IRA account, Keogh plan, mutual fund or pension plan like a 401(k). For most of the waves the composition of these funds is provided as a categorical variable, so for indirect holders I consider them to be stockholders if they hold any such plan which is formed of "mostly or all stock".

### A.2.1 Bequest targets

The main bequest targets are based on Hurd and Smith (2001), who use the Asset and Health Dynamics among the Oldest Old (AHEAD) study from the Health and Retirement Study (HRS). This study focuses on households whose heads were born in 1923 or before, which is significantly earlier than the first cohort considered in this paper. Therefore, the bequest targets reflect bequests left by a generation which had potentially different characteristics to the ones I consider.

Bequest data for the 1940s cohort is not yet available, as the majority of it was alive at the end of my sample period. However, SCF data reveals that the generation born in the 1940s had accumulated around 30% more wealth at age 75 than the generation born around 1910-1920. Thus, for the main version of this model I adjust the average bequest target by increasing it by exactly as much as average wealth increased at age 75 between these cohorts. This imperfectly captures several possible reasons for holding more wealth during retirement (longer life expectancies, different patterns of medical expenditure, different histories) - future data on wealth decumulation by this cohort can impose more discipline on this assumption. I do not adjust the targeted percentage of people with zero bequests, but the calibration tends to underpredict it.

### A.3 Higher order moments of earnings

I define skewness and kurtosis as the third and fourth standardized moments of log earnings changes, respectively. Kelley's skewness ($KS$) and Crow-Siddiqui kurtosis ($CS$) are defined following Guvenen et al. (2016):

$$KS = \frac{(P_{90} - P_{50}) - (P_{50} - P_{10})}{P_{90} - P_{10}} \tag{A.3}$$

$$CS = \frac{P_{97.5} - P_{2.5}}{P_{75} - P_{25}} \tag{A.4}$$

where $P$ represents a percentile in the distribution of earnings changes. Thus, Kelley's skewness is more positive the further away the 90th percentile is from the median; and more negative the further away the 10th percentile is from the median, while Crow-Siddiqui kurtosis is larger the fatter the tails of the distribution are. I refer to both as *robust* measures because they are less affected by outliers than standard skewness and kurtosis.

## B Computational appendix

### B.1 EGM method

For a given set of parameters, the model is solved using a combination of a nonlinear maximizer and the endogenous gridpoint method (EGM), following the algorithm described in Fella (2014).

The model has several discrete states (housing, aggregate state) and continuous states (safe assets, risky assets, earnings). After the last period of life (age $T + 1$), utility is known as it can be directly derived from the bequest function (6). From then I proceed via backwards induction.

For any age $t$, given a set of states $(y, a, f, h, m, \Omega)$ we need to find the policy functions for the household for current period's consumption $c$ and next period's safe assets $a'$, risky assets $f'$, housing $h'$, and mortgages $m'$. Using standard methods, this would imply computing the value associated with each of the feasible choices and maximizing over the 4-D space (as we can always solve for one of the choices using the budget constraint) to find the optimal choice for each set of states.

Using the EGM method allows to substantially speed up the computation of a pair of these choices. For this paper, I use the EGM method to solve the $(c, a')$ choice conditional on the $f', h'$ choice. For computational purposes, $m = -a$, and I allow for the grid of $f$ to include some points that correspond to possible positive holdings of $a$. Given $f'$ and $h'$, I use the inverted Euler equation to compute the consumption choice $c$ that corresponds to each future choice of assets $a'$.

By the budget constraint, the sum of consumption and all savings must equal current cash on hand. This means that, given $f'$, $h'$ and the pair $c$, $a'$ we have found with the Euler equation, we can interpolate the endogenous grid of consumption to the exogenous grid of cash on hand that is determined by the states in period $t$, and obtain the $f', h'$-conditional choices of $c$ and $a'$ for those particular states.

The only point left is to then run a nonlinear maximizer over the $f'$ and $h'$ choices, thus obtaining all required policy functions. Using this procedure, the nonlinear maximizer is only run over a 2-D space, which implies the algorithm is significantly faster.

The Euler equation does not necessarily hold in all scenarios for safe assets (for instance, when the household is borrowing constrained with no housing, or at the boundary of the condition that requires it to pay interest on its debt). These situations are dealt with specifically.

## B.2 Global minimization

I solve the model using FORTRAN 2008. Due to the large state space, it is very computationally intensive - in a workstation with 44 cores it takes roughly 25 minutes to solve for a given parametrization. In order to find the parameter values that minimize the weighted square distance between the targets and their values in the data, I use a modified version of the NEWUOA numerical optimization algorithm.

I acknowledge the use of the UCL Myriad High Throughput Computing Facility (Myriad@UCL), and associated support services, in the completion of this work.

# C Intergenerational differences: additional evidence

The changes across cohorts described in Section I are based on the SRC, which is the PSID's representative sample of the 1968 US population and their offpsring, are deflated with the CPI, and consider household earnings for all households, whether married or not. In this Appendix, I begin by comparing changes in male and household earnings (Appendix C.1.1) and showing the changes in higher-order moments of earnings risk (Appendix C.1.3), and then I describe the qualitative and quantitative implications of considering several alternative approaches: picking the whole PSID and weighting it (Appendix C.2.1), deflating with the PCE (Appendix C.2.2), selecting married households only (Appendix C.2.3), splitting by education (Appendix C.3.2) and geographical area (Appendix C.5.1).

## C.1 Earnings dynamics

### C.1.1 Male vs. household earnings

The earnings of the median male earner in the United States at age 25 have decreased from the cohort born in the 1940s, which entered the labor market in the early 1960s, to the cohort born in the 1960s by around 12% in real dollars (see top left panel of Figure C.1). Similarly, Guvenen et al. (2017), using Social Security data, find that median income at labor market entry peaked for the generation born in 1947 and decreased thereafter. As the shape of the life-cycle profile of earnings has changed little, both median earnings at each age and median lifetime earnings are lower for younger generations.

However, during this period there was a significant increase in female labor force participation and women's wages, which acted as a counteracting force and almost completely reversed this decrease in terms of household earnings (bottom left panel of Figure C.1). After age 30, when most household formation has taken place, median household earnings are higher for the younger cohort than for those born in the 1940s.

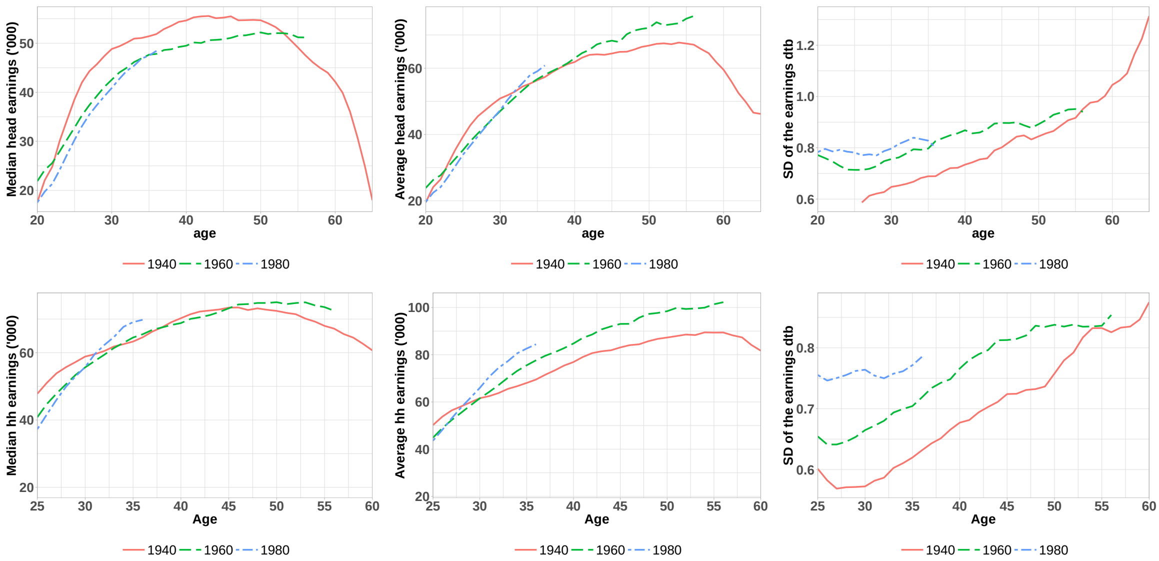


Figure C.1: Changes in the earnings distribution over the generations. Top: household heads; bottom: household earnings. Left: median earnings, center: average earnings, right: standard deviation of the log earnings distribution. PSID data, deflated using the CPI.

### C.1.2 Explaining the increase in earnings volatility

The variance of household earnings changes, which I report in the middle right panel of Figure 1, is determined by a plurality of factors: on-the-job earnings risk for both head and spouse, job finding and job separation rates, correlation of shocks within the household, the average duration of unemployment, etc. In this section I show how the variance of earnings fluctuations can have increased over time for younger generations, even if short duration jobs have become less frequent (Hyatt and Spletzer (2016)), by looking at the dynamics of unemployment.

In Figure C.2 I report the counterpart of the middle right panel of Figure 1 for those households in which neither head nor spouse experienced any unemployment spell in the two years of reference for the computation of the variance. This selected group displays a much lower variance of earnings fluctuations than the overall population. However, whilst the variance increased significantly between the 1940s and 1960s cohort, it has stayed constant, or even decreased, between the latter two. This observation suggests that the increased volatility of the 1980s cohort was mostly driven by the households who are excluded from this graph: those who have experienced unemployment spells during the year, who are mostly located in the lower part of the income distribution.

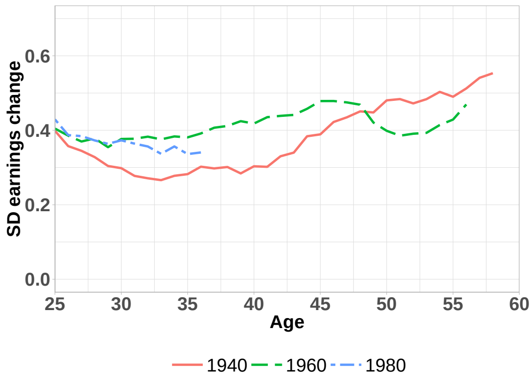


Figure C.2: Standard deviation of log household earnings changes, excluding households where the head or the spouse have suffered an unemployment spell. PSID data.

However, Figure C.3, left panel, shows that people in 1980s generation households are less likely to go through a spell of unemployment than the earlier two cohorts, implying that the share of households affected by unemployment in a given year has gone down over time. Absent any other changes, this development, together with Figure C.2, should imply a reduction in the variance of log earnings changes. But, as the right hand panel of Figure C.3 shows, the duration of unemployment increased significantly. The average 30 year-old head of household of the 1940s cohort that lost his job spent a bit more than a month on that state; for the 1980s cohort, the same person could expect to be unemployed for around 15 weeks.[1]

This evidence suggests that changes in the conditional duration of unemployment may have had a key role in pushing the variance of earnings up. I do not attempt, due to data limitations derived from the small sample in the PSID, to perform a full decomposition of the contribution of these different factors to the increase in earnings volatility, including for example female labor force participation or the role of shocks to the second earner in the household, but it is a very interesting avenue for future research.

[1]The measures reported in Figure C.3 differ from standard measures of unemployment and unemployment duration because they impose the same sample selection measures as in my main sample (most importantly, that households have total labor income higher than $ 1,500, implying households who were unemployed for the whole year are not in the sample) and because I report average unemployment duration during the past year, which by construction is capped at 52 weeks. However, the increase in average unemployment duration is consistent with the historical increase documented on CPS data.

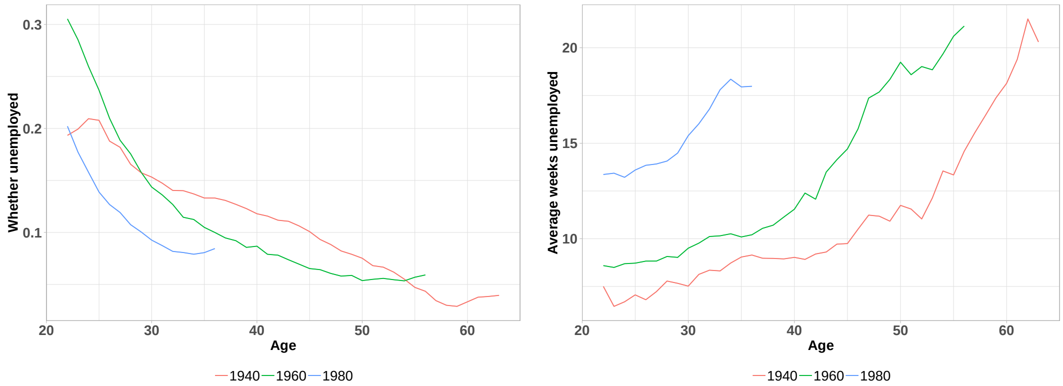


Figure C.3: Left: whether head of household was unemployed at some point over past year, by age and cohort; right: average duration of unemployment during that year, conditional on having been unemployed. PSID data.

### C.1.3 Higher order moments of earnings changes

As Figure C.4 shows, earnings changes display negative skewness and high kurtosis for all cohorts, but there has been little change in those measures over time[2]. However, this observation does not imply that the tails of all three distributions are equally fat: given a level of kurtosis and skewness, increasing the variance makes large shocks more likely than before.

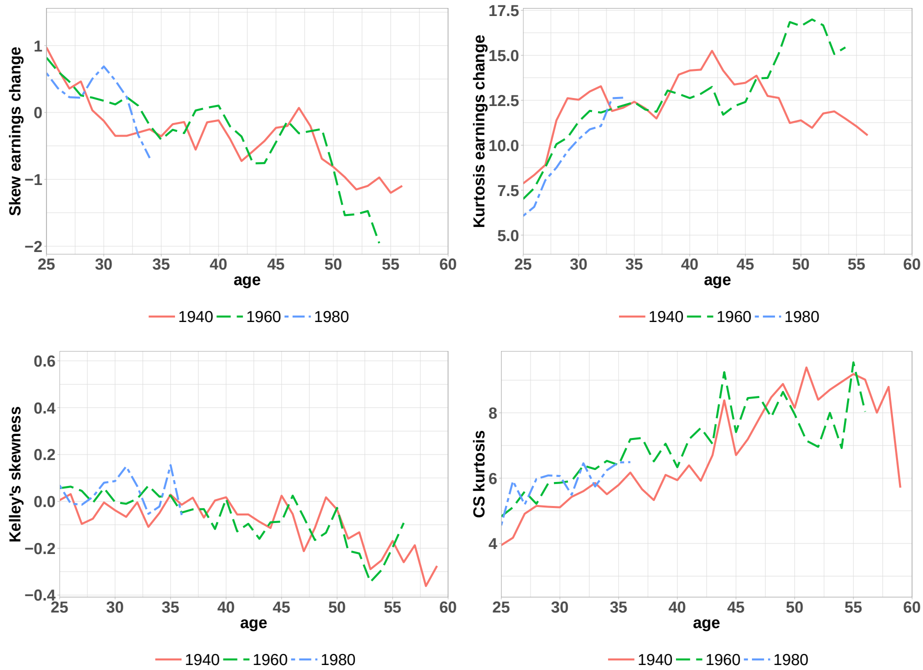


Figure C.4: Higher order moments of log earnings changes, by cohort

[2]Appendix A.3 provides definitions for these.

## C.2 Sample and deflator choices

### C.2.1 Sample composition

In this section, I make use of the whole PSID rather than the SRC. Because only the SRC is a random sample, this also requires making use of the PSID-provided weights. In the earlier years of the survey, this means considering the Survey of Economic Opportunity part of the PSID, that oversamples the poor; in later years of the survey, in particular after 1997, it implies taking into account the immigrant population that has arrived to the US since. Using the SRC rather than the whole PSID for the main results leads to a cleaner comparison - keeping the offspring of the same population of reference helps to ascribe the changes in labor market dynamics to structural changes in the labor market, opportunities, and family formation, rather than changing demographics across the whole society. However, it has the disadvantage on missing out on additional population growth of potentially different socioeconomic characteristics, which has implications for house prices and more broadly any general equilibrium effects.

Figure C.5 shows median and average earnings for this broader sample. Including immigrants reduces the median earnings of younger cohorts with respect to the oldest generation.

Turning to distributional features, we observe in Figure C.6 that considering all immigrants has the interesting implication that the difference between the 1940s and 1960s cohort is preserved, or even larger than before, but the difference between the 1960s and the 1980s cohort becomes almost insignificant. While earnings have become more unequal for the sons and daughters of the original PSID sample members, the entrance of immigrants has contributed to reduce the variance of the earnings distribution of the 1980s cohort with respect to the 1960s.

The measure of homeownership considered in this paper can also depend on sample choices, particularly if immigrants and newer incorporations to the PSID sample have substantially different homeownership patterns. Figure C.7 shows the resulting comparison. All main patterns are similar: if anything, taking into account the whole population implies a marginally larger gap between the 1940s and 1960s cohort, and a marginally smaller gap between the 1960s and 1980s cohort, which is consistent with the smaller gap in earnings inequality and risk in this wider sample.

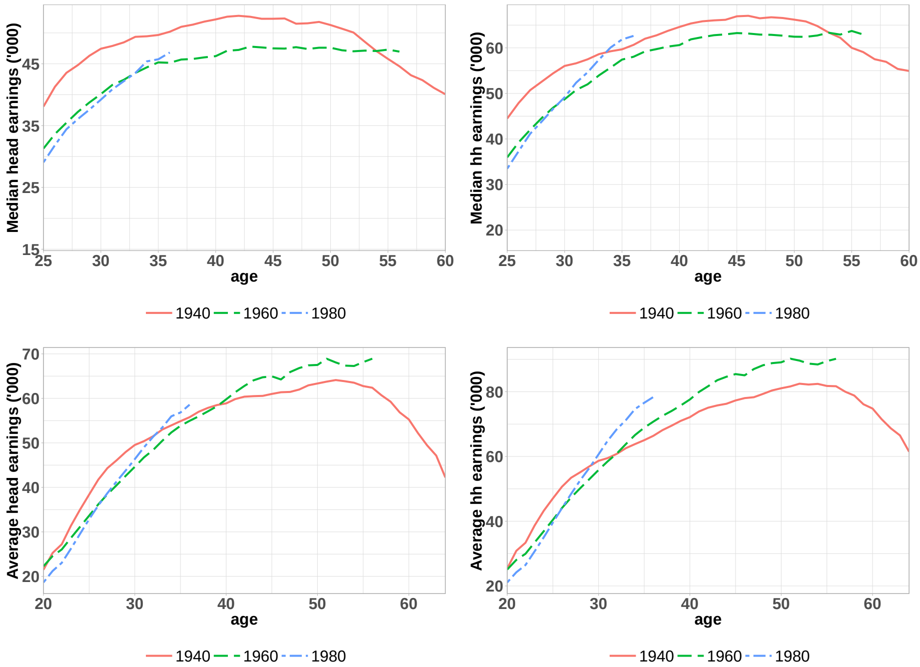


Figure C.5: Median earnings (top) and average earnings (bottom), for household heads (left) and households (right), 2013 dollars, sample including SEO and immigrants.

### C.2.2 Choice of deflator

In this section, I deflate earnings with the PCE or personal consumption expenditure deflator rather than the CPI. These two measures differ slightly on their scope and their computation procedure. While the PCE takes into account all expenditure made by households and also on behalf of households, such as total medical expenditures, the CPI only considers what households spend out-of-pocket. The PCE is based on business surveys, while the reference basket for the CPI is based on data from the Consumer Expenditure Survey or CEX. Given that the focus of the paper refers to the consumption and portfolio possibilities of all but the richest of households, the main results are deflated with the CPI, which more closely reflects the changes in prices of the goods and services that households actually pay. The PCE index is instead more frequently used when performing aggregate macroeconomic analysis.

In this sample period, the PCE implies overall lower cumulative inflation than the CPI and, therefore, implies that median and average earnings of younger cohorts have grown more than with the CPI. However, because cross-sectional inequality within a cohort-age cell is not affected by the choice of deflator, the facts regarding changes in the distribution of earnings that lie at the core of this paper are unchanged when considering the PCE.

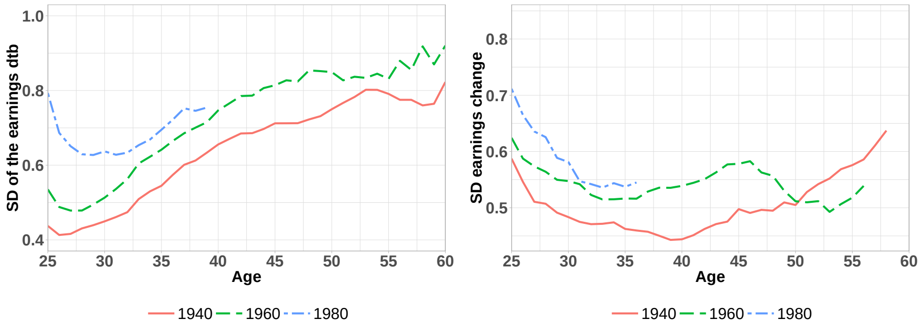


Figure C.6: Standard deviation of log earnings (left) and earnings changes (right), sample including SEO and immigrants

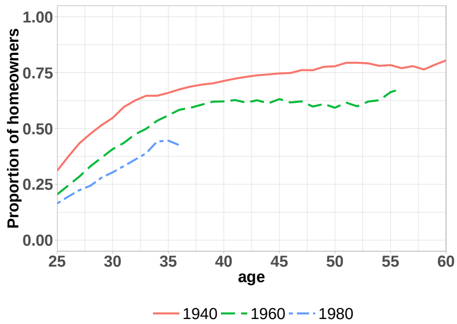


Figure C.7: Homeownership, by cohort, sample including SEO and immigrants

Figure C.8 shows median and average earnings by cohort, for male and head and spouse earnings. Deflating with the PCE increases the differences between cohorts, particularly for household earnings, which implies that it acts in the opposite direction as the inclusion of a broader sample described in Appendix C.2.1. Naturally, the choice of deflator does not affect earnings inequality within age and cohort, nor measures of earnings risk, nor homeownership.

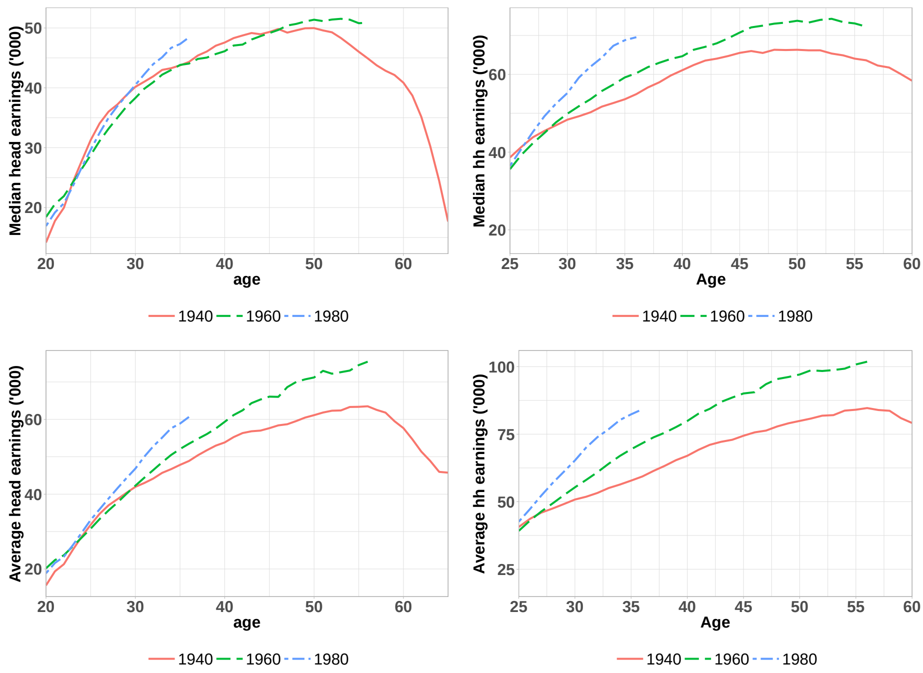


Figure C.8: Median (top) and average (bottom) earnings, 2013 dollars. Left: household heads, right: households. PCE-deflated sample.

### C.2.3 Marital dynamics and family composition

Figure C.9 compares the profiles in Figure C.1 with those for married households. While it is clear that family composition affects the profiles for the first ten years of age, and that earnings inequality is lower in the more homogeneous sample of married couples, the main picture is pretty similar, which suggests that there are differences in labor earnings across cohorts, particularly in distributional terms, which are not fully explained by the differential timing of marriage.

Figure C.10 shows that there are also large differences in homeownership over different cohorts if we restrict the sample to married households or to households with children, which provides additional evidence to suggest that earnings dynamics are relevant over and above changes in family composition. Naturally, in these selected samples homeownership tends to be larger than in the general population.

Additionally, the main hypothesis proposed in this paper (changes in the earnings distribution and earnings risk affecting homeownership) can also partially operate via later marriage and/or fertility decisions.

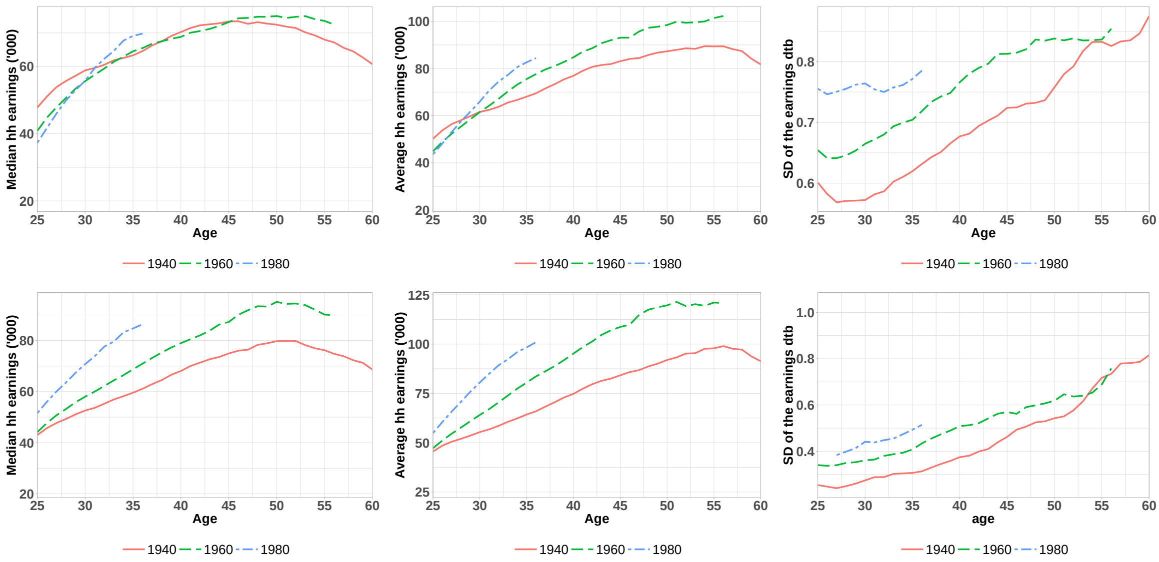


Figure C.9: Changes in the earnings distribution over the generations. Top: household earnings; bottom: household earnings for married households. Left: median earnings; center, average earnings; right: standard deviation of the log earnings distribution.

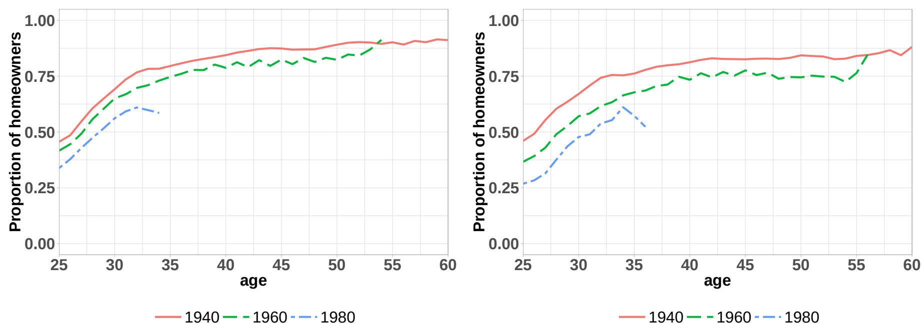


Figure C.10: Homeownership by cohorts, PSID data. Left, sample restricted to married couples; right, sample restricted to households with at least one child.

## C.3 Other factors related to the labor market

### C.3.1 Intergenerational mobility patterns

There is a close link between job insecurity, earnings volatility, and mobility. A generation like that of the 1980s, with more earnings instability, might be more ready to move, which in turn would be an additional factor to contribute to the drop in homeownership rates that we observe. There is limited data on mobility in the PSID, particularly within narrow geographical regions. However, there is information, which I report in Figure C.11, about whether individuals have ever moved state. According to this measure, younger generations do not seem to be more likely to move than older ones: if anything, we observe a drop in the interstate mobility patterns of the 1960s generation with respect to those of the 1940s, and a recovery for the 1980s that brings them in line with the oldest generation.

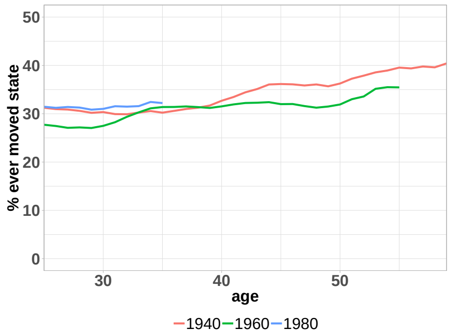


Figure C.11: Share of heads of household that have ever moved state, by cohort

However, interstate mobility does not paint the whole picture, as workers are also likely to move within shorter distances that might also imply that they need to quit their homes and rent or buy in a different location. Johnson and Schulhofer-Wohl (2019) use the National Longitudinal Survey of Youth (NLSY), confirm the finding that interstate migration has gone down for younger cohorts, and show that shorter-distance mobility changed little between the cohorts, although there are some compositional effects (the mobility of college graduates went down, but some age-education groups of the most recent cohort are more mobile). However, shorter-distance moves represent a small share of all moves (around 20%).

### C.3.2 Education

As shown in the previous section, the gap in homeownership rates is not driven by pure compositional effects due to later marriage or childbearing. The same is true for the case of education. As Figure C.12 shows, the drop in homeownership rates has happened both for non-college graduates and for college graduates. The drop is more salient for households whose head does not have college education, which have lower homeownership rates throughout. Although education is not explicit in the model, it captures these differences to the extent that they are embedded in household income.

Given that there has been an increase in the number of college graduates, who are also more likely to be homeowners, if anything changes in education would be a force in the opposite direction to my main results and increase the homeownership rates of the youngest cohort. Additionally, highly educated people display higher homeownership rates even at age 25, thus suggesting that their delayed entry to the labor market is not the key driver of the results either.

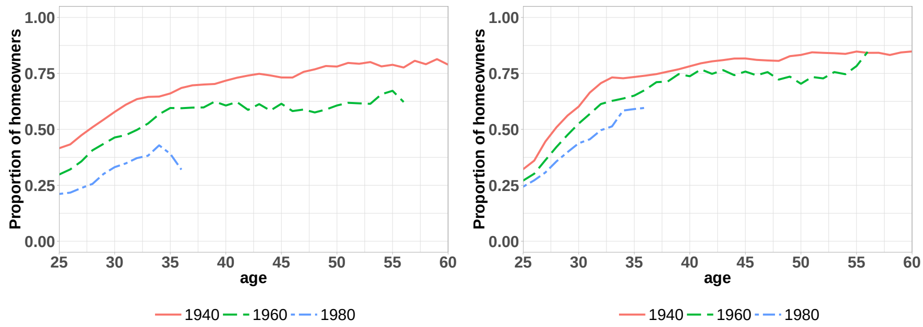


Figure C.12: Homeownership by cohorts, PSID data. Left, high school graduates and lower education; right: college graduates

## C.4 Equivalence scales by generation

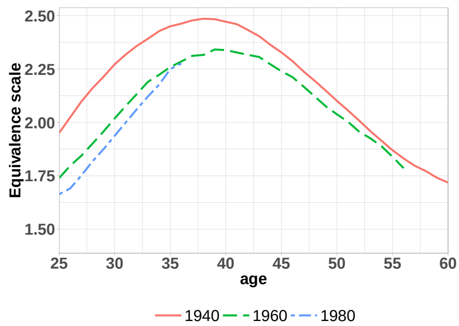


Figure C.13: Average OECD equivalence scale, by cohort

## C.5 Homeownership and portfolio composition

### C.5.1 Census data: aggregation and geographical differences

The PSID has limited geographical information about households, and it is not a frequent source of aggregate homeownership rates. Thus, I turn to IPUMS data (Ruggles et al., 2020) from the American Community Survey and other comparable historical samples for these two purposes. I begin by comparing the evidence it provides with the PSID.

The data for older generations is noisier, given that the data is only available every 10 years before 2000, but it also shows an intergenerational drop in homeownership rates which is broadly consistent with PSID evidence (Figure C.14).

This alternative data source also allows me to show how the contribution of different cohorts has aggregated into the national homeownership rate over time (Figure C.15). Although the level of the aggregate homeownership rate has been quite stable over time, this apparent stability masks slow-moving developments that have affected the age distribution of homeowners, which I show with the different colors. For instance, in 1960 households over 60 (red and brown areas) were less than a third of all homeowners; in 2018, households over 58 (green and blue areas) are almost half of all homeowners.

The drop in homeownership rates is true for both urban and rural areas (Figure C.16). In the framework in this paper, increased urbanization is reflected in higher average house prices faced by households. To the extent that this is driven by transformations in the labor market, the main message in the paper still holds true. However, an interesting future avenue for research could add geographical heterogeneity to this framework, and explicitly study the role of urbanization.

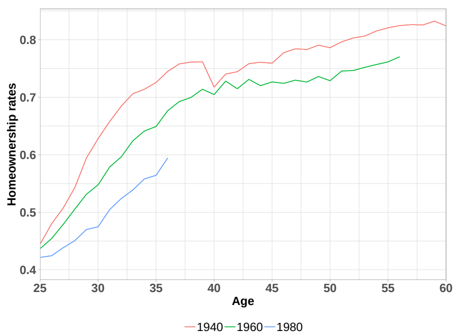


Figure C.14: Homeownership rates by age and generation, IPUMS data

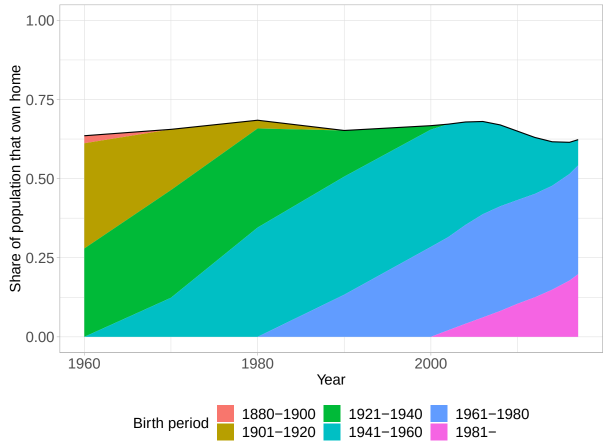


Figure C.15: Aggregate homeownership rate by year (black line), and decomposition of homeowners by decade of birth. At each given year (x-axis), each colored area represents the share of the total population that was born in a given period and who owns a home. Source: IPUMS census data. See Figure C.14 for homeownership rates by cohort with the same data.

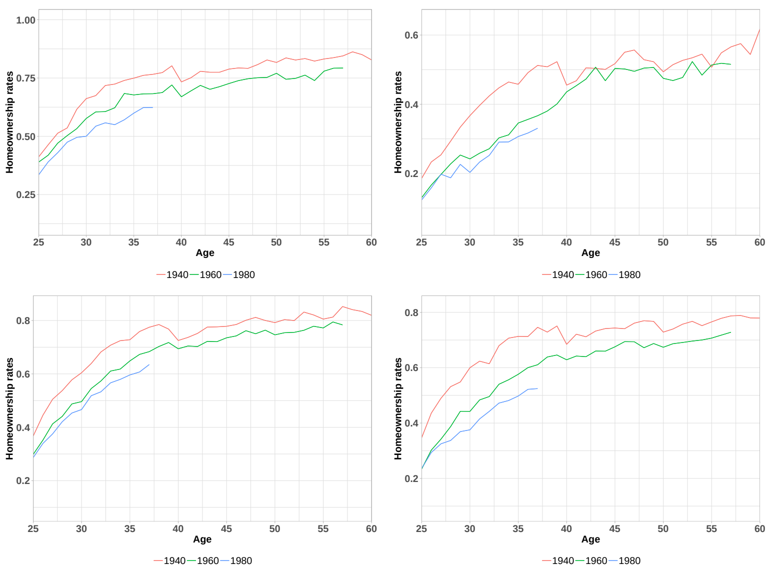


Figure C.16: Homeownership rates by age and generation, IPUMS data. Top left: not in metropolitan area; top right: in central/principal city; bottom left: not in centra/principal city; bottom right: intermediate status.

### C.5.2 Portfolio composition, additional Figures

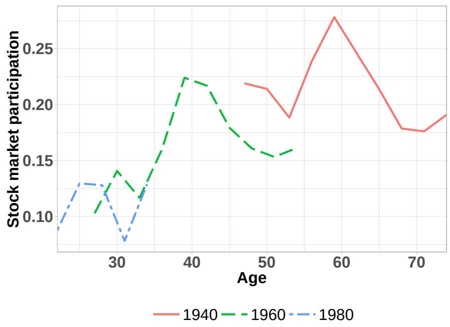


Figure C.17: Direct stock market participation, three generations. SCF data.

# D Earnings process

## D.1 Implementation

I estimate the earnings process described in Section II by parameterising the quantile functions with a set of Hermite polynomials:

$$Q_\eta(q|\eta_{i,t-1}, age_{it}, c_i, \Omega_t^y) = \sum_{j=0}^{J} a_j^\eta(q, c_i, \Omega_t^y)\psi_j(\eta_{i,t-1}, age_{it}) \tag{D.1}$$

$$Q_{\eta_1}(q|age_{i1}, c_i, \Omega_1^y) = \sum_{j=0}^{J} a_j^{\eta_1}(q, c_i, \Omega_1^y)\psi_j(age_{i1}) \tag{D.2}$$

$$Q_\epsilon(q|age_{it}, c_i) = \sum_{j=0}^{J} a_j^\epsilon(q, c_i)\psi_j(age_{it}) \tag{D.3}$$

where the coefficients $a_j^i$, $i = \epsilon, \eta_1, \eta$, for all states are modelled as piecewise-linear splines on a grid $\{q_1 < \ldots < q_L\} \in (0, 1)$.[3] The intercept coefficients $a_0^i(q)$ for $q$ in $(0, q_1]$ and $[q_L, 1)$ are modelled as the quantiles of an exponential distribution with parameters $\lambda_1^i$ and $\lambda_L^i$ respectively. All coefficients are allowed to differ across cohorts.

If one could directly observe the two components $\epsilon_{it}$ and $\eta_{it}$, it would be possible to find the coefficients above by quantile regression at each point of the quantile grid $q_j$. However, both components are latent. To deal with this, the estimation starts at an initial guess for the coefficients and iterates between draws of the posterior distribution of the latent persistent components and proceeds to find the coefficients by quantile regression. The process is repeated until convergence of the sequence of coefficient estimates.

## D.2 Fit of life-cycle variances

Figure D.1 shows how the earnings process fits the changes in cross-sectional variances of log earnings for these three different generations at each age.

[3]Following Arellano, Blundell and Bonhomme (2017), I use tensor products of Hermite polynomials of degrees (3,2) in $\eta_{i,t-1}$, and age for each state $k$ of $Q_{\eta,\Omega}(q|\eta_{i,t-1}, age_{it})$ and second-order polynomials in age for $Q_\epsilon(q|age_{it})$ and $Q_{\eta_1,\Omega}(q|age_{i1})$.

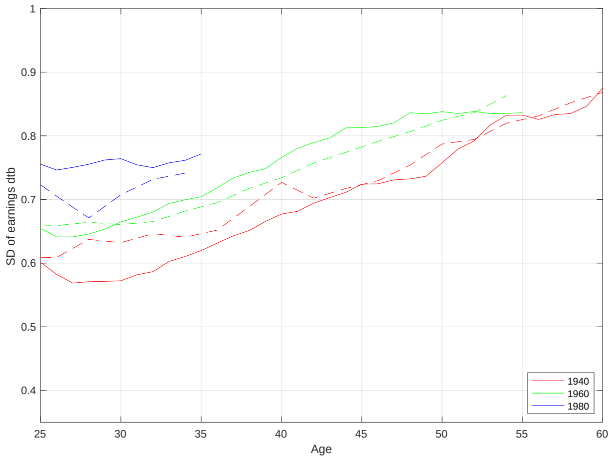


Figure D.1: Variance of log earnings over the life cycle, PSID data vs model-implied

## D.3 Canonical earnings process

This process nests more standard earnings process such as that proposed in Storesletten, Telmer and Yaron (2004), which I refer to as *canonical process*:

$$y_{it} = \eta_{it} + \epsilon_{it} \tag{D.4}$$

$$\eta_{it} = \rho\eta_{it-1} + \xi_{it} \tag{D.5}$$

with $\xi_{it} \sim N(0, \sigma_t^2)$, $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ and

$$\sigma_t^2 = \begin{cases} \sigma_{r,c}^2 \text{ if } \Omega^y = \text{Recession} \\ \\ \sigma_{b,c}^2 \text{ if } \Omega^y = \text{Boom} \end{cases} \tag{D.6}$$

where usually $\sigma_{r,c}^2 > \sigma_{b,c}^2$. Unlike in this process, my procedure implies that there is no need to assume age-independence or normality of earnings shocks, nor linearity in the dependence of the persistent component on its past realizations.

I obtain its parameters by fitting the cohort-conditional profiles of variances and autocovariances over the life-cycle. Figure D.2 shows the fit of the life-cycle variances, and Table D.1 shows its estimated parameters.

The estimates for the 1940s cohort are more precisely estimated and thus as expected (variances are larger in recessions than in expansions). For the 1960s cohort, the difference between expansions and recessions is quite imprecisely estimated, but the model

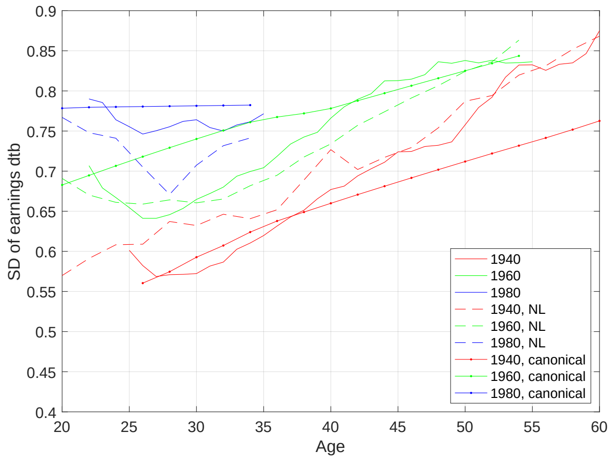


Figure D.2: Variance of earnings over the life cycle. Sold lines: data; dashed lines: NL process; dash-dot lines: canonical process

| Cohort | $\rho$ | $\sigma^2_{r,c}$ | $\sigma^2_{b,c}$ | $\sigma^2_{\epsilon}$ |
|---|---|---|---|---|
| 1940 | 1.0 | 0.027 | 0.0112 | 0.13 |
| 1960 | 0.99 | 0.0010 | 0.0205 | 0.16 |
| 1980 | 0.61 | 0.34644 | 0.38276 | 0.0001 |

Table D.1: Parameter estimates, business-cycle varying canonical process

succesfully replicates the higher level of earnings inequality that the cohort faces. Finally, for the 1980s cohort there are very few years of observations - whilst the process matches the variance profiles well, the persistence parameters and the variances for shocks are very noisily estimated.

The canonical process relies on the sequences of variances and autocovariances faced by each of the sub-cohorts that form a broad generation, and thus uses, for example, 122 observations. On the other hand, the NL process relies directly on pairs of observations for earnings in $t$ and $t+1$, and uses 7500 such observations for the 1980s cohort.

## D.4 History-dependence of the earnings process

The Markov-switching earnings process captures history dependence of each household's earnings. In particular, the recovery from recessions is usually sluggish. A broad literature has studied both the large negative long-run effects of displacement for individual workers (e.g. Jacobson, LaLonde and Sullivan (1993)), that are particularly severe within recessions (Davis and Von Wachter, 2011), and the slow recovery of employment after downturns like the Great Recession (Ravn and Sterk, 2017). Figure D.3, left panel, shows that the earnings process I propose replicates this feature without large increases in the state space. It represents, for the simulated earnings process of the 1940s cohort, the percentage difference in average earnings between a cohort that underwent a single recession at age 44 ("NL process") and one that never lived through a recession throughout its entire labor market history. Suffering one recession has important effects on impact that last for relatively long. In contrast, the canonical earnings process generates a counterfactual *increase* in average earnings because higher variances in logs, at a constant average, imply higher averages in levels. The purple line represents it for the estimated parameters in Storesletten, Telmer and Yaron (2004), while the yellow line represents the canonical counterpart to the process I estimate for the 1940s cohort (see Appendix D.3 for details).

The rich earnings process also captures differential impacts by initial position in the earnings distribution (right panel). Recessions affect the earnings of the lowest and highest earners by more than those around the median. By construction, the canonical earnings process does not replicate either of this facts.

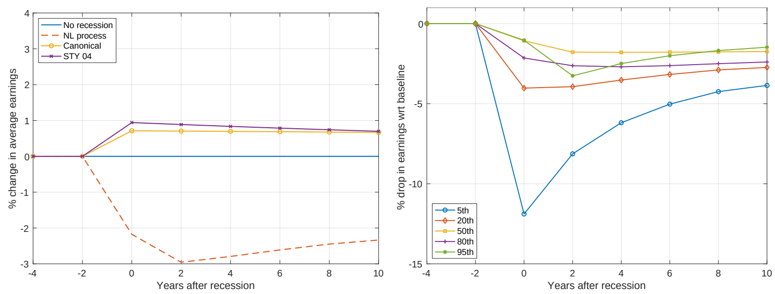


Figure D.3: Earnings by age with respect to the counterfactual in which a recession never occurs. Left: average earnings, recession at age 44. Right: by initial earnings percentile, recession at age 44.

# E Model, additional elements

## E.1 Household's problem

The state variables are labor market income $y_{it}$, risk-free asset holdings $a_{it}$, housing status $h_{it}$, financial assets $f_{it}$, age $t$ and the aggregate state $\Omega_{it}$.

At the beginning of period, shocks to labor market income, risky asset returns, and house prices (i.e., shocks to $y_{it}$ and $\Omega_t$) realize, together with the moving shock with probability $\pi_t$. Then, households who still have a mortgage decide whether they want to default or continue repaying. Finally, households make consumption, savings, and portfolio decisions.

Thus, utility at the beginning of period $U_t$ is:

$$U_t(y,a,h,f,m,\Omega) = \begin{cases} \tilde{U}_t(y,a,h,f,m,\Omega) & \text{if } h=0 \\ (1-\pi_t)\tilde{U}_t(y,a,h,f,m,\Omega)+\pi_t\tilde{U}_t(y,a+p_t^h(1-\kappa^h),0,f,m,\Omega) & \text{if } h>0 \end{cases} \tag{E.1}$$

After the moving shock, households with a mortgage decide whether to Default or Repay:

$$\tilde{U}_t(y,a,h,f,m,\Omega) = \begin{cases} \max_{D,R}\{U_t^R(y,a=0,h=0,f=0,m=0,\Omega)+\chi^{bk}, U_t^R(y,a,h,f,m,\Omega)\} & \text{if } m<0 \\ U_t^R(y,a,h,f,m,\Omega) & \text{if } m=0 \end{cases} \tag{E.2}$$

where $\chi^{bk}$ is a utility penalty, and utility after the moving shock and the repayment decision $U_t^R$ is:

$$U_t^R(y,a,h,f,m,\Omega) = \max_{c,a',h',f',m'}\left\{[(\theta_t c_t^{\nu} s_t^{1-\nu})^{\frac{(\psi-1)}{\psi}}+\beta(\mathbb{E}_t U_{t+1}(y',a',h',f',m',\Omega')^{1-\gamma})^{\frac{1}{1-\gamma}\frac{\psi-1}{\psi}}]^{\frac{\psi}{\psi-1}}\right\} \tag{E.3}$$

subject to the no-shorting condition for safe and risky assets (8, 9), LTV and LTI constraints when buying a home (11 and 12), the requirement to at least pay interest on debt in every period (13), the restriction on holding both risky and safe assets while having a mortgage (15), and the budget constraint (E.4):

$$\begin{aligned} p_t^h(\Omega_t^h)h_{t+1} + \kappa^h p_t^h(\Omega_t^h)h_{t+1}\mathbb{I}(h_{t+1} \neq h_t) + r_t^s(\Omega_t^h)\mathbb{I}(h_t = 0) + \\ f_{t+1} + \kappa^f \mathbb{I}(f_{t+1} > 0, f_t = 0) + a_{t+1} + m_{t+1} + c_t = \\ p_t^h(\Omega_t^h)h_t + (1 + r_t^f(\Omega_t^f)(1-\tau_a))f_t + (1 + r^a(1-\tau_a))a_t + \\ (1+r^b)m_t + T(y_t(\Omega_t^y), m_t) \end{aligned} \tag{E.4}$$

where $T(y, m)$ represents the tax system described in Section III.D.

**Retired households.** Their social security income $p$ is a function of their last realization of labour earnings before mandatory retirement (they cannot retire before 65). They solve the following problem (where $y_l$ is their last realization of income before retirement):

$$\begin{aligned} U_t^R(y_l, a, h, f, m, \Omega) = \max_{c,a',f',h',m'} \Big\{ [(\theta_t c_t^\nu s_t^{1-\nu})^{\frac{(\psi-1)}{\psi}} + \\ \beta \xi_t(y_l)(\mathbb{E}_t U_{t+1}(y_l, a', h', f', m', \Omega')^{1-\gamma})^{\frac{1}{1-\gamma}\frac{\psi-1}{\psi}} + \\ (1-\xi_t(y_l))v(b))]^{\frac{\psi}{\psi-1}} \Big\} \end{aligned} \tag{E.5}$$

where $v(b)$ is determined by Equation 6, and $\xi_t(y_l)$ are income-dependent survival rates, taken from De Nardi, French and Jones (2010). Their maximization problem is subject to the no-shorting condition for safe and risky assets (8, 9), LTV and LTI constraints when buying a home (11 and 12), the requirement to at least pay interest on debt in every period (13), the restriction on holding both risky and safe assets while having a mortgage (15), and a budget constraint with no income risk (E.6). Additionally, I assume that retired households cannot buy a bigger home than the one they currently live in ($h_{t+1} \leq h_t$).

$$p_t^h(\Omega_t^h)h_{t+1} + \kappa^h p_t^h(\Omega_t^h)I_t^h + f_{t+1} + \kappa^f I_t^f + a_{t+1} + m_{t+1} + c_t + r_t^s(\Omega_t^h)\mathbb{I}(h_t = 0) =$$
$$p^h(\Omega_t^h)h_t + (1 + r_t^f(\Omega_t^f)(1 - \tau_a))f_t + (1 + r^a(1 - \tau_a))a_t + (1 + r^b)m_t + T(p(y_l), m_t) \tag{E.6}$$

where $p(\cdot)$ represents social security.

Retired households with a mortgage can default in a similar manner to working-age households.

## E.2 Fit of the aggregate state

Figure E.1 shows how biennial stock returns (left) and housing price-to-income (PTI) ratios in the model compare with the data.

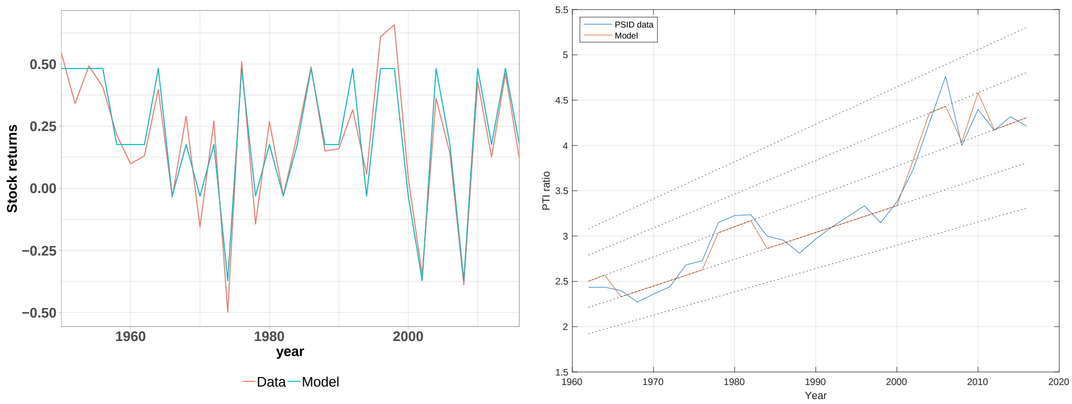


Figure E.1: Stock market returns, housing median price-to-income ratio

## E.3 Standard earnings process counterfactual

Figure E.2 represents an alternative way of measuring the role of earnings dynamics in explaining lower homeownership rates. It shows the changes predicted by the model if we attribute the earnings process of the 1940s generation to the younger generations, whilst keeping all other factors constant. This experiment differs from the previous decomposition because it also incorporates possible interaction effects between factors, which make the effect of the changes in labor market income dynamics even larger.

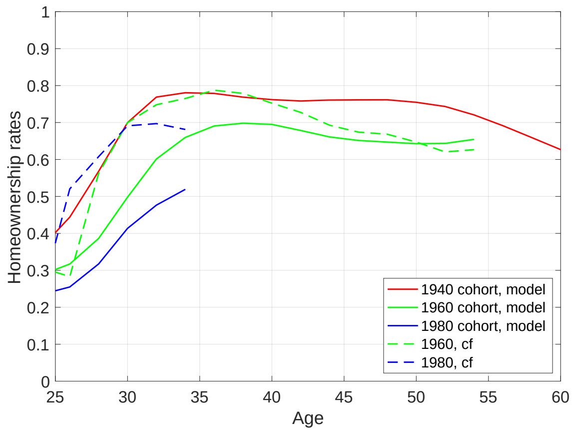


Figure E.2: Homeownership by cohorts, the role of earnings dynamics.

## E.4 Adjusting housing prices

My main counterfactual experiments abstract from general equilibrium effects. However, as the earnings process for the 1960s and 1980s cohort counterfactually changes, so do household decisions, which may impact the evolution of aggregate prices in the economy. It is likely that the increase in housing demand would have had equilibrium effects manifested in an increase in house prices, which could dampen the increase in homeownership rates implied by the experiments.

As such, all results so far can be seen as an upper bound of the possible effects of income dynamics on homeownership, calculated under two equivalent assumptions: either housing supply is perfectly elastic or a non-modelled investor owns all rental housing and is willing to sell or buy any of it at the observed prices.

In this section, I provide an approximation to these equilibrium effects. I assume alternatively that housing supply is fully inelastic and that housing supply can be summarized by an isoelastic supply function with elasticity of 1.75, an empirical value estimated for the average U.S. metropolitan area by Saiz (2010). Then I compute the variation in housing prices induced by the increase in housing demand, and find homeownership rates for each cohort under those new prices.

First, I begin by defining the *baseline stock of housing* $H_t^s$ as the total number of houses that are occupied by thier owners, which is equivalent to the number of households that live in owner-occupied housing. In order to aggregate across cohorts, I simulate a total of 31 birth-year cohorts (born in all even years from 1930 to 1990), and I attribute the earnings process of the 1940s cohort to the group 1930-1949, the earnings process of the

1960s cohort to the group 1950-1969, and the earnings process of the 1980s cohort to the group 1970-1990. Like in the main experiment, each birth cohort experiments aggregate shocks as they happened in the data in each calendar year, that corresponds to a specific age for each of the 32 cohorts.

Given that I do not have information on the earnings processes of the relevant years for the cohorts born before 1930s, I make the simplifying assumption that their home-ownership profiles are not impacted by any of the changes introduced in the paper and they hold a constant amount of housing. The impact of this assumption would depend on the reaction of these non-modelled cohorts, but it is only particularly restricting for the earlier cohorts when they are relatively young. Additionally, for this experiment I assume that households are born with zero initial wealth.

Thus, $H_t^s$ is computed as summarized in Equation E.7, where I am aggregating over all households $i$ that belong to each of these 31 birth-year cohorts. I then assume that, at given prices $p_t^h$, $H_t^s$ is the total amount of housing supplied for these cohorts; which implies that $p_t^h$ is the price that clears the market given housing supply and demand.

$$\int_i H_i^d(p_t^h) = H_t^s \tag{E.7}$$

Then, I am interested in computing how the quantities of housing bought by each of the different cohorts change as external factors, such as the earnings process, change. A change in the earnings process will induce a change in the housing demand functions $H_i^{d*}$ for each household. To which extent this gets translated into changes in quantities exchanged and changes in prices depends on the elasticity of housing supply.

Assuming a fully inelastic housing supply implies fixing $H_t^s$ at every year $t$ and finding $p_t^{h*}$ such that Equation E.8 holds. I do so sequentially for $t = 1, \ldots, Y$, where $Y$ is the total amount of years in the simulation, and to that extent the model continues to capture history dependence of past prices. Furthermore, the slow-moving nature of these changes and the definition of $H_t^s$, which captures cyclical variations which the model is attributing to housing supply or other non-modelled factors, implies that the housing growth aggregate state is still consistent with the evolution of house prices.

$$\int_i H_i^{d*}(p_t^{h*}) = H_t^s \tag{E.8}$$

Assuming an elastic housing supply implies, at a given (empirical) housing supply elasticity $\eta$, that the price that clears the market $p_t^{h'}$ satisfies:

$$\int_i H_i^{d*}(p_t^{h'}) = H_t^{s'} \tag{E.9}$$

such that

$$\frac{\frac{p_t^{h'} - p_t^h}{p_t^h}}{\frac{H_t^{s'} - H_t^s}{H_t^s}} = \eta \tag{E.10}$$

By substituting E.10 into E.9, one can solve for $p_t^{h'}$ in every period.

These experiments represent an approximation to actual equilibrium determination of housing prices. On the one hand, I do not model the agents that make housing supply decisions and approximate them with an isoelastic function (with elasticity which is either zero or 1.75). On the other hand, from the perspective of households, housing prices are still exogenous shocks with the same process as in the main version of the model. They are not aware that house prices are determined in equilibrium in a way that depends on total housing demand, and they do not perceive that intergenerational changes could be affecting house prices.

Figure E.3 compares the homeownership rates by age and cohort between the baseline (solid lines), the counterfactual with fully elastic housing supply (dashed lines), and the counterfactual with empirically determined housing supply elasticity (dash-dot lines). For the 1960s cohort, I also represent the counterfactual with financial conditions becoming more flexible in the early 2000s (dotted lines). Although naturally homeownership is a bit lower for most cohorts and ages, the joint effect of earnings inequality and risk is still very relevant even if we allow for adjustments in average house prices.[4]

Figure E.4 shows the results for the case in which housing supply elasticity is assumed to be zero.

All results in this section still assume that stock market returns and income dynamics are exogenous. The stock market is very integrated internationally, so it is less harmful

[4] A more detailed approach could imply modelling the housing supply and rental market sectors, together with a realistic representation of housing devaluation and renovation, and thus obtaining a more flexible formulation of the housing supply function. While such a study could shed light on slow-moving dynamics of housing prices, it is beyond the scope of the model presented in this paper given current computational constraints.

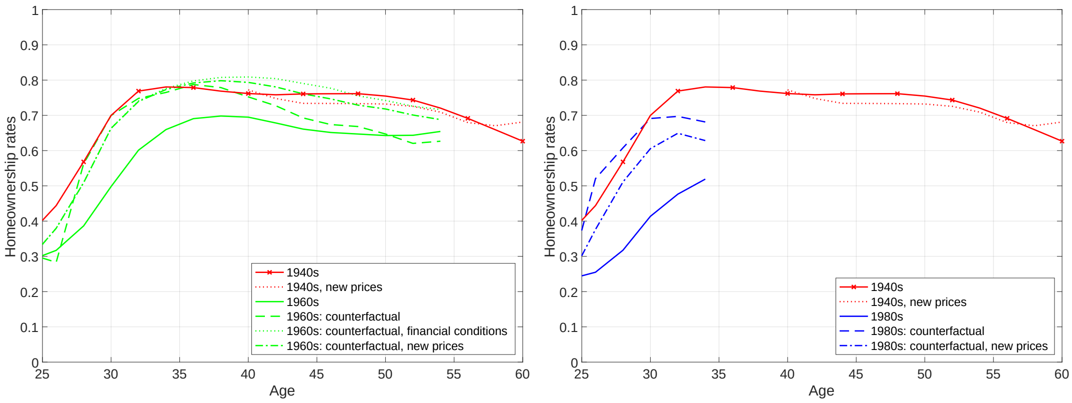


Figure E.3: Homeownership by cohorts, benchmark vs. counterfactual earnings processes, empirical housing supply elasticity. Left: 1960s generation, right: 1980s generation.

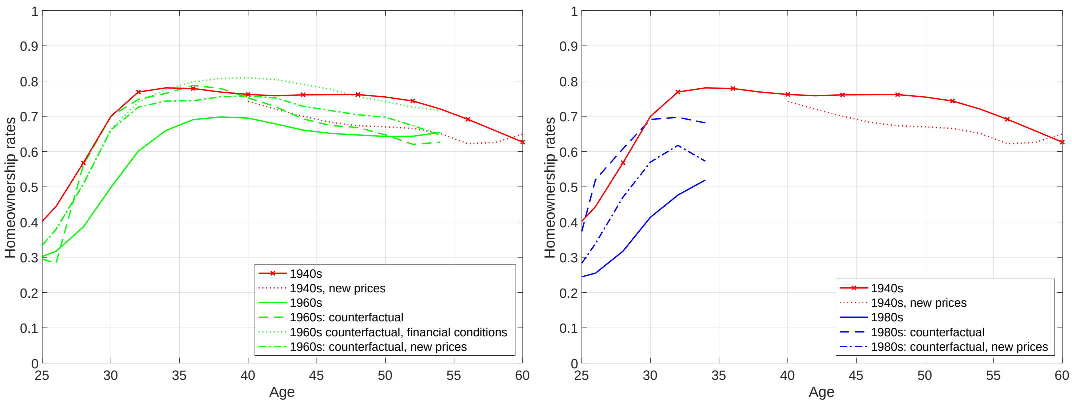


Figure E.4: Homeownership by cohorts, benchmark vs. counterfactual earnings processes. Assuming fully inelastic housing supply.

to assume that changes in domestic household demand for stocks do not impact stock returns. With respect to income dynamics, the model is already capturing very well their changes over the cohorts and the business cycle, and endogeneizing them would imply losing much of this richness. However, both are interesting questions that are left open for future research.

# F Robustness checks and extensions

## F.1 Initial zero wealth

Figure F.1 (left panel) shows the fit of the model with respect to homeownership in the case in which I assume that all households are born with zero wealth and recalibrate parameters accordingly. To give agents some more time to build up wealth, for this experiment I start them out at age 20 rather than 25. Although the fit of homeownership at earlier ages is not as good, it is still true that the model can reconcile the changes in homeownership rates across generations without resorting to changes in preferences. The right panel of Figure F.1 shows that, without taking into account the initial condition, the model underpredicts stock market participation at earlier ages.

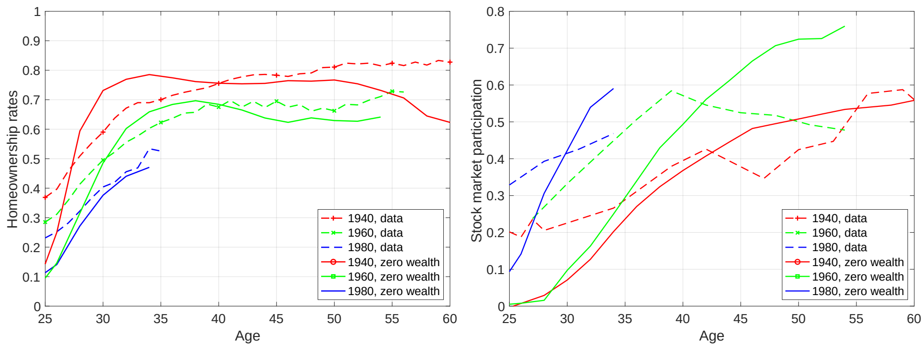


Figure F.1: Homeownership (left) and stock market participation (right) by cohorts, data vs. model. Model with zero initial wealth.

## F.2 Robustness to earnings process

### F.2.1 Canonical process

I now to turn to evaluating to which extent a *canonical* earnings process, such as that described by Equations D.4-D.6 in Appendix D.3, with changes over generations, can explain the observed changes in homeownership.

I recalibrate the model for the 1940s cohort following the same procedure as in my main results, and then simulate the model for the 1960s and 1980s cohort changing only earnings process, asset returns, and financial conditions. Figure F.2 shows that the model also generates a decrease in homeownership rates across cohorts, which supports the argument that changes in earnings inequality and earnings risk are key drivers of the observed changes. However, the canonical process substantially overestimates the decrease for the 1960s generation. Earnings are estimated to be a random walk or close to it, and thus the effects of large initial inequality are more persistent than in the more flexible process proposed in this paper.

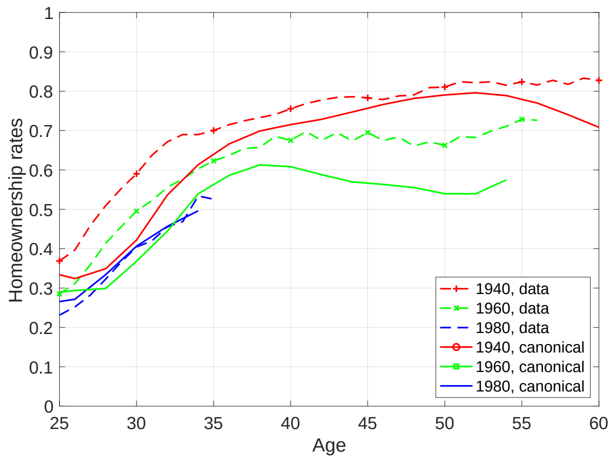


Figure F.2: Homeownership by cohorts, data vs. model, canonical earnings process

Additionally, as argued in Section II.A, this process has a set of counterfactual implications. It does not replicate the countercyclical skewness of earnings and it implies increases of average earnings when recessions hit. Besides, as shown in Gálvez (2017), it also generates counterfactual implications for stock market participation decisions.

### F.2.2 Marital dynamics and family sizes

Over the past few decades, marriage rates have fallen, fertility has decreased, and the average age of women at both marriage and first childbearing has steadily increased (Lundberg and Pollak (2007)). These developments offer a possible alternative explanation for the reduction and delay in homeownership.

In the framework proposed in this paper, all of those changes are implicitly considered in the earnings process, which is estimated in all households (married or not) and thus embeds marriage and divorce risk into earnings risk. In order to disentangle these two effects, the left panel Figure F.3 replicates the analysis by replacing the earnings process by one estimated only on continuously married couples. Given that this subset of households have on average higher and more stable earnings, their implied homeownership rates within the model are larger, particularly at older ages. However, differences across cohorts are comparable. This suggests that, while family dynamics can play a relevant role (e.g., Chang (2018) shows that marital and divorce risk is a relevant force to explain changes in homeownership of singles versus couples), the increase in inequality and earnings risk seems to be of first order to explain the changes in homeownership. To verify this hypothesis, the right hand side of Figure F.3 replicates the counterfactual in which the 1940s earnings process is attributed to younger generations within the subsample of married households. Effects are similar to those in the main results.

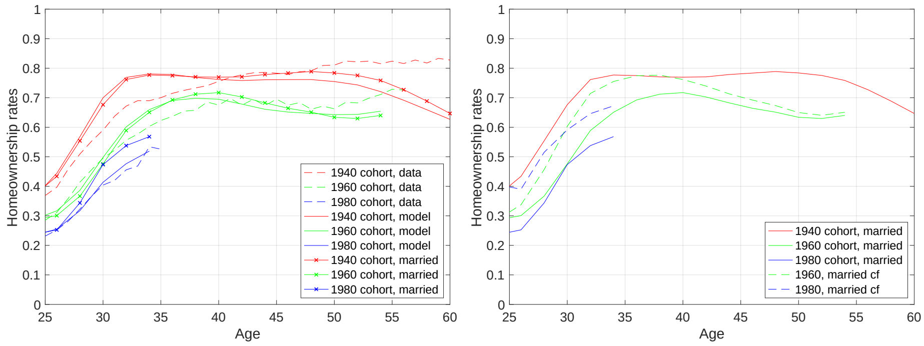


Figure F.3: Homeownership by cohorts, married people only.

## F.3 Robustness to asset structure

### F.3.1 House sizes

In the main version of the model, households can choose to own two types of housing, which I denote $h_1$ and $h_2$. This reflects that houses are lumpy and have limited divisibility, and that frequently households cannot access their optimal house size and quality because it is scarcely available or disadvantageously priced on the market. In this section, I check the robustness of my results with respect to different specifications of house sizes. There are three main assumptions that I now turn to discuss: (1) the size of the minimum house, (2) the changes over time in the relative sizes of the different types of housing, and (3) the assumption that there are only two types of houses.

The size of the small house $h_1$ conditions who is the marginal person who is indifferent between buying a house and renting, and thus homeownership rates. As described in the calibration section, in current U.S. dollars, for the latest periods in the model, the price of a small house is around \$120,000 in 2015 dollars, which corresponds to about twice median household income, or alternative half the median value of a home in my PSID sample during that period. This assumption is conservative with respect to what is standard in the literature. For example, Doepke, Schneider and Selezneva (2015) set their minimum house size at \$150,000 and Garriga and Hedlund (2020) at 2.75 times average income.

Besides, very few households live in houses that are cheaper than that. For instance, looking at the 1980s generation, only 9.7% of households lived in a house with a price lower than $h_1$, with most of them concentrated nearby.

With respect to the changes over time in the relative sizes of houses and, in particular, of the smallest house, Figure F.4 shows that younger generations are not buying cheaper (left) or smaller (right, measuring size as the number of rooms) houses to compensate for the increased average house price. This provides support to the assumption that the two house types available do not vary over time, and that their price is a constant fraction of the median house price.

A relevant question, beyond the scope of this paper, is why younger generations haven't bought smaller homes, which could be driven by demand or supply considerations. For instance, it could be that households really dislike housing units below a certain size, quality, or level of amenities. On the other hand, it could be that there are market imperfections preventing the supply of smaller, cheaper houses. Glaeser, Gyourko and Saks (2005) point out that housing supply regulations have become more stringent over time. Falcettoni and Schmitz (2018) argue that regulations and monopoly power have reduced the production of prefab or factory-built houses below its efficient level, thus reducing the number of cheap houses available on the market.

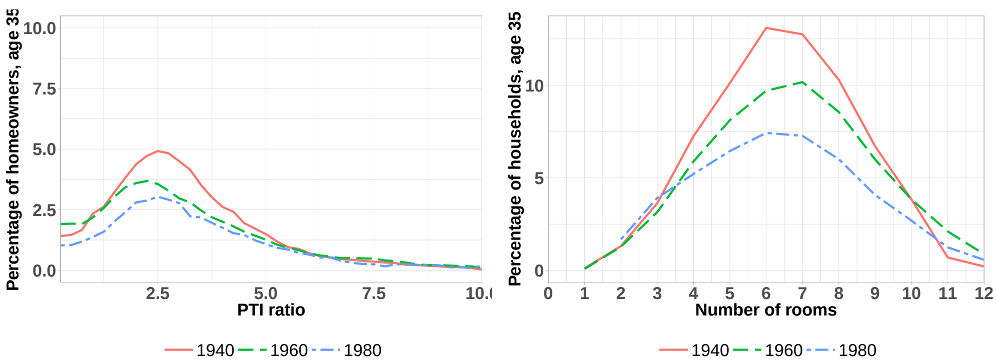


Figure F.4: Share of households with a certain housing price-to-income ratio (left) and number of rooms excluding bathrooms (right), at age 35, by decade of birth. For clarity, non-homeowners are not reported, but they are taken into account to compute shares. PSID data.

For further robustness, I report in the left panel of Figure F.5 what the model would deliver if $h_1$ were set to be 25% smaller and cheaper than in the baseline. Although in that case the model would overestimate how many households live in the small, cheap house compared with the data in Figure F.4, it still delivers a reduction in homeownership rates across generations that is in line with what occurred in reality.

In order to compensate for the multiple factors that pushed down the howeownership rates of the young, one would have to assume that the minimum house size has dropped for younger generations (right panel, Figure F.5). In particular, for this particular illustration I assume that the price of $h_1$ dropped by 25% for the 1960s and 1980s cohorts, without changing how much enjoyment these cohorts obtained from living in these properties. This would counterfactually generate no change in homeownership rates, but at the cost of significantly increasing the share of households living in smaller houses within younger generations (blue line with crosses in Figure F.6), which is at odds with Figure F.4.

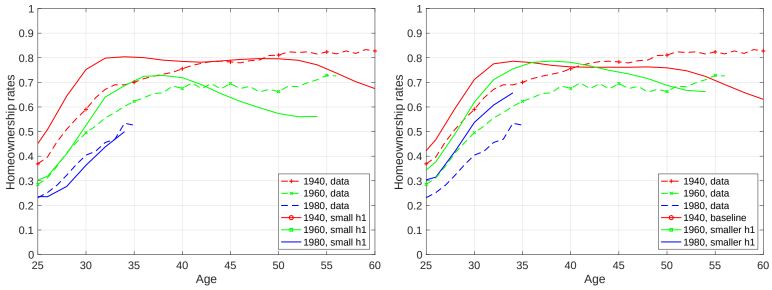


Figure F.5: Alternative house size for $h_1$, main experiments

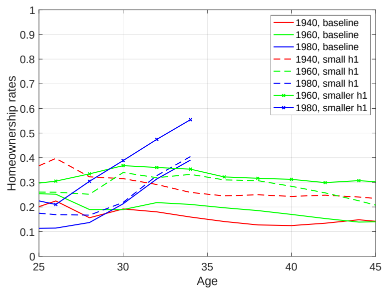


Figure F.6: Percentage of households owning the small house by age: baseline vs. small $h_1$ vs. case in which $h_1$ becomes smaller over time.

Finally, although there is large heterogeneity in the size, quality, and price of housing units in the data, I set the total amount of housing qualities in the main version of the model to $H = 2$. This choice is mostly driven by computational considerations, and also by taking into account that the key element that determines homeownership, which is my main object of interest, is the size of the cheapest of those houses available. However, in order to verify that this does not impact my results, I have conducted several robustness checks, which I report in Figure F.7, in which I set the number of housing qualities to $H = 3$. In the left panel, I do so by allowing for a middle-sized house exactly between the prices of the small house and the big house. In the right hand side panel, I allow for a large house, twice the size of the big one. In all cases I recalibrate housing preference parameters accordingly so that homeownership for the 1940s cohort at age 40 is within the ballpark of the data.

Results are almost identical with either of the $H = 3$ assumptions, thus suggesting that the choice of $H = 2$ is not key in driving the results I obtain. Setting $H = 3$ and allowing for a large house does improve the fit of the model in terms of the portfolio composition of the richest, which slightly underestimates their housing share (see Figure 5).

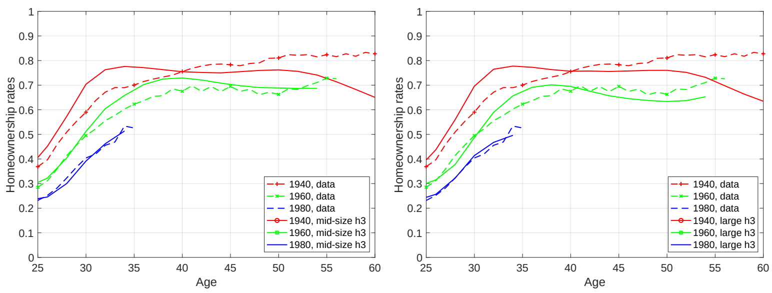


Figure F.7: Specifications with $H = 3$. Left: intermediate house; right: large house.

### F.3.2 Free housing adjustment during retirement

In the main version of the model, households are not allowed to move to larger houses during the retirement period. Assuming that, instead, they can freely optimize and acquire mortgages leads to a worse fit of homeownership rates during this period (left panel of Figure F.8): many households take advantage of the relatively high period of house prices between their 55-60 years of age to sell, release equity, and many of them buy again when houses become cheaper. As a result, counterfactually too many houses are bought during the retirement period, although the spike before age 60 disappears (central panel of Figure F.8) However, under this more flexible assumption the implications in terms of both model fit during the working age period and intergenerational differences are unchanged (right panel of Figure F.8).

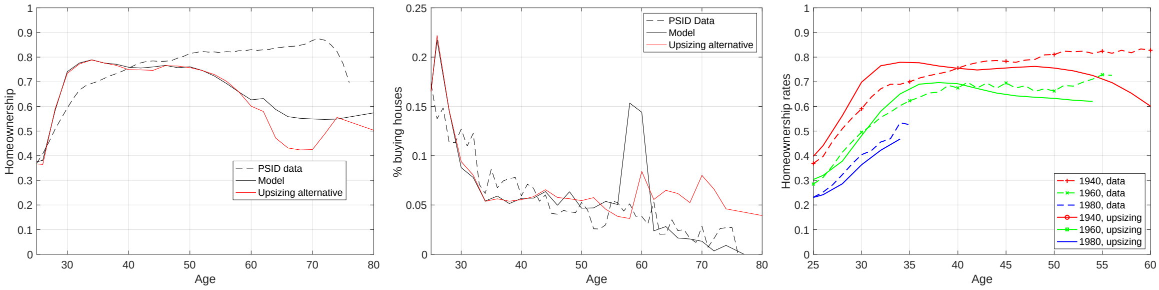


Figure F.8: Homeownership rates if households are allowed to freely adjust housing and acquire mortgages during retirement. Left, whole life-cycle, 1940s generation; right: intergenerational comparison, working-age period.

### F.3.3 Per-period participation costs

There is a long standing discussion in the household finance literature about whether one-off entry costs, which I consider in the main version of this model, or per-period participation costs rationalize better the patterns of stock market participation that we observe in the data. While the former is used in studies like Cocco (2005) or Gomes and Michaelides (2005), Vissing-Jorgensen (2002), Gálvez (2017), or Bonaparte, Korniotis and Kumar (2018), amongst others, find that the latter seems to be the most promising avenue to explain the observed patterns of stock market participation. However, the estimated value for the per-period participation cost is frequently relatively high (for instance, Bonaparte, Korniotis and Kumar (2018) estimate it to be around 3.2% of average household income every year).

Figure F.9 shows that the implied profiles for an alternative version of the model with only per-period participation costs are very similar to the baseline model. As in previous studies, the estimated cost which is necessary to reconcile the low levels of stock market participation is quite high (around 5% of average household income for the 1940s cohort), but decreases down to 1% for younger cohorts.

### F.3.4 Stocks as 401(k)

In order to investigate whether the fiscal incentives associated with IRAs and 401(k)s could be an alternative explanation for the increase in stock market participation, Figure

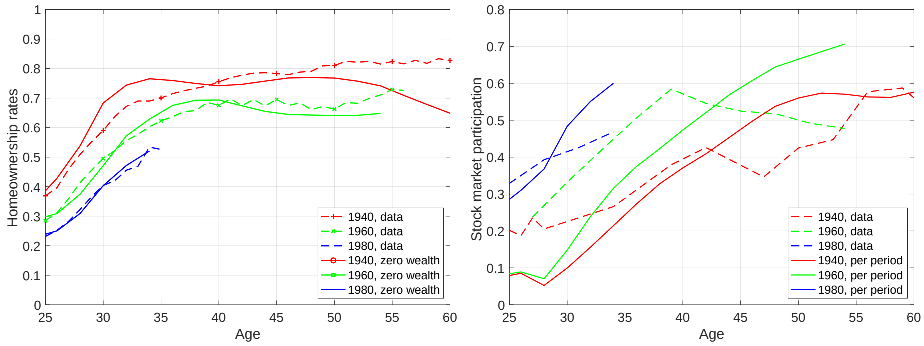


Figure F.9: Homeownership (left) and stock market participation (right) over the life-cycle, by cohorts, case with calibrated per-period participation costs

F.10 represents the results of a counterfactual exercise in which participation costs are kept constant, but I modify the nature of the financial asset or stock $f_t$ in the model to closely replicate a 401(k). I keep participation costs constant across generations, but assume that contributions to the account are tax-exempt below a certain limit, the interest it generates is tax free, households pay income tax on all amounts withdrawn, and there are penalties for withdrawal before age 60 (10%).

As a result, households in the model would actually invest less in these accounts. This reaction is related to the illiquidity of 401(k)s, which makes it costly for househols to withdraw from their stocks in response to a bad labor income shock, and suggests that the ease of access and auto-enrolment were the key features that explained the success of these accounts.

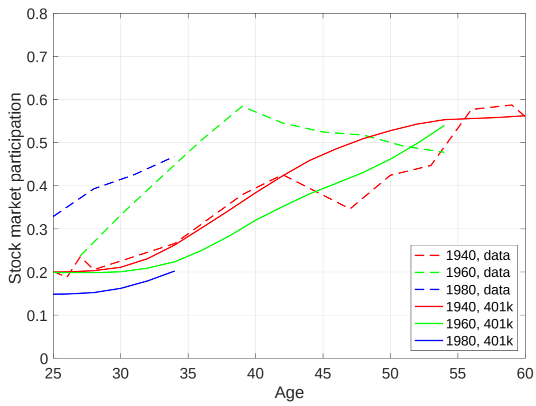


Figure F.10: Stock market participation: model with constant participation costs and stocks with 401(k) tax properties

### F.3.5 Costs of bankruptcy

In the model, the possiblity of bankruptcy is key to determine how households form expectations when are thinking about buying a house and take into account the possible future realizations of house prices and labor market income that might occur. If the model does not allow households to ever foreclose or go bankrupt, they might perceive that houses are too risky of an investment; if it assumes that it is easy and costless, it might underestimate the risk associated with homebuying.

I model default as a choice that implies that households that don't pay back their mortgages forego all of their assets and suffer a utility cost. This framework is closest to the regulation in recourse states, where lenders may have a claim to the borrower's assets even after the house has been sold. For simplicity and computational feasibility I do not explicitly model the difference between foreclosure and bankruptcy, the possibility of renegotiating debt with the bank, or the decision to file for bankruptcy under either Chapter 7 or Chapter 13. However, in the model households can choose to delay the payment of the principal of their mortgage, which already captures some of this flexibility.

There is limited information about foreclosure and bankruptcy in my survey data. In the SCF, there is a question since 2001 on whether the household has ever gone through bankruptcy, without reference to the reasons. However, many households file for bankruptcy because of reasons not related to housing, such as medical expenditures or consumer debt. Indeed, Domowitz and Sartain (1999) found that homeownership was actually negatively associated with the probability of going bankrupt.

In the model, even at zero bankruptcy penalties $\chi^{bk}$, there are very few households in the 1940s and 1960s generations who choose to default (see Table F.1). This occurs because they bought their houses under a 20% downpayment constraint, they face the evolution of average national house prices, which did not suffer large drops, and if they default they lose all of their assets. However, in the 1980s cohort many had little equity in their homes when they went through the 2000s housing boom and bust episode: a zero bankruptcy penalty would vastly overestimate how many choose this option. I choose $\chi^{bk} = -5$ as a compromise between keeping the 1980s cohort bankruptcy rates positive but below the data. In Figure F.11 I show that, whilst the model with no bankruptcy cost would overstate the amount of homeowners in the 1980s cohort, results are robust to increasing or decreasing $\chi^{bk}$ by 50% and repeating the main analysis, recalibrating the preference parameters for the 1940s cohort and keeping them fixed through the generations. The main difference between all three cases is the number of households who file for bankruptcy in the 1980s generation, which is closer to the data in the baseline case.

Given the limited availability of data and these features of the model, I do not explore the possibility that the stigma of default has changed over the generations, but it is an interesting avenue for future work.

| Generation | Age | SCF data | Model | | | |
|---|---|---|---|---|---|---|
| | | | Baseline | $\chi^{bk} = 0$ | $\chi^{bk} = -2.5$ | $\chi^{bk} = -7.5$ |
| 1940s | 54 | 8.6% | 0% | 0.1% | 0.1% | 0% |
| 1960s | 54 | 19.08% | 0.01% | 0.2% | 0.1% | 0% |
| 1980s | 34 | 8.15% | 4.06% | 29.29% | 14.33% | 2.37% |

Table F.1: Share of households that have ever filed for bankruptcy

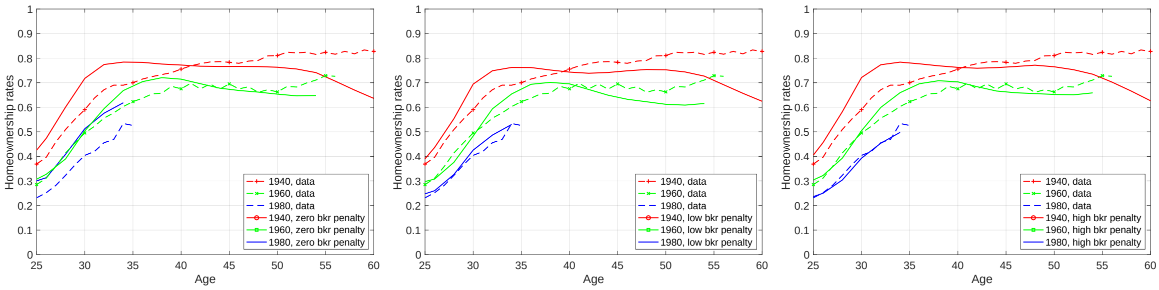


Figure F.11: Homeownership by generation: no cost of bankruptcy (left), low cost of bankruptcy (middle), high cost of bankruptcy (right)

## F.4 Robustness to the specification of the aggregate state

### F.4.1 Stock market predictability and correlations

As argued in the main text, households expect stock market returns to be correlated with the state of the labor market, which in itself is persistent. However, this introduces little predictability in stock returns. First, given that the model period is two years, the persistence of the labor market state is not very high. For example, conditional on being in an expansion, the probability of staying in one in two years is 0.72. Second, the conditional distribution of stock returns in expansions and recessions has large variance.

Joining together both factors, less than 1% of the variance of stock market returns can be explained by the recession/expansion dummy I take into account, implying that over 99% of the variation of stock returns in $t + 1$ is not predictable in the model.

In Figure F.12 I show that, in the case in which I assume that stock market returns are i.i.d and keep all preference parameters constant, stock market participation is almost identical. That said, the assumption that stock market returns are correlated with labor market income shocks impacts portfolio decisions. From a cyclical perspective, in the baseline model a reduction of 16 percentage points in the probability of a recession (as an economy exits one) generates an increase in stock market participation of 0.6 percentage points and an increase in the risky share of financial assets (unconditional on participation) of 6 percentage points. This effect is not present in the version of the model where stock market returns are uncorrelated with the labor market state.

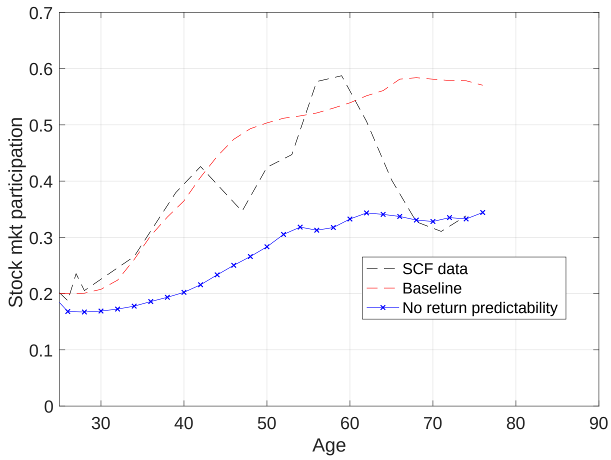


Figure F.12: Stock market participation for the 1940s cohort, comparing main case against case in which stock returns are uncorrelated with labor market state

### F.4.2 Cyclical dynamics of house prices

An additional assumption in the main version of the model is that there is autocorrelation in the house price process: house price growth is persistent. This assumption is important from a cyclical perspective: without it, housing sales would be more countercyclical: households would sell more housing when house prices are relatively high, which is at odds with what we observe in the data. In the left panel of Figure F.13 I compare my baseline model with a version in which there is no persistence in house price growth. Such a model would underestimate homeownership rates for the 1940s generation during all house price growth periods, and conversely overestimate their stock market participation by about the same amount. For instance, it would be around 2 percentage points lower during the 2000s house price boom.

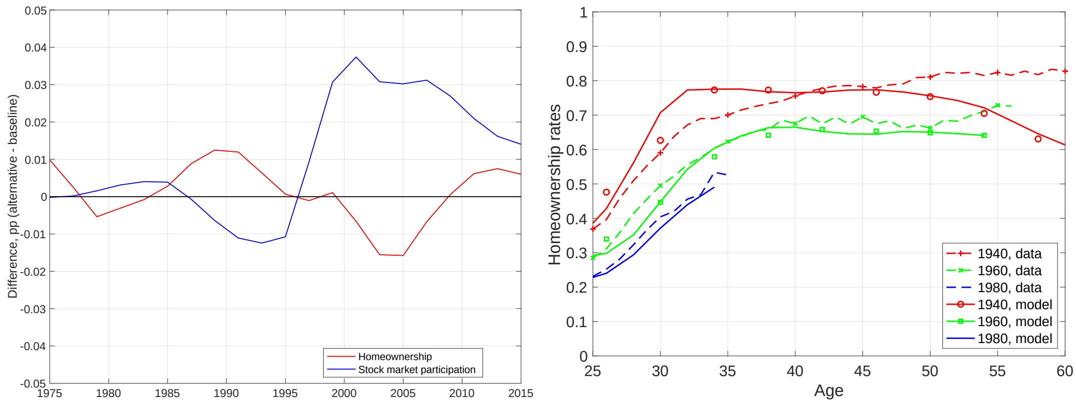


Figure F.13: Role of autocorrelation in house prices. Left: difference in homeownership and stock market participation for the 1940s generation between a case with no persistence in house price growth and baseline case; right: homeownership over the generations with no persistence in house price growth.

### F.4.3 Local correlation of income shocks and house prices

An additional element that increases the riskiness of housing is the correlation at the local level between house prices and income changes. For instance, in areas that benefit in particular from an expansion it is likely that both incomes and house prices go up. When households incorporate this information into their decision making, it influences both homeownership and portfolio choices.

To approximate this effect, I allow for income shocks to be correlated with housing price shocks at the idiosyncratic level. Given that in the baseline version of the model both are exogenous, this correlation can be directly imposed from data estimates. I rely on Davidoff (2006) for the empirical quantification of this correlation and fix it at 0.29. This correlation affects household expectations, but it also affects the realization of the shocks that households face as I simulate them. Thus, in this case, unlike in the baseline model, I allow for house price heterogeneity within a year-age-cohort.

I then recalibrate the main preference parameters. In order to fit the profile for the 1940s generation (Figure F.14), the homeownership taste parameter and the stock market participation cost must be adjusted upwards. The reason is that the correlation of housing price shocks with income shocks raises the riskiness of housing as an asset, which also increases the attractiveness of stocks in relative terms. However, as Figure F.14, the intergenerational implications of this alternative specification are very similar to that of the baseline model.

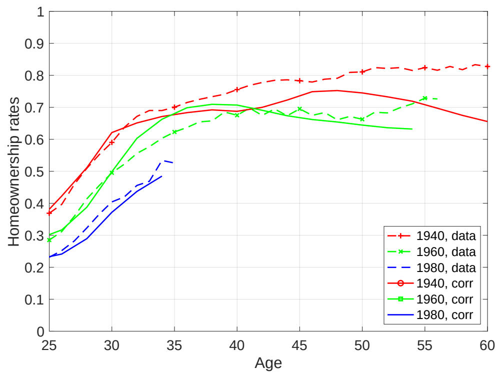


Figure F.14: Homeownership by cohorts, local correlation of house price shocks with income.

This experiment abstracts from important elements such as endogenous determination of local house prices or endogenous mobility, which are beyond the scope of this project and are left for future research.

## F.5 Future projections

In order to compute future homeownership rates for the 1980s cohort, I assume that house prices will continue to grow on average with respect to median income at a rate of 1.8% per year, and that the earnings process of the 1980s cohort will be that of the 1960s cohort for all unobserved years. I then simulate 1000 possible histories of the realizations of house price shocks and aggregate states, consistently with their conditional probabilities in the sample I observe, and plot the median homeownership rates in Figure F.15. The dotted lines are percentiles 2.5 and 97.5 within the simulations. Broadly, the model predicts that the 1980s generation will almost catch up with the 1960s, but not with the 1940s, in terms of homeownership.

Looking at the retirement period, the median projection for these two younger generations shows a lower drop in homeownership rates than that observed in Figure 4 for the 1940s generation. The reason is that in the median simulation, unlike in the period 2000-2010, there is no big jump in house prices that leads households to sell their houses to release equity, and so they continue holding on to them for most of the retirement period. Although naturally the data counterpart for these cohorts is not yet available, this is likely to be a realistic feature, given that the data tends to show low decreases in homeownership rates after households retire.

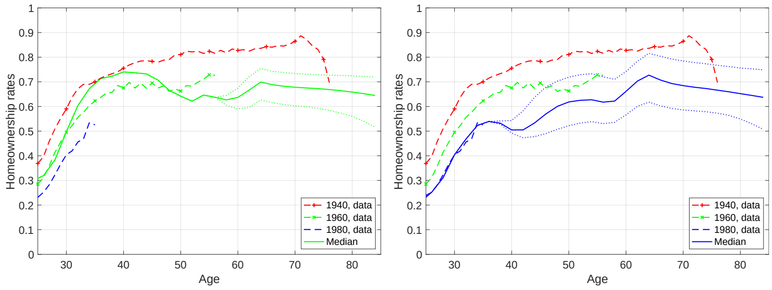


Figure F.15: Projecting the 1960s and 1980s cohorts into the future: homeownership

The reduction in homeownership for younger generations can be related with an increase in wealth inequality if fewer households accumulate housing wealth and financial assets are still concentrated amongst the rich. Table F.2 shows the wealth Gini index at retirement for the 1960s generation and for two different simulations for the 1980s cohort, which differ only in stock market participation costs $k^f$. The model predicts that wealth inequality will grow, unless stock market participation costs are reduced such that almost all of the population accesses the stock market by age 60. The larger the share of households that participate in the stock market, the stronger the negative effect on wealth inequality.

In any case, the model underestimates total wealth inequality, as it does not include a set of elements that are important to explain it, such as entrepreneurship or intergenerational links (De Nardi and Fella, 2017). The extent to which these vary over the generations will also have a determinant effect on the evolution of wealth inequality. These results also abstract from possible general equilibrium effects on stock returns induced by the increased accumulation of financial wealth.

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| Generation | 1960 | 1980 | |
|---|---|---|---|
| Reduction in $k^f$ | - | 0% | 75% |
| Implied participation at 60 | 77% | 83% | 97% |
| Wealth Gini, data | 0.83 | - | - |
| Wealth Gini, model | 0.51 | 0.55 | 0.51 |
| | | (0.019) | (0.014) |

Table F.2: Wealth Gini at retirement, data vs model. The data is obtained from people aged 55-64 in the SCF (2001 and 2016 SCF for the 1940s and 1960s cohort respectively). For the model, standard errors from simulation are in parentheses.

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