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Niizeki, Takeshi
Economic and Social Research Institute, Cabinet Office

Suga, Fumihiko
Economic and Social Research Institute, Cabinet Office

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The Impact of the Rise and Collapse of Japan's Housing Price Bubble on Households' Lifetime Utility[†]

Takeshi Niizeki[a,b] and Fumihiko Suga[a,c,*]

[a] Economic and Social Research Institute, Cabinet Office, Japan
[b] Faculty of Law and Letters, Ehime University
[c] Faculty of Economics, Kyushu University

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Abstract

This study estimates the impact of the dramatic changes in housing prices during Japan's bubble from the late 1980s to the 1990s on households' asset accumulation and utility over their life cycle. We construct a life-cycle model explaining households' consumption/saving and housing decisions under collateral and borrowing constraints. We estimate this model using data from the *Family Income and Expenditure Survey* (FIES), which includes data on households' housing wealth estimated from objective information. Using the estimated model, we then conduct a counterfactual simulation in which we assume that housing prices remained constant during the bubble period. Doing so allows us to quantify the gains/losses of lifetime utility due to the housing price boom and bust. We find that 72.2% of the households experienced an average decrease in lifetime utility equivalent to 5.7% of lifetime income. On average, Japan's housing price boom and bust caused a loss in lifetime utility equivalent to 4.7% of lifetime income. Moreover, we compare the impact of the housing price bubble across cohorts and find that the impact was greatest for those who experienced the bubble at ages 35–45.

Keywords: Asset Bubbles, Housing
JEL classifications: D12, D31, R21

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[*] Corresponding author: Suga (f.suga37@gmail.com).

1. Introduction

What is the most expensive good that households purchase? The answer, for most Japanese households, is a house. To buy a house, it is quite common for households to save money to make a down payment and borrow five to eight times their annual income. Moreover, the value of a house tends to affect how much the bank will lend. Therefore, fluctuations in housing prices over time can have a significant impact on households' lifetime resources.

The fluctuations in housing prices during Japan's bubble were dramatic. Figure 1 shows the average housing wealth held by Japanese households.[1] As can be seen from the figure, housing wealth increased rapidly, especially in the Tokyo area, from the late 1980s to the early 1990s. Households' housing wealth almost doubled within five years and then gradually declined over ten years. This dramatic change in housing wealth primarily reflects changes in land prices, which are shown in Figure 2. Since residential real estate prices in Japan primarily reflect the price of the land on which a house sits, the dramatic changes in housing wealth were largely driven by changes in land prices.

How did Japanese households react to such dramatic changes in housing prices? Figure 3 presents homeownership rates by age across different cohorts. Homeownership increases by age, and a typical Japanese household buys a house when the head is aged between 35 and 45. The larger markers in Figure 3 are for observations falling into Japan's bubble period (1988–1992). The figure suggests that homeownership rates did not change in response to the boom and bust of housing prices. That is, despite the dramatic increase in housing prices, there was no discernible change in the life stage (age of the household head) at which households typically buy a house. Therefore, instead of delaying buying a house, households may have reduced consumption or

[1] We constructed the data on households' housing assets using the FIES and other data. The specific procedure is explained in Section 4.

settled for a lower-quality house, receiving poorer housing services for a prolonged period. Since most Japanese households tend to prefer a new house and the average price of a house is five to eight times households' income (see, e.g., Ito, 1991), Japan's housing price boom and bust may have had a significant impact on households' lifetime utility.

The goal of this study is to quantify the impact of Japan's housing price boom and bust on Japanese households using household data. Specifically, we use data from the *Family Income and Expenditure Survey* (FIES) conducted by the Statistics Bureau, Ministry of Internal Affairs and Communications. The FIES data contain detailed information about households' consumption, income, and financial assets. Moreover, the data provide information about household dwellings, such as the location, size, and type (apartment or house). We combined the FIES data with other datasets to estimate the objective value of households' housing wealth. To concentrate on households that were most likely to be affected by the fluctuations in housing prices, we mainly focus on households with a head born from 1951–1955 and living in the Tokyo Metropolitan Employment Area (MEA). [2] We construct a structural model that describes the consumption/saving and housing behavior of these households and estimate the model using the indirect inference method. Using the estimated model, we then conduct a counterfactual simulation in which housing prices are held constant from 1987–1999.

The simulation result indicates that 27.8% of the households experienced an average lifetime utility gain equivalent to 2.1% of lifetime income, while the 72.2% experienced an average lifetime utility loss equivalent to 5.7% of lifetime income. On average, Japan's housing price boom and bust caused a loss in lifetime utility equivalent to 4.7% of lifetime income. Moreover, we conduct a counterfactual "no bubble" simulation by using the households with a head born in

[2] Tokyo MEA is defined as the collection of municipalities where at least 10% of the population commute to the 23 special wards. See Kanemoto & Kurima (2005) for detail.

the early 1940s (older cohort) and those with a head born in the early 1960s (younger cohort). Figure 4 describes the cohorts we focus on. We find that the housing price bubble also had a negative impact on the lifetime utility of the households of older and younger cohorts, but the magnitude of the impact was smaller than that for households with a head born in the early 1950s.

The remainder of this paper is organized as follows. Section 2 outlines the background to our study and provides an overview of the previous literature. Section 3 presents the structural model that we estimate, while Section 4 describes the dataset we employ, and Section 5 discusses the empirical methods. Sections 6 and 7 present the results of the estimation and counterfactual simulations, respectively. Finally, Section 8 concludes the paper.

2. Background and Related Literature

How can we assess the impact of temporal fluctuations in housing prices? The easiest way would be to evaluate the impact on the basis of capital gains/losses. If, for example, a household paid \$500,000 for a house during the bubble period and the price of the house dropped to \$300,000, the bubble caused a loss of \$200,000. The problem with this approach is that the endogeneity of housing choice is ignored: even if there had been no bubble, the household might have paid \$500,000 but would have got a better house for that money.

Another approach is to take advantage of the information about the relationship between households' housing wealth and consumption. According to the life-cycle/permanent income hypothesis (LC-PIH), households' consumption reflects changes in their available life-cycle resources. Attanasio and Weber (1994) proposed an approach to analyze how households' consumption responds to changes in housing prices. Hori and Niizeki (2019) applied the same approach to FIES data to estimate the marginal propensity to consume by regressing consumption on housing wealth. This approach is useful for examining whether housing wealth should be regarded as a life-cycle asset and whether the LC-PIH holds. However, it is unclear by what margin lifetime utility is increased or decreased due to the boom and bust of housing prices. If, for example, a household changed only the quality of the house it purchased in response to the change in housing prices, consumption may not reflect the change in lifetime utility. Therefore, to assess the long-term impact of the housing price boom and bust, we employ a so-called "structural" approach, estimating a structural model to conduct counterfactual simulations. Such an approach has at least two advantages. First, counterfactual simulations are not subject to the Lucas critique. Second, we can evaluate the impact of the housing price boom and bust on the basis of households' lifetime utility.

We estimate a life-cycle model using the indirect inference method. Indirect inference is a simulation-based technique that has been employed in numerous studies estimating a structural model. Simulation-based estimation techniques were first used to estimate the life-cycle model by Gourinchas and Parker (2002) in their pioneering study using the method of simulated moments (McFadden, 1989). Similar estimation methods have been employed by French (2005), Laibson et al. (2007), and French and Jones (2011), among others. There are few studies estimating life-cycle models using Japanese data. One of them is the work by Abe and Yamada (2009). They estimated a life-cycle model and reached the conclusion that the observed consumption inequality could be explained using a precautionary savings model that allows for nonlinearity in the variance-age profile of income.

The estimation of life-cycle models with housing wealth, on the other hand, is not very common, since the model structure becomes complex when housing wealth is incorporated. One of the few studies to have done so is that by Attanasio et al. (2012), who, using United Kingdom data, constructed and estimated a life-cycle model that incorporates households' housing choices under borrowing and collateral constraints. Another study is that by Li et al. (2016), who, using

United States (U.S.) data, estimated a life-cycle model with housing wealth to measure the elasticity of substitution between non-durable and housing goods. Li et al. (2016) also examined the impact of the house price change in the U.S. for the period before and after the subprime mortgage crisis of 2007–2010. The magnitude of the change in housing prices and the duration of the bubble period in the U.S. during this period, however, is smaller and shorter compared to Japan's housing price bubble. Moreover, Japanese households prefer new houses and tend not to move frequently. Thus, the impact on lifetime utility is expected to be much larger. Our study is the first to employ this approach to examine the long-term impact of Japan's housing price boom and bust on households' lifetime utility.

Theoretical studies on economic bubbles (e.g., Hirano and Yanagawa, 2017) found that financial deregulation can result in the emergence of a bubble. This means that policymakers potentially face a trade-off between the benefits of financial deregulation and the risk of a bubble. Against this background, understanding the impact of Japan's housing price boom and bust on households' lifetime utility can provide important insights into the consequences of asset price bubbles.

Empirical studies on the Japanese economy revealed that there were dramatic changes that affected households' asset accumulation. Maki (2006) analyzed Japanese households' consumption and saving behavior by using micro data from the *National Survey of Family Income and Expenditure* and found that saving behavior changed dramatically after Japan's bubble burst. Using the FIES data, Horioka and Niimi (2020) revealed that the expansion in housing credit caused this dynamic change in Japanese households' saving behavior. Horioka and Niimi (2020) showed that the loan-to-value ratio and the loan-to-income ratio have changed dramatically over the last five decades.

This study focuses on the direct effect of the housing price bubble on households' asset accumulation, but the dramatic change in housing prices could affect households indirectly through a different channel. Hirakata et al. (2016) estimated a dynamic stochastic general equilibrium model that explicitly incorporated credit-constrained financial intermediaries and entrepreneurs. Hirakata et al. (2016) found that negative shocks to asset prices can cause financial intermediation malfunction, which can have a sizable impact on the macro-economy. Our model is a partial equilibrium model and do not consider the indirect effects of shocks to asset prices, because estimating a general equilibrium that explicitly incorporates households' financial and housing wealth accumulation is computationally too burdensome. Thus, the effect of change in housing demand on housing prices is ignored, but our model clearly describes how households make decisions about consumption and the accumulation of financial and housing wealth under realistic borrowing and collateral constraints.

3. Life-cycle Model

We construct a life-cycle model that incorporates consumption/savings and housing decisions under realistic borrowing and collateral constraints. The basic setup of the model, especially the budget constraint, is based on Attanasio et al.'s (2012) model.

Households live T periods. Since the number of periods considerably affects the time it takes to compute the model, we set one period in the model to three years in order to save computation time. We assumed that the initial period starts at age 25–27 of the household head and that the household exists until age 82–84 of the household head (T = 20). In each period, households make decisions about consumption c_{it} and housing h_{it} to maximize their lifetime utility:

$$\max_{c_{it}, h_{it}} \sum_{t=1}^{T} \beta^{t-1} E[u(c_{it}, h_{it})].$$

For simplicity, we assume that the choice of dwelling is discrete. Households can choose not to own a dwelling ($h_{it} = 1$), to own a low-quality dwelling ($h_{it} = 2$), to own a medium-quality dwelling ($h_{it} = 3$), or to own a high-quality house ($h_{it} = 4$). The quality of houses is defined on the basis of their value in each period, and we do not distinguish between houses and apartments. For simplicity, we assume that a household can own at most one house and has no bequest motive.

The current payoff depends on consumption c_{it} and housing choice h_{it} and is given by

$$\mathrm{u}(c_{it}, h_{it}) = \kappa \left[\frac{1}{1-\gamma} \left(\frac{c_{it}}{\sqrt{\bar{N}_t}} \right)^{1-\gamma} + \frac{f(h_{it})}{\sqrt{\bar{N}_t}} - F\mathbf{1}[h_{it} \neq h_{it-1}] \right] + \eta(h_{it}) \tag{1}$$

where $\bar{N}_t$ is the family size, $f(h_{it})$ is the utility derived from housing, F is the cost of moving, and $\eta(h_{it})$ is an idiosyncratic utility shock that takes different values for each housing choice, following the type 1 extreme value distribution.[3] The utility derived from consumption takes the constant-relative-risk-aversion (CRRA) form. To lower the computational burden, we assume that family size is constant across households. We calculate the mean of family size at each period and use them as $\sqrt{\bar{N}_t}$. The utility from housing is given by:

$$f(h_{it}) = \begin{cases} 0 & if \;\; h_{it} = 1 \\ \phi + 0.25\mu & if \;\; h_{it} = 2 \\ \phi + 0.5\mu & if \;\; h_{it} = 3 \\ \phi + 0.75\mu & if \;\; h_{it} = 4 \end{cases}.$$

Households' budget constraints depend on their homeownership status. If a household does not own a home, the budget constraint is written as

$$A_{it+1} = R_{it+1} \left[A_{it} + w_{it} - c_{it} - q_t d_{1it} - \sum_{j \in \{l,m,h\}} p_t^{(j)} d_{jit} \right] \tag{2}$$

where A_{it+1} represents the financial assets held by household *i* at the beginning of period $t + 1$ (assets carried over from period t), R_{it+1} is the gross mortgage/interest rate, w_{it} stands for the household (disposable) income, q_{it} is the housing rent, d_{jit} $(j = 1, 2, 3, 4)$ are dummy

[3] We incorporate idiosyncratic utility shocks to randomize the housing choice. The reason is that the randomness from the idiosyncratic income shocks is not sufficient to replicate the observed pattern of housing asset accumulation.

variables that take a value of one if $h_{it} = j$ and zero otherwise, and $p_t^{(j)}$ are the prices of low-, medium-, and high-quality houses ($j \in \{l, m, h\}$). The gross interest rate that a household pays or receives, R_{it+1}, depends on the amount of financial assets held by household *i* at the end of period *t*. If the household carries over negative financial assets into the next period, R_{it+1} is the mortgage rate $\left(R_{it+1} = R_{t+1}^{(b)}\right)$; if the household carries over positive financial assets, R_{it+1} is the interest rate on bank deposits $\left(R_{it+1} = R_{t+1}^{(d)}\right)$.

We assume that the value of the house is discounted by the rate δ when a household sells a house. When a household owns a *j*-quality house ($j \in \{l, m, h\}$), the budget constraint can be written as

$$A_{it+1} = R_{it+1}\left[A_{it} + w_{it} - c_{it} - q_t d_{1it} - \sum_{k \neq j} p_t^{(k)} d_{kit} + (1-\delta) p_t^{(j)} \left(1 - d_{jit}\right)\right]. \qquad (3)$$

For simplicity, we assume that mortgage payments m_{it} are not fixed and are given by

$$m_{it} = (R_{it} - 1)\frac{A_{it-1}}{R_{it-1}}. \qquad (4)$$

If household *i* owns a *j*-quality house ($j \in \{l, m, h\}$) at the beginning of period *t* and chooses to continue to live in that house, the household does not pay any housing costs except the mortgage payments m_{it}. In this case, the household's budget constraint can be written as

$$A_{it+1} = R_{it+1}[A_{it} + w_{it} - c_{it}]. \qquad (5)$$

If household *i* that owns a *j*-quality house ($j \in \{l, m, h\}$) at the beginning of period *t* buys a *k*-quality house ($k \neq j$), it has to sell the existing (*j*-quality) house at the beginning of period *t* and pay for a new house:

$$A_{it+1} = R_{it+1}\left[A_{it} + w_{it} - c_{it} + (1-\delta) p_t^{(j)} - p_t^{(k)}\right]. \qquad (6)$$

If household *i* that owns a *j*-quality house ($j \in \{l, m, h\}$) at the beginning of period *t* wants to sell the house and not buy a new one (renting a house instead), the budget constraint can be written as

$$A_{it+1} = R_{it+1}\left[A_{it} + w_{it} - c_{it} + (1-\delta)p_{it}^{(j)} - q_t\right]. \tag{7}$$

We assume that a household's borrowing limit depends on the value of the dwelling it owns:

$$A_{it+1} \geq 0 \qquad\qquad \text{if } h_{it} = 0 \tag{8}$$

$$\frac{A_{it+1}}{R_{it+1}} \geq -\lambda_t^{(h)} p_t^{(j)} \qquad \text{if } h_{it} = j, j \in \{l, m, h\} \tag{9}$$

where $0 < \lambda_t^{(h)} < 1$. Equation (8) indicates that borrowing is allowed only when the household owns a dwelling.[4] Equation (9) represents the collateral constraint, that is, the purchased house is pledged as collateral and the household makes a down payment $\left(1 - \lambda_t^{(h)}\right) p_t^{(j)}$. Furthermore, we impose the assumption that the borrowing limit depends on the household's annual income, that is,

$$\frac{A_{it+1}}{R_{it+1}} \geq -\lambda_t^{(w)} w_{it}. \tag{10}$$

We assume that $\lambda_t^{(h)}$ and $\lambda_t^{(w)}$ change over time (have subscript *t*) because, as Horioka and Niimi (2020) pointed out, the expansion of housing credit dramatically changed households' financial constraints. Moreover, we assume that households are not allowed to die in debt, that is, $A_{iT} \geq 0$. Thus, there is a natural debt limit at each period as an implicit constraint.

Household income w_{it} depends on the age of the household head:

$$\ln w_{it} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \nu_{it}, \qquad \nu_{it} = \nu_{it-1} + \xi_{it} \tag{11}$$

where $\xi_{it} \sim N\left(0, \sigma_\xi^2\right)$ and $\nu_{i1} \sim N\left(0, \sigma_{\nu_1}^2\right)$. Note that ν_{it} follows a random walk and ξ_{it} is an idiosyncratic permanent income shock. Although the income function is simple, persistent household characteristics, such as the household head's educational attainment, are captured by

[4] Since in Japan the majority of households' debt consists of housing loans, this assumption is not as strong as it may appear.

ν_{it}.

The income process differs across households, while households are faced with the same housing price and mortgage rate (interest rates). The price of a medium-quality house $p_t^{(m)}$ is also assumed to be exogenous and follows a random walk:

$$\ln p_t^{(m)} = \ln p_{t-1}^{(m)} + \epsilon_t^p. \tag{12}$$

The house price shock ϵ_t^p follows a normal distribution $\epsilon_t^p \sim N(0, \sigma_p^2)$. Since we discretize the state variable and solve households' utility maximization problem at each state point, the number of continuous state variables we use is an important determinant of the time it takes to compute the model. To keep the number of continuous state variables small, we therefore assume that the prices of low- and high-quality houses form a log-linear relationship with the price of medium-quality houses:

$$\ln p_t^{(l)} = \zeta_0^{(l)} + \zeta_1^{(l)} \ln p_t^{(m)} \tag{13}$$

$$\ln p_t^{(h)} = \zeta_0^{(h)} + \zeta_1^{(h)} \ln p_t^{(m)}. \tag{14}$$

In theory, one would expect housing rents to be related to housing prices. In practice, however, this does not appear to be the case. Figure 5 shows housing rents in the Tokyo MEA. The figure indicates that housing rents remained relatively constant even during the bubble period. We therefore assume that housing rents depend only on time:

$$q_t = \zeta_0^{(q)} + \zeta_1^{(q)} t + \zeta_2^{(q)} t^2. \tag{15}$$

As shown in Figure 6, mortgage rates changed dramatically during the bubble period. If we assume deterministic mortgage and interest rates, households in the model would behave as if they knew in advance that mortgage rates would suddenly drop. We therefore incorporate uncertainty about mortgage and interest rates in the model, i.e.:

$$\ln R_t^{(b)} = \ln R_t^{(b)} + \epsilon_t^{(R)}. \tag{16}$$

We assume that shocks to mortgage rates follow a normal distribution $\epsilon_t^{(R)} \sim N(0, \sigma_R^2)$. So as not to increase the number of continuous state variables, we assume that the interest rate on savings is determined by the mortgage rate:

$$\ln R_t^{(d)} = \zeta_1^{(d)} + \zeta_1^{(d)} \ln R_t^{(d)}. \tag{17}$$

4. Data

We use the FIES data to estimate the model. The FIES is a monthly survey currently covering approximately 9,000 households per month. We use data from 1983 to 2012, containing observations on 500,000 households. The survey tracks each household for three months in the case of one-person households and six months in the case of other households.[5] Respondents keep a diary on their monthly income and expenditures. The FIES data is designed to provide the basic information needed to construct the consumer price index (CPI) and other important statistics related to consumption and the prices of goods. As mentioned earlier, we focus on households with a head born from 1951–1955 who lived in the Tokyo MEA during the observation period. Since the Tokyo MEA covers municipalities where more than 10% of the population commute to the center of Tokyo, households living in municipalities in other prefectures close to Tokyo are included in the sample (see Figure 7). Furthermore, we focus on households with two or more members because information about financial assets is not available for one-person households. In the model, households accumulate financial assets and borrow money to buy a house on their own; that is, obtaining a house through inheritance is not included in the model. We therefore exclude households with a member older than the head, because those living with their parents are likely to share and inherit their house. Furthermore, for the same reason, we exclude households with a head who was aged 25 or younger when their house was built. We also

[5] The FIES has a panel structure, but the information about assets is available only for the first period. We therefore cannot take advantage of the panel structure and use the data as cross-sectional data.

exclude self-employed households because the life-cycle path of income is considered to be different from that of employed workers.

As a result of excluding observations based on these criteria, our sample consists of 5,253 households. Because one period in the model corresponds to three years, we divide the observation period overall into 10 subperiods. The sample size for each subperiod ranges from 300 to 550 households.

By using the FIES data, we calculate the mean of household income, prices of financial and real assets, and homeownership for each period. Household income and prices of financial and real assets are deflated by the CPI. Moreover, we calculate the loan-to-income ratio and loan-to-value ratio using the FIES data to obtain $\lambda_t^{(w)}$ and $\lambda_t^{(h)}$.

4.1 Household income

Although the FIES data are panel data, each household is tracked for six months only, so that the monthly income data is subject to seasonality. Moreover, the seasonally adjusted income data are quite noisy, and the fit of the income function regression is poor. Therefore, we use the previous year's income multiplied by the average ratio of households' disposable income to pretax income.[6] Following Attanasio et al. (2012), each household is treated as a single decision-maker; thus, we use the entire household's disposable income .

Figure 8 shows the mean household disposable income by age across the three cohorts shown in Figure 4. We can see that the life-cycle path of income is hump-shaped and that the shape differs across cohorts. As Hamaaki et al. (2012) pointed out, the life-cycle income path of younger cohorts in Japan is flatter than that of older cohorts. This pattern may reflect the collapse

[6] We calculate the ratio of disposable income to pretax income from seasonally adjusted monthly income. Specifically, we calculate this ratio for each household as the average over the six month-period the household is tracked and used this as the disposable income of the household.

of the traditional Japanese seniority wage system.

4.2 *Financial assets*

Figure 9 shows the mean of financial assets by household heads' age across the three cohorts. Larger markers indicate the period of the asset price bubble (1988–1992). The figure suggests that households' financial asset holdings did not change much during the asset price bubble. This is perhaps because the majority of financial assets held by Japanese households are bank deposits. For this reason, we do not investigate the effect of the bubble in financial markets on households' lifetime utility and exclusively focus on the effect of the bubble in housing prices.

4.3 *Housing wealth*

While the FIES provides rich information about households' characteristics, income, consumption, and financial assets, it unfortunately does not contain information on the value of households' housing wealth. However, the dataset does offer detailed information about the approximate address, type (apartment or house), age, land area, and floor space of households' dwellings. Combining this information with other data sets such as official land price data allows us to estimate the value of the dwelling in which a household lives and thus provides us with an objective estimate of households' housing wealth.[7] The benefit of these estimates over subjective housing asset values, if they were available, is that they likely reflect the housing price boom and bust more accurately. That is, those who bought their house before the bubble and were not interested in selling it may not have been aware of the dramatic change in the housing wealth they held.

[7] Note that having to rely on this approach means that housing assets other than the household's home are not included in housing wealth.

To estimate land values, we use households' addresses and match this to the price of residential land in the area. Land prices are taken from the "Land Market Value Publication" (*Chikakoji*) provided by the Ministry of Land, Infrastructure, Transport and Tourism. We multiply the land area by the unit land price of the closest point for which land prices are available.

We estimated house values using information about the type of dwelling, the age of the house, and the floor area. Information about the link between housing construction costs, the type of dwelling, the municipality, and the floor area are taken from the "Annual Report of Building Construction" (1953–2012). Employing such information, we estimate the price of a new house in a particular locality and then estimate its value at the time of the survey, taking depreciation based on the age and type of dwelling into account.[8]

Figure 10 shows households' housing wealth by age across the three cohorts. The figure indicates that households accumulate housing wealth until age 45–48 of the household head. The rapid increase in housing wealth for those in their 30s and 40s across all three cohorts reflects the increase in homeownership rates. In addition, for the two older cohorts, the house price boom during the bubble economy also contributed to the increase in their housing wealth, as indicated by the larger markers representing years during the bubble period. In the model, we discretize housing wealth into three levels: low-, medium-, and high-quality dwellings. We define low-quality dwellings as the 25th percentile, medium-quality dwellings as the median, and high-quality dwelling as the 75th percentile of the values of housing wealth. Thus, the prices of low-, medium-, and high-quality houses in the model correspond to the 25th, 50th, and 75th percentile of the housing wealth distribution, respectively. Note that households of other cohorts living in the Tokyo MEA are included when we calculate the value of housing wealth.

To examine how housing behavior responded to the housing price bubble, we calculate the

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[8] For more detailed information about the estimation procedure, see Hori and Niizeki (2019).

share of "good houses" by the year in which the house was built. We measure the quality of houses by the percentiles of unit land price,[9] and we define "good houses" as those above the median for each year. Figure 11 shows the share of "good houses" by the year in which the house was built. As can be seen, the share of "good houses" declined from 1989 to 1997. Thus, some households might choose to build a house in a less expensive area during the bubble period.

4.4 Borrowing limits

As shown by Horioka and Niimi (2020), the expansion of housing credit changed households' financial constraints, and the loan-to-value ratio and loan-to-income ratio changed accordingly. This indicates that the borrowing limits (Equation (9) and (10)) should be time-dependent. Thus, we calculate the percentiles of the loan-to-value ratio of the households living in a house aged three years or less to obtain $1-\lambda_t^{(h)}$. Moriizumi (1996) reported that a typical minimum down-payment-to-house value ratio (λ_t^h in our model) in Japan is approximately 20%, and we assume that $1-\lambda_t^h$ should be close to 0.8 in the mid-1990s. The top 25th percentile of the loan-to-value ratio, shown in Figure 12 (A), is close to 80% in the mid-1990s, but it was too low in 1990 and before for most households in the model to buy a house. Therefore, we impose a lower bound of 0.6, and use the top 25th percentile of the loan-to-value ratio as $1-\lambda_t^h$. Similarly, we calculate the loan-to-income ratio of the households living in a house aged three years or less in the FIES data to obtain the value of $\lambda_t^{(w)}$(Figure 12 (B)). As mentioned earlier, previous studies showed that $\lambda_t^{(w)}$ is approximately five to eight, which is close to the top 5th percentile of the loan-to-income ratio. Since the 5th percentile of the loan-to-income ratio ranges from 4 to 10, we imposed a lower bound of 5 and use it as $\lambda_t^{(w)}$.

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[9] The housing wealth includes the value of the building; thus, it depreciates over time. Since we need to measure the quality of the house when it was built, we use only the land price. We attempt to construct quality measures using information on size and location; however, we could not find clear evidence.

5. Estimation Procedure

This section describes our estimation procedure. It should be noted that some of the parameters in the model cannot be estimated from the data, so we set them a priori. Specifically, we set the value of the CRRA coefficient, γ, because it is not clear whether it can be identified separately from β. We set γ at the value estimated by Attanasio and Weber (1995), following Attanasio et al. (2012). We also need to set the value of the resale discount rate of houses, δ, because it cannot be identified separately from the moving cost, *F*. Since Japanese households prefer a new house to a second-hand house, the value of the building is considered to comprise only a small fraction of the resale value. Since approximately 80% of households' housing wealth comprise the land value, we assume that the resale discount rate δ is 20%.[10] Furthermore, we calculate the variance of the shocks to housing prices and mortgage rates directly from the FIES data and the *Financial and Economic Statistics Monthly*, provided by the Bank of Japan, respectively. These parameters are summarized in Table 1.

5.1. Estimation of the parameters in the income, housing price, and mortgage rate processes

We assume that household income, housing prices, and interest rates are exogenous. We therefore estimate the parameters in Equations (11), (13), (14), (15), and (17) directly from the data.

To estimate the household income function (Equation (11)), we regress the log of annual disposable income on age and age squared. We then estimate the variance of the income shock, σ_ξ and the initial variance of the error term, σ_{ν_1}, using the residual from the log wage regression. It is typically observed that (within-cohort) cross-sectional wage variation increases with age. In

[10] The assumption that households can sell only the land on which their house sits may appear too strong, but we can assume that selling cost includes other pecuniary costs associated with moving, such as the transaction cost and the cost of new furniture.

our model, the increase in the (within-cohort) cross-sectional variance of household income is attributable only to the idiosyncratic income shock ξ, that is,

$$Var(v_{it}) = Var(v_{it-1}) + Var(\xi_{it}).$$

Therefore, the variance of the error term of the household income function can be written as

$$Var(v_{it}|Age) = \mathrm{E}\left(v_{it}^2|Age\right) = \sigma_{v_1} + \sigma_{\xi}(Age - 24). \tag{18}$$

Thus, to estimate σ_ξ and σ_{v_1}, we regress the squared residuals from income regression $\hat{u}_{it}^2$ on a constant term and $\mathrm{Age} - 24$. The coefficient of $\mathrm{Age} - 24$ can be regarded as an estimate of the income shock variance. Since the initial period of the model starts at age 25, the constant term can be regarded as the variance of income in the initial period.

As mentioned above, the median of housing wealth obtained from the FIES data was used as the price of medium-quality houses, which was then used to estimate the prices of low- and high-quality houses. Since housing wealth is only observed from 1983–2012, we need to extend the series of housing prices to find those in periods before 1983 and after 2012. Thus, we use the *Land Market Value Publication* to extend the series of housing prices, assuming that housing prices change parallel to land prices.

5.2. Estimation procedure of the structural parameters

We now turn to the structural parameters, such as the discount factor β. We estimate the structural parameters by employing the method of indirect inference proposed by Gouriéroux et al. (1993), taking the parameters estimated directly from the data as given. The indirect inference estimator of the structural parameter minimizes the “distance” between the ordinary least squares (OLS) estimates of the following auxiliary model obtained from the FIES data and those from the data generated from the simulations with the structural model:

$$A_{it} = \sum_{t=1}^{10} \omega_t^{(A)} d_{it} + u_{it}^{(A)} \tag{19}$$

$$H_{it} = \sum_{t=1}^{10} \omega_t^{(H)} d_{it} + \omega_w w_{it} + u_{it}^{(H)} \tag{20}$$

$$D_{it} = \sum_{t=1}^{10} \omega_t^{(D)} d_{it} + u_{it}^{(D)} \tag{21}$$

where A_{it} represents households' financial wealth, d_{it} is a time dummy representing three-year intervals, H_{it} represents households' housing wealth, w_{it} is households' income, and D_{it} is a dummy variable indicating that household *i* is a homeowner at period *t*.

The estimation procedure is as follows: First, we estimate the auxiliary model using the FIES data. Let $\overline{\boldsymbol{\omega}}$ denote the parameter vector of the auxiliary model obtained from the FIES data. Second, we solved the dynamic programming problem of households by backward induction for the set of structural parameters $\Theta \equiv \{\beta, \kappa, \phi, \mu, F\}$ to obtain the policy and value functions.[11] Using these functions, we conduct simulations to obtain the simulated data. Using the simulated data, we then estimate the auxiliary model. Let $\boldsymbol{\omega}(\Theta)$ be the vector of the OLS coefficients of the auxiliary model obtained from the simulated data. Finally, we calculate the distance between the coefficients obtained from the FIES data, $\overline{\boldsymbol{\omega}}$, and those obtained from the generated data, $\boldsymbol{\omega}(\Theta)$. The distance is defined by

$$[\overline{\boldsymbol{\omega}} - \boldsymbol{\omega}(\Theta)]' W [\overline{\boldsymbol{\omega}} - \boldsymbol{\omega}(\Theta)] \tag{21}$$

where *W* is a weighting matrix whose diagonal elements are the inverse of the variance of the corresponding elements of $\overline{\boldsymbol{\omega}} - \boldsymbol{\omega}(\Theta)$. The indirect inference estimator is the minimizer of

[11] To solve the dynamic programming problem, we discretize the continuous state variables and linearly interpolate the policy and value functions. Furthermore, to approximate the expected values with respect to the random shocks that follow a normal distribution, we use Gauss-Hermite quadrature. We use 20 sample points and impose the assumption that the shocks cannot be smaller than the smallest sample point.

Equation (21).

5.3. Identification of the structural parameters

We incorporate utility shock $\eta(h_t)$ (in Equation (1)) to randomize households' housing choices, while κ dictates the relative magnitude of the utility shock and utility from consumption and housing. A smaller κ indicates a weaker link between households' housing choice and state variables, and vice versa. This is why we include w_{it} in Equation (20). By matching the ω_w obtained from the FIES data with ω_w from the simulated data, we ensure that κ is uniquely identified.

If we did not include utility shock $\eta(h_t)$, we would not need to include w_{it} in Equation (20). In that case, matching the coefficients in the auxiliary model would be equivalent to matching the mean of financial wealth, housing wealth, and home-ownership rates in each period. Therefore, let us consider how the structural parameters other than κ are identified by matching the mean of financial and housing wealth in each period.

We can identify the structural parameters, except for κ, if, in the model, the levels and growth rates of financial and housing wealth are determined when the values of these parameters are given. Let us consider the identification condition for each parameter. First, the relative magnitudes of financial and housing wealth are determined by the combination of ϕ and μ, while ϕ and μ also determine the growth rate of housing wealth. Thus, ϕ and μ can be identified from the levels of financial and housing wealth and the rate of increase in housing wealth. Second, the discount factor β dictates the relative importance of consumption across different points in time. Thus, the value of β is determined when the growth rate of financial assets is given. Finally, the moving cost F dictates the frequency of house purchases and sales, and the frequency determines the growth rate of housing wealth and homeownership rates. Therefore, the moving cost F is identified by matching the growth rates of housing wealth and homeownership rates.

6. Estimation Results

6.1 Reduced-form estimation

This section presents our estimation results. We start with the reduced-form estimation. As mentioned above, the parameters governing the exogenous processes that determine income, housing prices, and mortgage (interest) rates are estimated directly from the data. The values of these parameters are summarized in Table 1.

In order to graphically show the fit of the model, we draw the fitted regression lines of income and housing prices. Figure 13 shows the estimated household income over the life cycle. As can be seen from the figure, the predicted income captures the hump-shaped life-cycle income path well. Note that, in the model, household income is halved age 60 and remains constant thereafter. Figure 14 shows the estimated prices of low- and high-quality housing. As mentioned earlier, we assume that the prices of low- and high-quality housing form a log linear relationship with medium-quality housing to save computation time. Although this may appear to be a strong assumption, the predicted prices of low- and high-quality houses are very close to the actual prices.

6.2 Structural estimation

The estimates of the structural parameters are summarized in Table 2. Note that the estimated discount factor β discounts the value for one period in the model. Since one period in the model is three years, the annual discount rate is approximately 2.56%.

To provide an overview of the fit of the structural model, we draw the means of actual and predicted financial and housing wealth and home-ownership rates. Figures 15 (A)–(C) show the means of actual and predicted financial and housing wealth and home-ownership rates in each period. Solid lines depict the means calculated from the FIES data, while dashed lines depict those calculated from the generated data. Although housing wealth over the life cycle is slightly under-predicted, the model fit seems good for the most part, except for financial wealth at age 36–45 and home-ownership rates at age 51–57. Since the sample consists of households that were aged 36–45 during the bubble, the estimated model overestimates households' financial asset holdings during the bubble period. Households in the FIES sample held less financial assets than simulated households during the bubble period, perhaps because some of the households knew that they were going to inherit financial or housing wealth from their parents and did not need to save in preparation for purchasing a house, as the model predicts. Despite this discrepancy, the estimated model successfully replicates the overall pattern of financial and housing wealth accumulation.

In order to take a closer look at the housing behavior of households, we present the shares of renters as well as low-, medium-, and high-quality housing owners in Figure 16. As can be seen, renters gradually tend to become homeowners, and the share of households living in better dwellings increases as households get older.

7. Counterfactual Simulation

7.1 No-bubble simulation

To quantify the effect of the housing price boom and bust, we conduct a counterfactual simulation in which housing prices are held fixed from the third period (ages 30–32, years 1983–85) to the 11th period (ages 45–47, years 1998–2000). The actual and counterfactual housing prices of medium-quality housing are shown in Figure 17. In each period, households make decisions about their consumption/saving and housing based on the belief that housing prices are uncertain and follow a random walk. In the counterfactual simulation, however, the realized housing prices are constant over time. Moreover, in the simulation, the variance of housing price shocks is replaced with the variance of housing price shocks calculated from data before the housing price boom (1983–1986) and after the bust (1997–2012). Since housing price fluctuations were smaller during these periods before and after the bubble, the variability of shocks to housing prices is smaller than the actual variability. This means that in the counterfactual simulation, households are faced with less uncertainty and more stable housing prices.

Figures 18 (A)–(C) present the results of the counterfactual simulation. They show households' accumulation of financial and housing wealth based on the counterfactual housing prices. As can be seen from Figure 18 (B), under counterfactual housing prices, households tend to hold less financial wealth after the age of 33. Why do households save less in the counterfactual simulation in which they can buy a house at a lower price? There are two possible reasons. First, as can be seen from Figure 18 (C), households buy a better house earlier in the counterfactual simulation. Second, households face less uncertainty about housing prices and do not need to save in preparation for dramatic changes in housing prices. Furthermore, in the counterfactual simulation, consumption is 0.34% higher than in the simulation with actual housing prices, perhaps because households do not spend too much money to buy a house. In summary, in the counterfactual simulation, households hold less financial wealth to buy a better house and consume more.

As mentioned above, one of the greatest advantages of structural estimation is that we can assess the effect of the housing price boom and bust on the basis of households' utility. The average lifetime utility from consumption and housing based on the actual housing prices is -14.74, while that of the simulation based on the counterfactual simulation is -13.98. To lower lifetime utility by 0.76 in the no-bubble simulation, lifetime household income would need to decrease by 4.7%. Therefore, the loss of lifetime utility is equivalent to 4.7% of lifetime income. We find that the impact of the housing price boom and bust is heterogeneous across households.

Japan's housing price boom and bust had a positive impact on 27.8% of households and a negative impact on the remaining 72.2%. The average utility gain for those who experienced a positive effect was equivalent to only 2.1% of lifetime income, while the average utility loss for those that experienced a negative impact was equivalent to 5.7% of lifetime income. Moreover, consumption of those that benefited from the housing boom and bust increased by 0.25%, while consumption of those who experienced a utility loss decreased by 0.57%. The contribution of the changes in consumption to the changes in lifetime utility is only 0.1% for those who benefited from the housing price bubble and 4.1% for those who did not. Thus, households change the timing and quality of houses in response to the change in housing prices to sustain the consumption level.

Why are there households that benefit from the housing price bubble? There are two reasons: First, in the counterfactual simulation, households are faced with less uncertainty about the housing prices because we use the variance of housing price shocks calculated from data before the housing price boom and after the bust. If we use the variance calculated from the data of the whole observation period, the utility gain decreases to the amount equivalent to 0.6% of the lifetime utility. However, the effect of the variance on the share of those who benefit from the housing price bubble is only marginal. Second, in the model, households make decisions about housing and consumption without knowing future income, future housing prices, and future interest rates. At each period, households choose the optimal consumption and housing choice that maximize the "expected" utility, but their choice may end up not maximizing their lifetime utility when they look back at the end of their lives. This is why there can be households that happened to be better off thanks to the housing price bubble. For example, let us consider a household that receives only positive income shocks after the bubble period. If there is no housing price bubble, this household may buy a low-quality house without knowing that it will receive positive income shocks for the rest of its life and become rich in the future. The household may notice, 10 or 20 years after buying a house, that it could afford a better house. Since moving is costly, the household may end up living in a low-quality house for the rest of its life, in the no-bubble simulation. Such a household can benefit from the housing price bubble if the housing price bubble prevents it from buying a low-quality house before it learns about its income profile after the bubble period.

7.2 Comparison across cohorts

We mainly focus on the cohort born in 1951–55, because we assume that the impact of the housing price bubble is greatest for this cohort. To verify this hypothesis, we conduct counterfactual simulations by using the households with a head born three periods earlier (older cohort, born in 1942–1946) and those with a head born three periods later (younger cohort, born in 1960–1964) than the baseline cohort (born in 1951–55).

As previous studies, such as Hamaaki et al. (2012) and Yamada and Kawaguchi (2015), revealed, the life-cycle income profile differs considerably across households.[12] Thus, we assume that households belonging to different cohorts face different household income functions. We estimate the household income function of these cohorts by using the FIES data. Figures 19 (A) and 19 (B) show the fit of the estimated household income functions. Figure 20 compares the household income function across cohorts. Figure 20 shows that household income function for younger cohorts is flatter, which is consistent with the age-income profile shown in Figure 8. Households are faced with the same interest (mortgage) rates and housing prices, but different cohorts experience the housing price bubble at different life stages. Since estimation of the structural parameters is computationally burdensome, we use the structural parameters that we

[12] Ohta (2019) also found across-cohort earnings differentials for younger cohorts.

estimated using households belonging to the baseline cohort (born in 1951–1955).

Under these setups, we conduct simulations based on actual housing prices and those based on counterfactual housing prices (no bubble). To assess how precisely the estimated model predicts the real households' asset accumulation pattern, we draw the data moments calculated from the FIES data and simulated moments calculated from the simulated data for older and younger cohorts in Figure 21 (A)–(C) and Figure 22 (A)–(C), respectively. Although we use only the baseline cohort to estimate the structural parameters, the model precisely predicts the financial wealth. However, the estimated model under-predicts the housing wealth of the older cohort and over-predict the homeownership of the younger cohort.

Figures 23 (A)–(C) show the simulation results of the older cohort, while Figures 24 (A)–(C) present those of the younger cohort. As can be seen from Figures 23 (A) and 24 (A), households tend to accumulate less financial assets if there were no bubble. Moreover, Figures 23 (B) and 24 (B) show that the housing price bubble delayed the timing of buying a house.

The impact of the housing price bubble on lifetime utility is equivalent to 1.4% of lifetime income. The impact was not as large as on the other cohorts, because approximately 50% of the households had bought a house before the housing price bubble, as can be seen from Figure 21 (C). The impact of the housing price bubble on the younger cohort, on the other hand, is equivalent to 3.6% of their lifetime income. The housing price bubble had a sizable impact on those belonging to the younger cohort, because they experienced the housing price bubble early in their lives. Although the number of households that bought a house during the bubble period is small, the impact on them is significant because they will live in the house for a long period. However, the magnitude is still smaller than that for the baseline cohort.

8. Conclusion

We constructed a theoretical model illustrating households' financial and housing asset accumulation over their life cycle. In each period, households make decisions with regard to their consumption/saving and housing under realistic collateral and borrowing constraints and while facing uncertainty about their income, housing prices, and interest rates. We estimate the model using the method of indirect inference, so that OLS estimates of the auxiliary model calculated from the simulated data mimic those calculated from the FIES data. The overall fit of the model is good, but the model slightly underestimates households' housing assets and overestimate households' financial assets during the bubble period. Using the estimated model, we conduct a counterfactual simulation assuming that housing prices remained constant from the mid-1980s through the 1990s. Doing so enabled us to quantify the impact of Japan's housing price boom and bust on households' lifetime utility.

The estimated impact was heterogeneous across households: 27.8% of households experienced an average increase in lifetime utility equivalent to 2.1% of lifetime income, while 72.2% experienced an average decrease in lifetime utility equivalent to 5.7% of lifetime income. On average, Japan's housing price boom and bust caused a loss of utility equivalent to 4.7% of lifetime income. We compare the impacts of the housing price bubble across the three cohorts and find that the impact was greatest for the baseline cohort (born in 1951–1955), because many of them bought their houses during the housing price bubble.

Moreover, we found that those who experienced an increase in lifetime utility experienced an increase in consumption as well, and vice versa. However, the changes in the amounts of consumption and lifetime utility are quite different. This indicates that the changes in consumption may not precisely reflect the changes in lifetime utility due to housing price fluctuations. Thus, for the purpose of evaluating the impact of housing price fluctuations on lifetime utility, a structural approach is more appropriate than a reduced-form approach that relies on the regression of consumption on housing wealth.

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Table 1. Pre-set parameters

The CRRA coefficient γ	1.43
Standard deviations of shocks and disturbances	
Income shock σ_{xi}	0.0045
Initial income disturbance σ_{ν_1}	0.0812
Housing price shock σ_{p}	0.1029
Housing price shock (no-bubble case) σ_{p}	0.0565
Mortgage rate shock σ_{R}	0.1529
Parameters in household income function	
Constant α_0	-2.9045
Age of household head α_1	0.1902
Age of household head squared α_2	-0.0019
Parameters in housing equations	
Constant $\zeta_0^{(l)}$	-0.1069
Log of medium-quality house $\zeta_1^{(l)}$	0.8968
Constant $\zeta_0^{(h)}$	-0.0394
Log of medium-quality house $\zeta_1^{(h)}$	1.168
Parameters in housing rent function	
Constant $\zeta_0^{(q)}$	0.3213
Time variable (year - 1982) $\zeta_1^{(q)}$	0.0415
Time variable (year - 1982) squared $\zeta_1^{(q)}$	-0.0009
Parameters in the equation relating to mortgage and interest rates	
Constant $\zeta_0^{(d)}$	-3.1297
Mortgage rate $\zeta_1^{(d)}$	1.3752

Table 2. Estimates of structural parameters

Discount factor β	0.928
Weight on deterministic part of utility function κ	1.398
Constant term in the utility from a house ϕ	1.090
Slope parameter in the utility from a house μ	0.354
Moving cost F	6.600

Notes: The discount factor is for three years. Standard errors are not calculated, because it is computationally too burdensome.

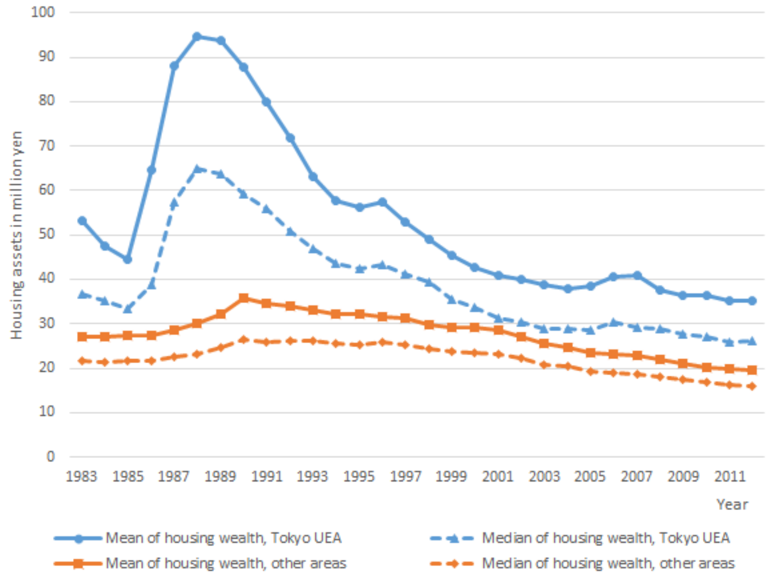


Figure 1: Households' housing wealth, 1983–2012

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

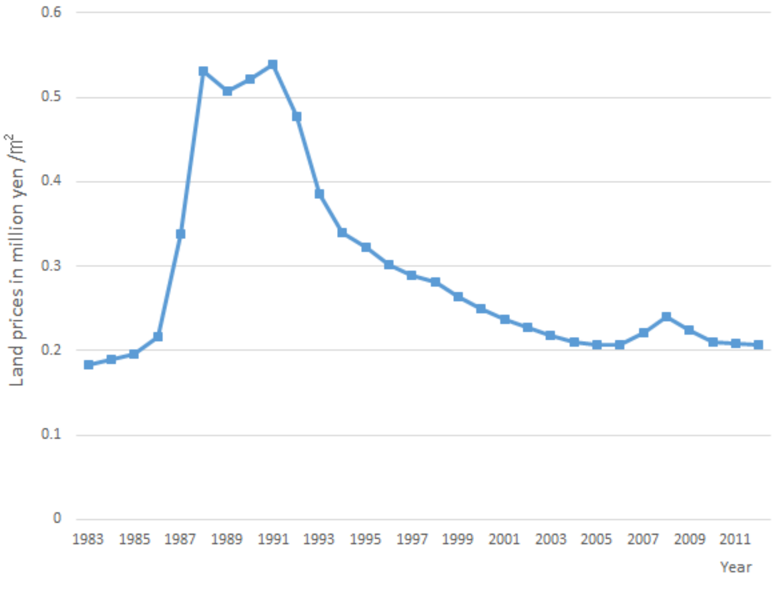


Figure 2: Land prices in residential areas, Tokyo, 1983–2012

Source: "Land Market Value Publication" (*Chikakoji*), Ministry of Land, Infrastructure, Transport and Tourism.

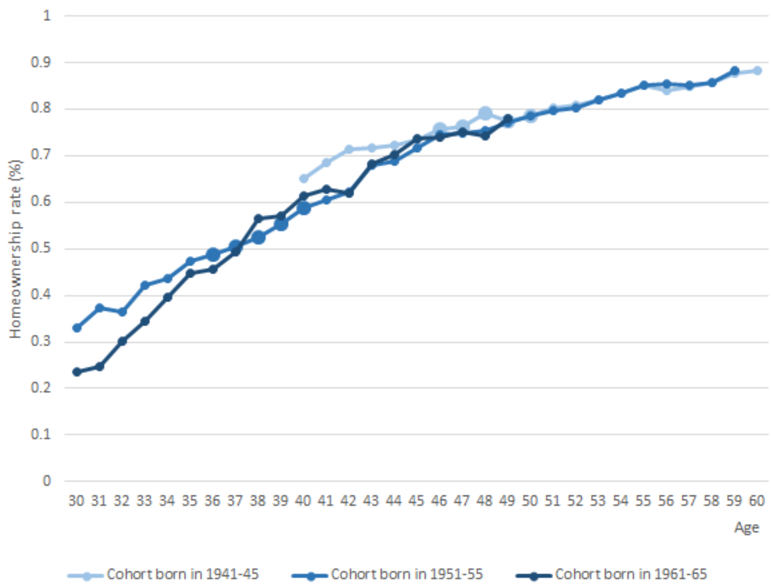
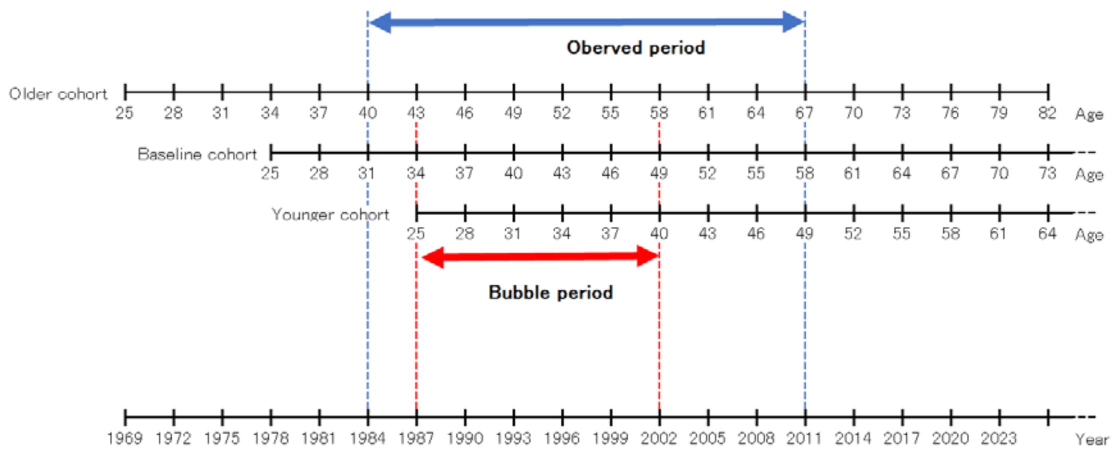


Figure 3. Homeownership rates, 1983–2012

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.



Note: One period is three years in the model. The older and younger cohorts are those born three periods earlier and later than the baseline cohort

Figure 4. Older, baseline, and younger cohorts

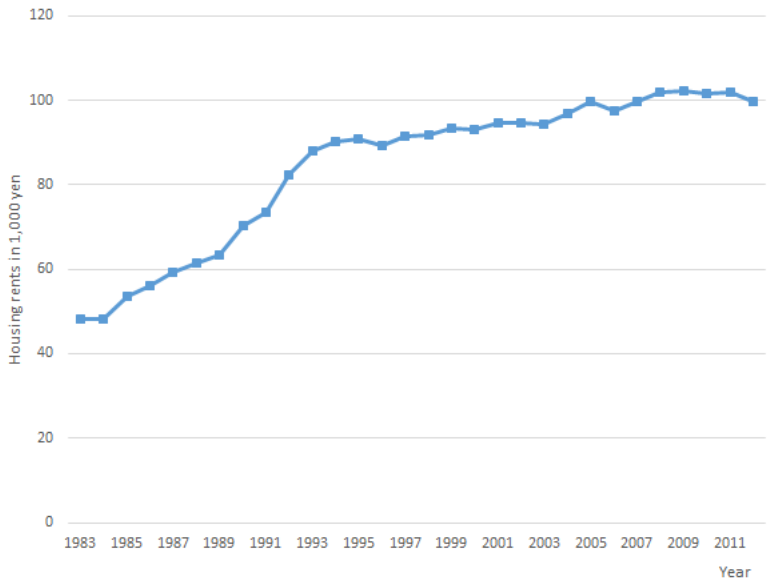


Figure 5. Housing rent

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

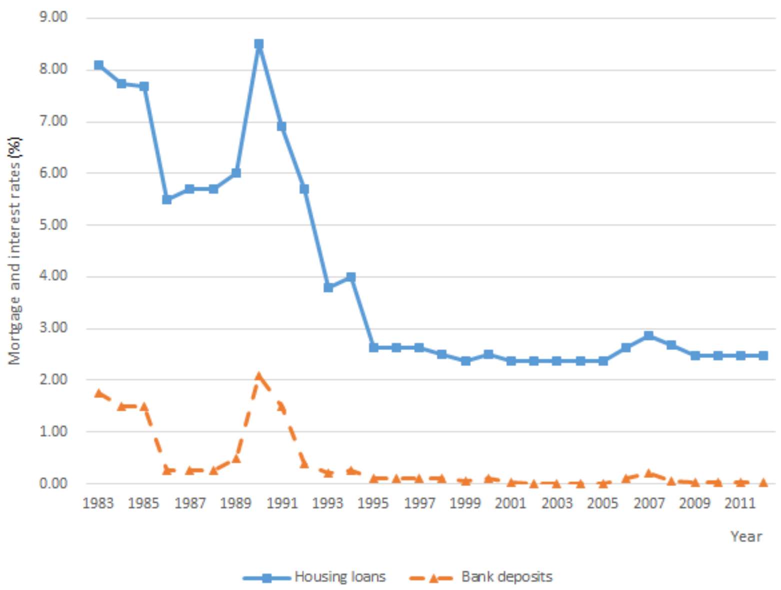


Figure 6. Mortgage and deposit interest rates, 1983–2012

Source: Financial and Economic Statistics Monthly, Bank of Japan.

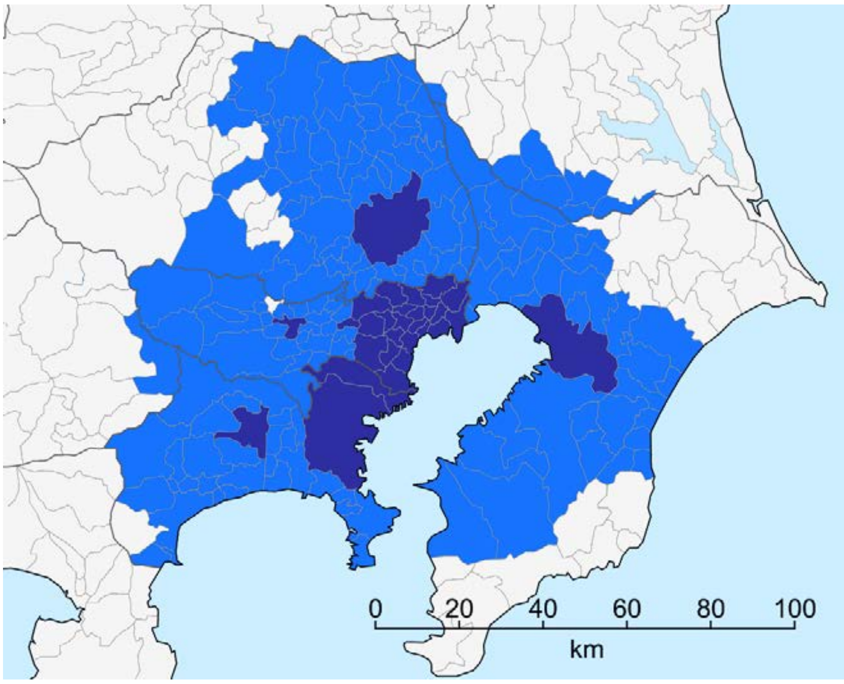


Figure 7. Tokyo Metropolitan Employment Area (MEA)

Source: Wikipedia

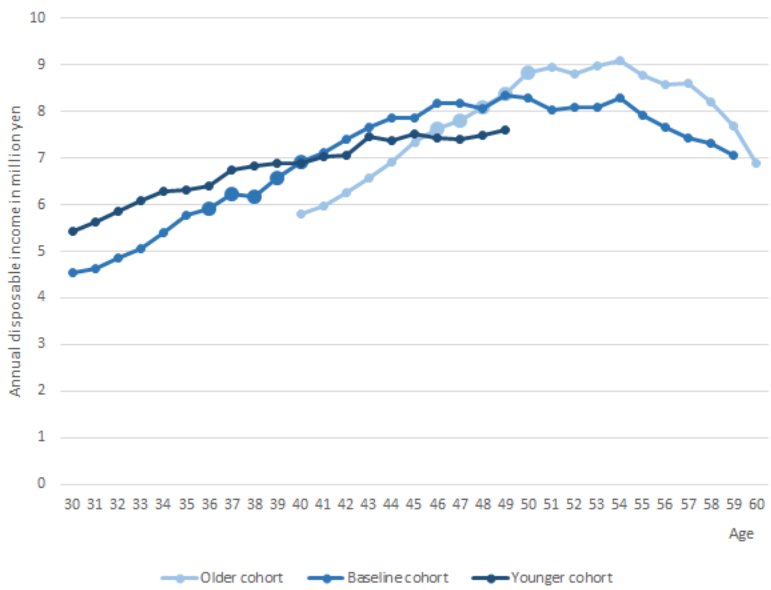


Figure 8. Annual disposable income, 1983–2012

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

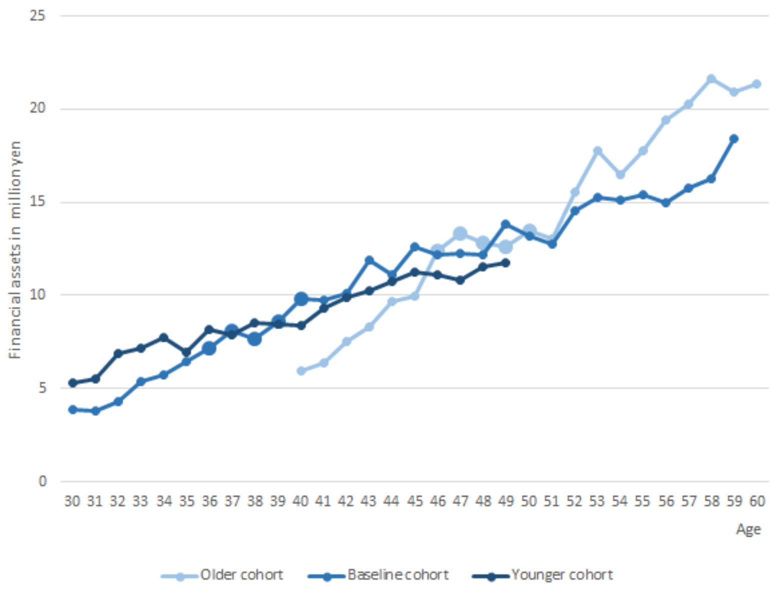


Figure 9. Household financial wealth, 1983–2012

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

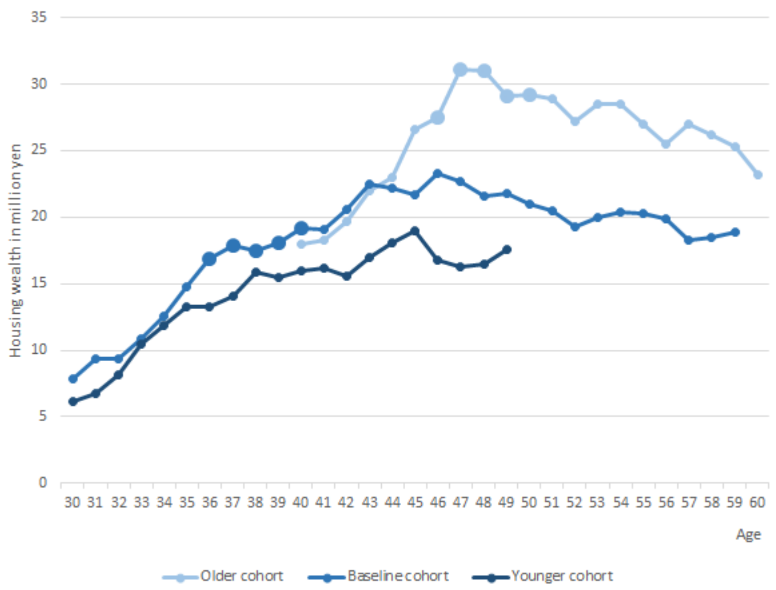


Figure 10. Housing wealth, 1983–2012

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

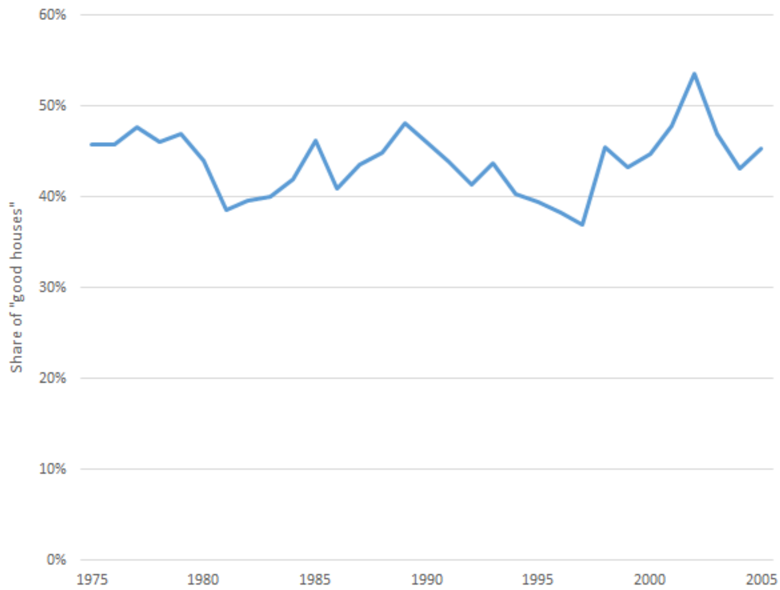


Figure 11. Share of the “good houses,” 1975–2005

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

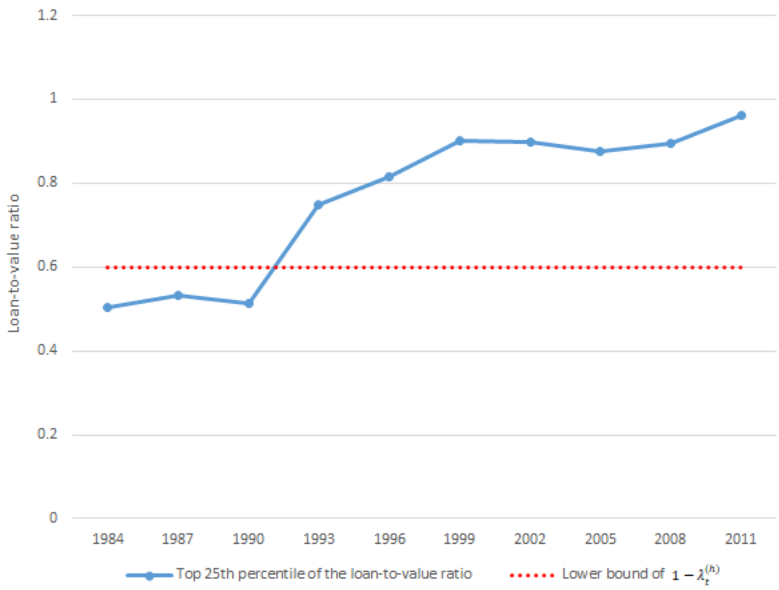


Figure 12 (A). Limit of the loan-to-value ratio $1-\lambda_t^h$

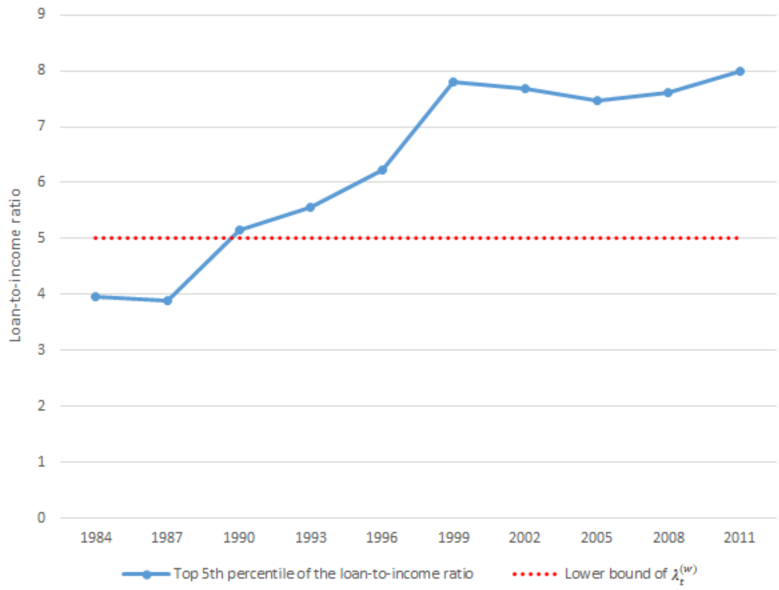


Figure 12 (B). Limit of the loan-to-income ratio λ_t^w

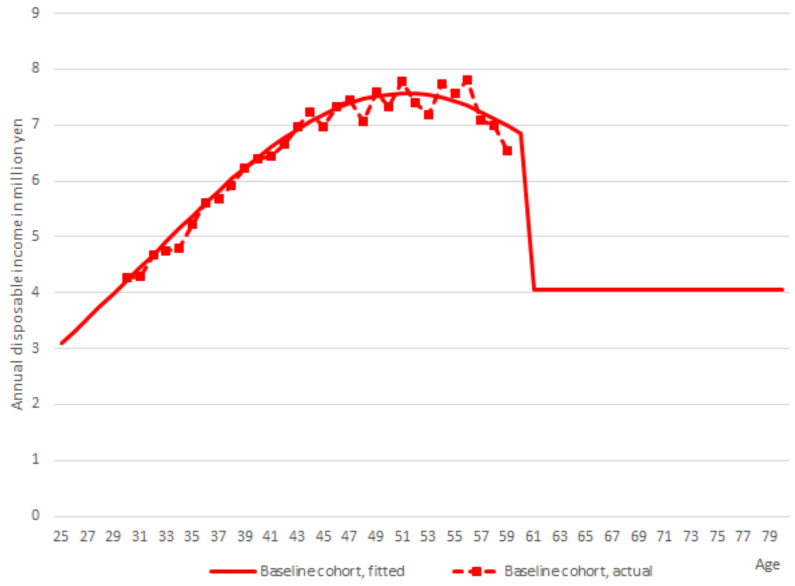


Figure 13. Model fit of household income function

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

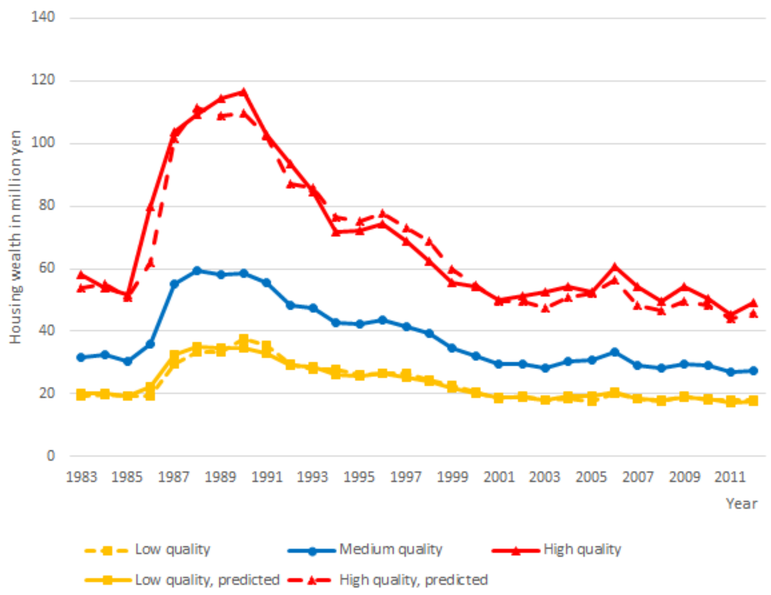


Figure 14. Model fit of housing wealth values

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

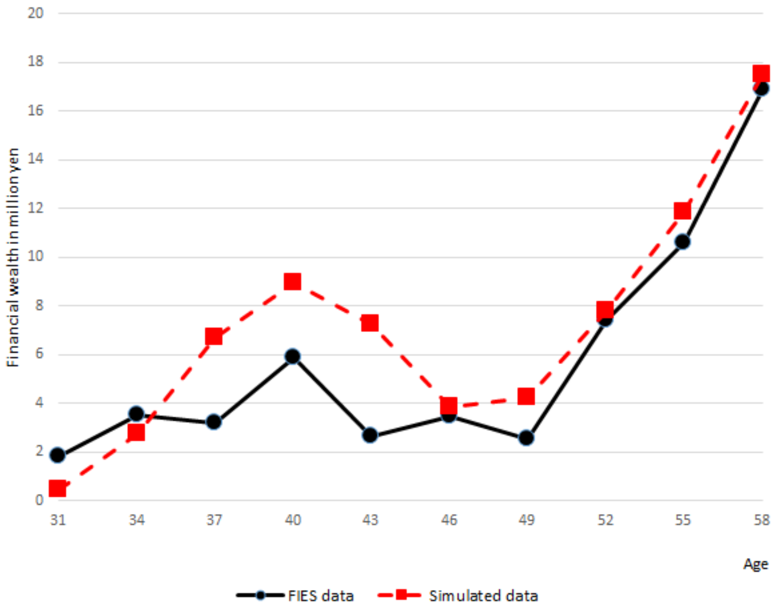


Figure 15 (A). Model fit: financial assets: baseline cohort

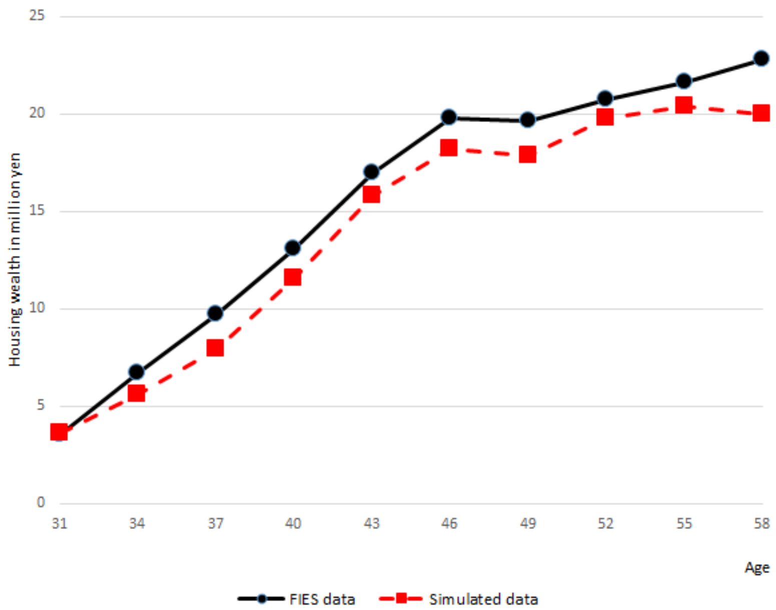


Figure 15 (B). Model fit: housing wealth: baseline cohort

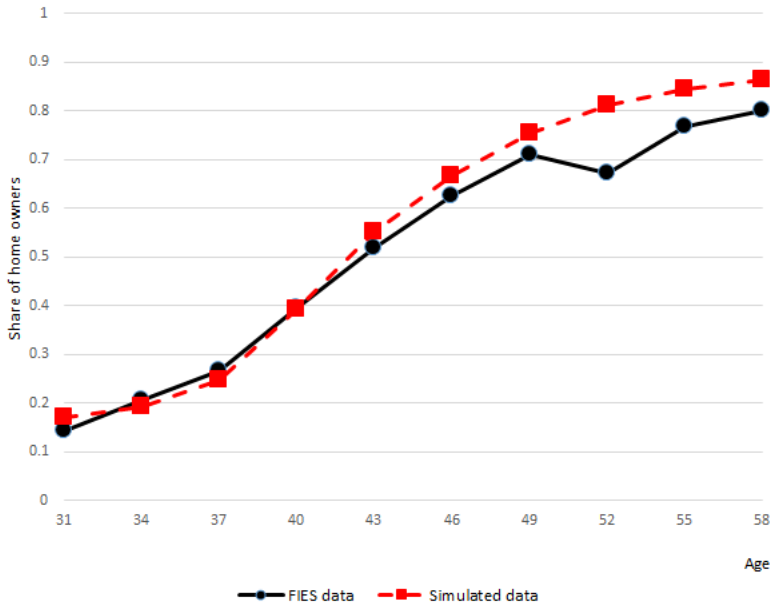


Figure 15 (C). Model fit: homeownership rates: baseline cohort

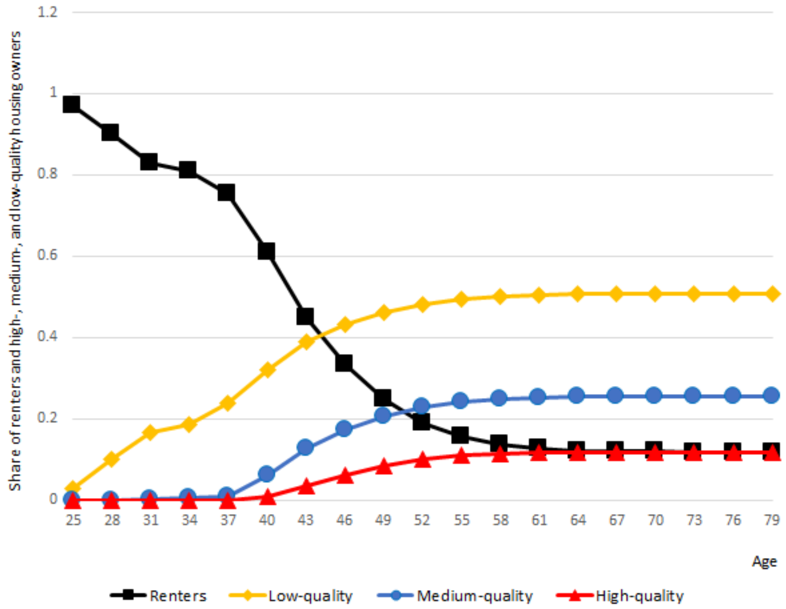


Figure 16. Predicted share of renters and homeowners (by quality of housing)

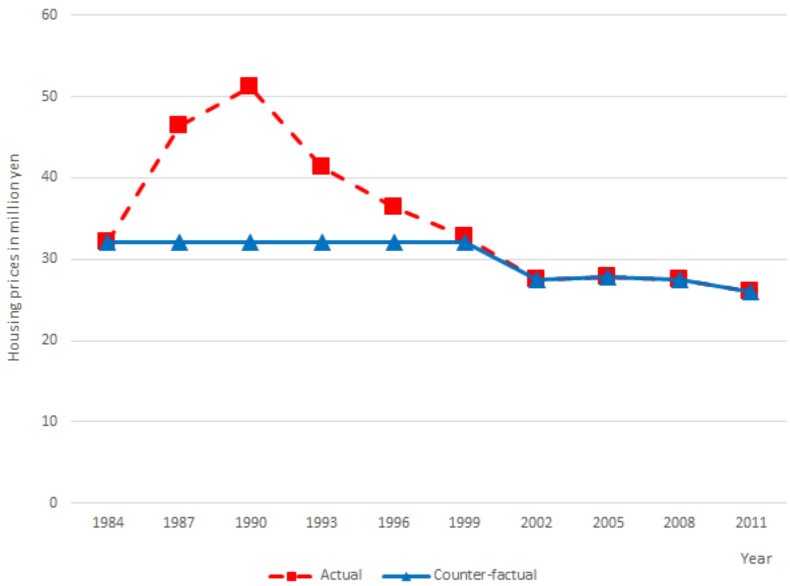


Figure 17. Actual and counterfactual price of medium-quality housing

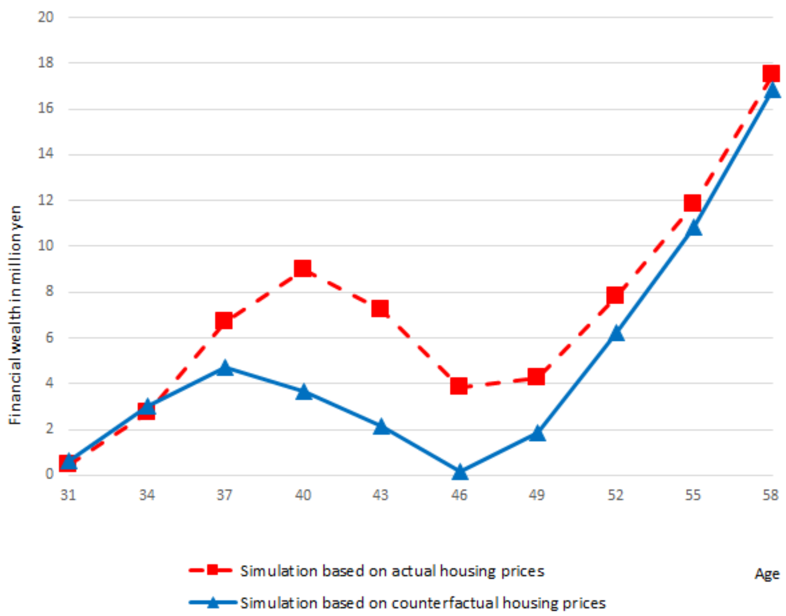


Figure 18 (A). Counterfactual simulation: financial assets

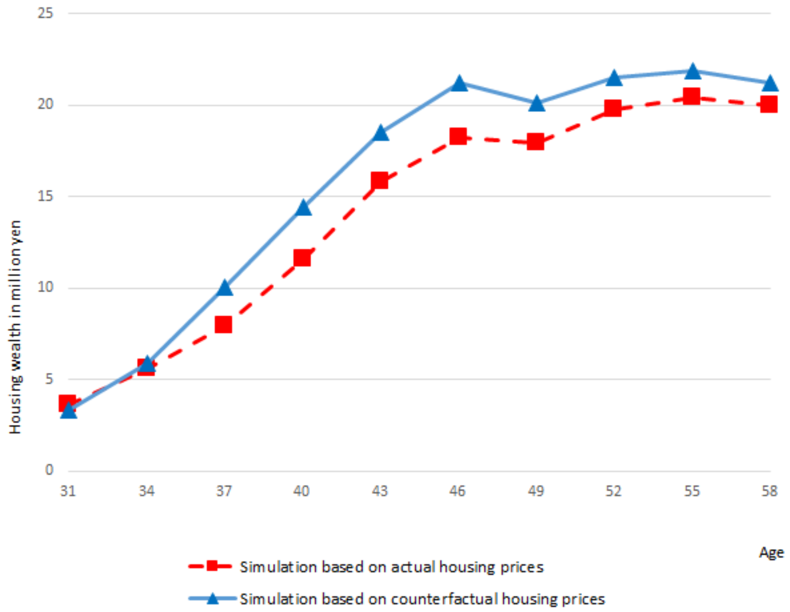


Figure 18 (B). Counterfactual simulation: housing wealth

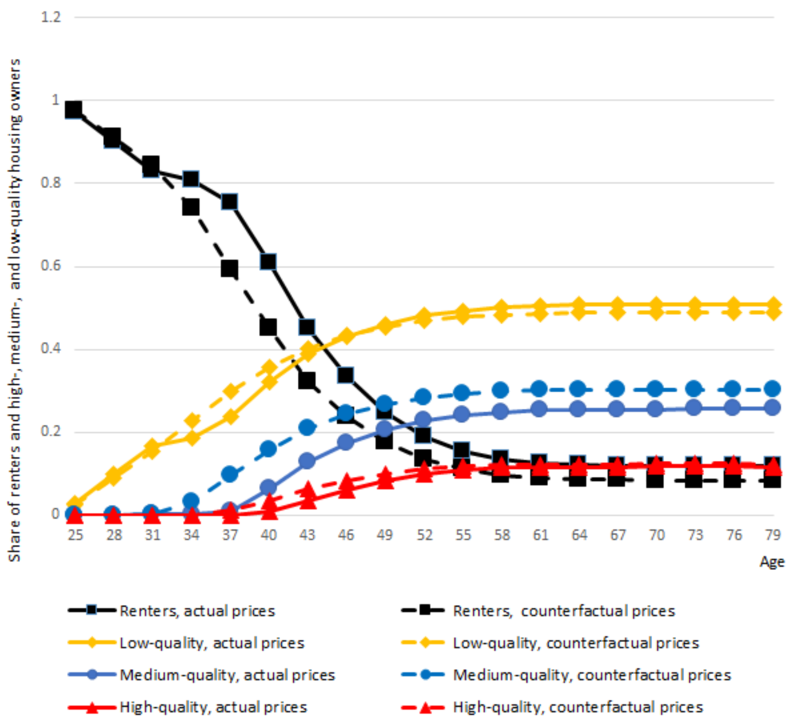


Figure 18 (C). Counterfactual simulation: share of renters and homeowners

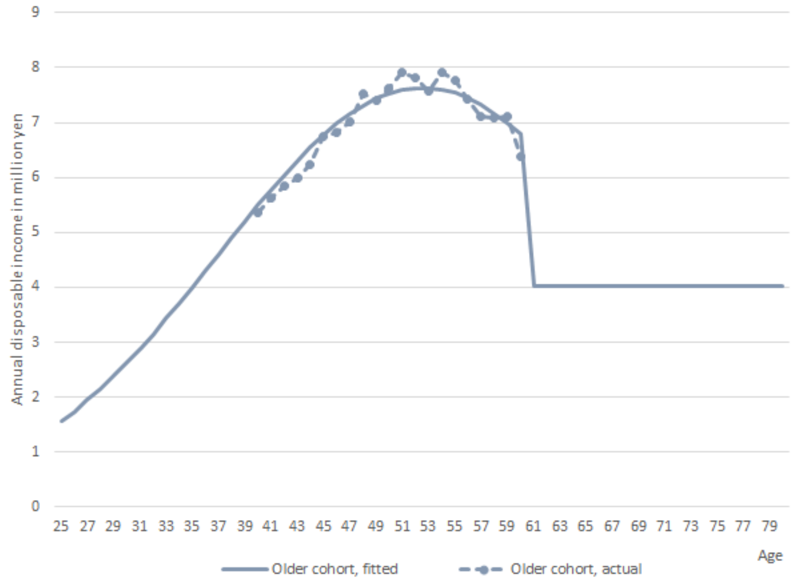


Figure 19 (A). Model fit of household income function of the cohort born in 1941–45

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

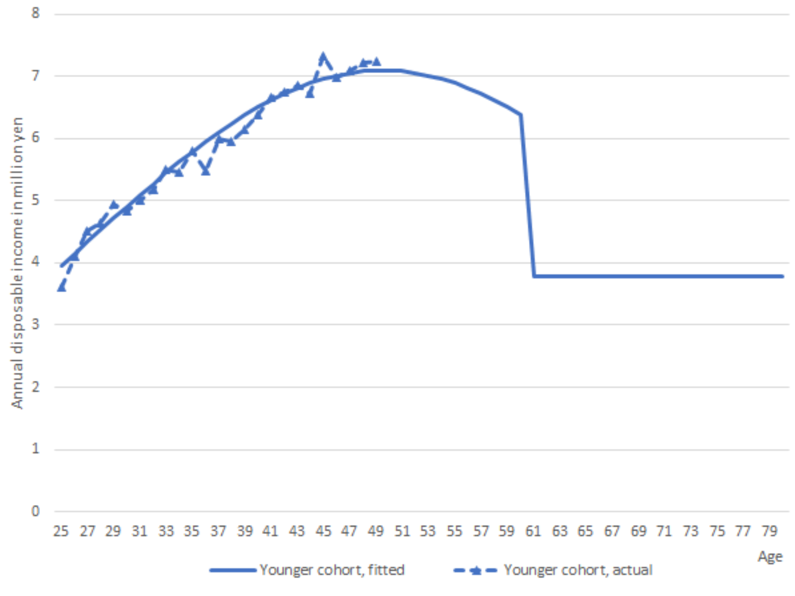


Figure 19 (B). Model fit of household income function of the cohort born in 1961–65

Source: Family Income and Expenditure Survey, Statistics Bureau, Ministry of Internal Affairs and Communications.

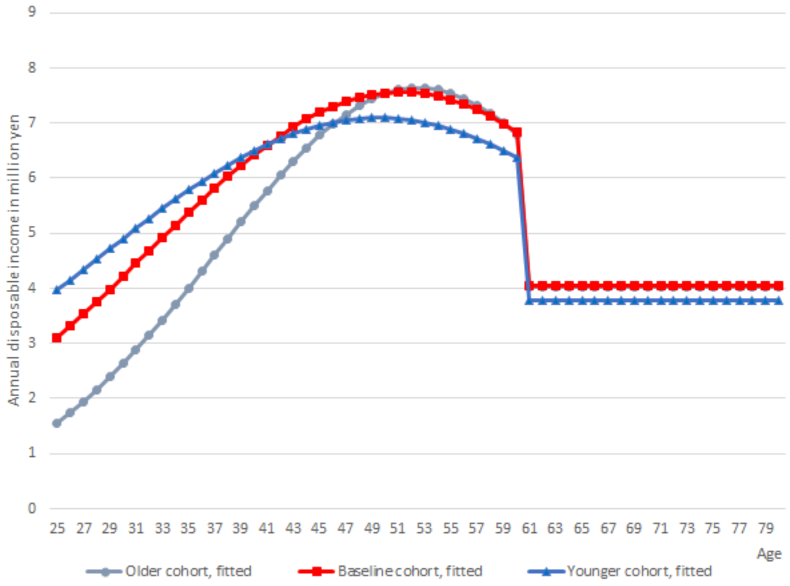


Figure 20. Household income functions across cohorts

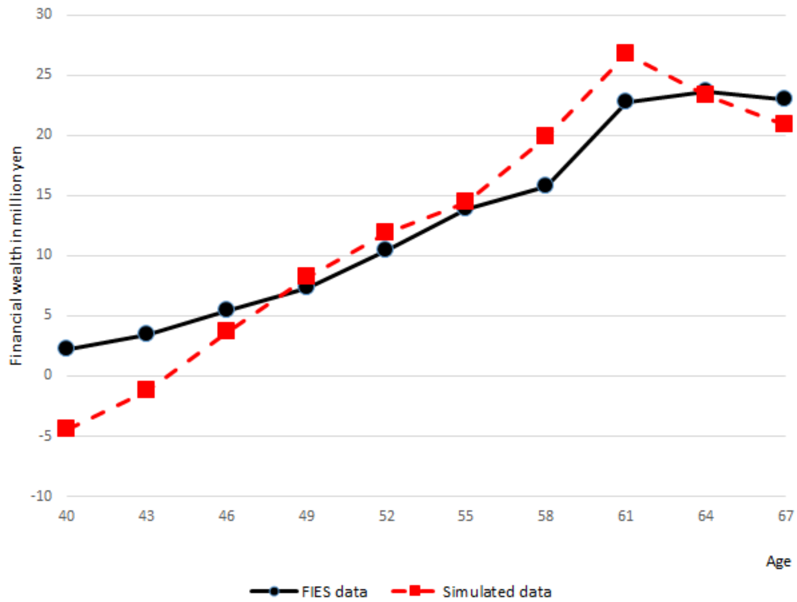


Figure 21 (A). Model fit: financial assets: older cohort

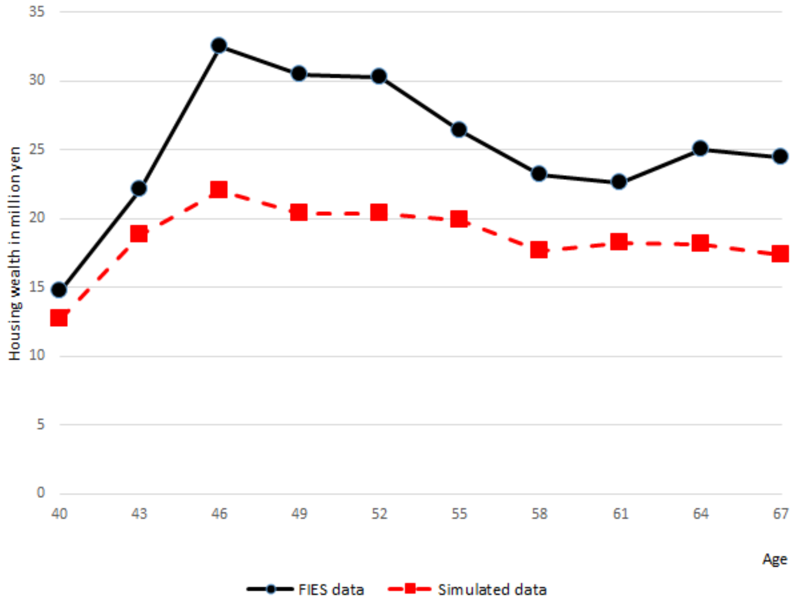


Figure 21 (B). Model fit: housing wealth: older cohort

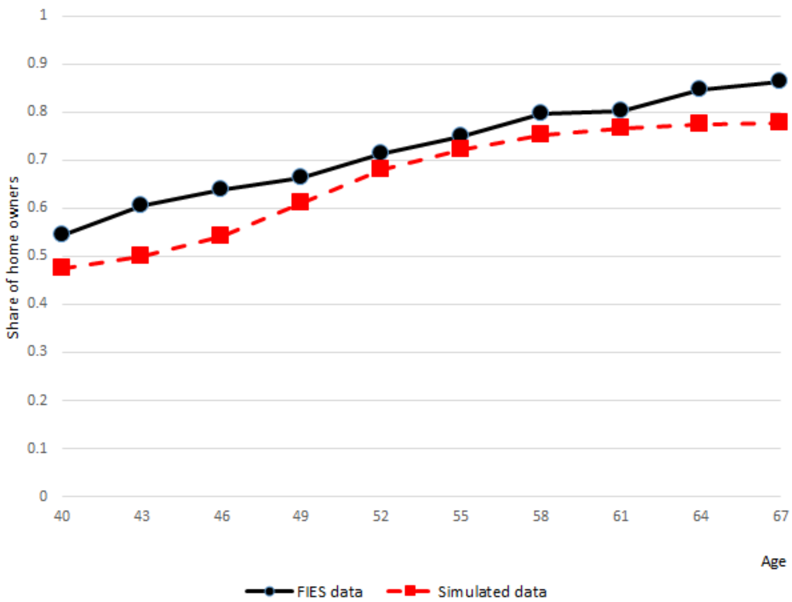


Figure 21 (C). Model fit: homeownership rates: older cohort

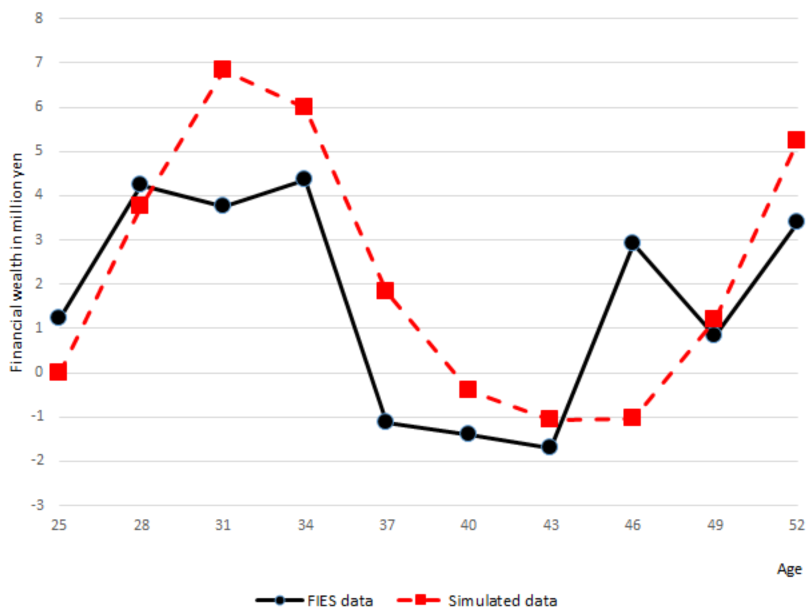


Figure 22 (A). Model fit: financial assets: younger cohort

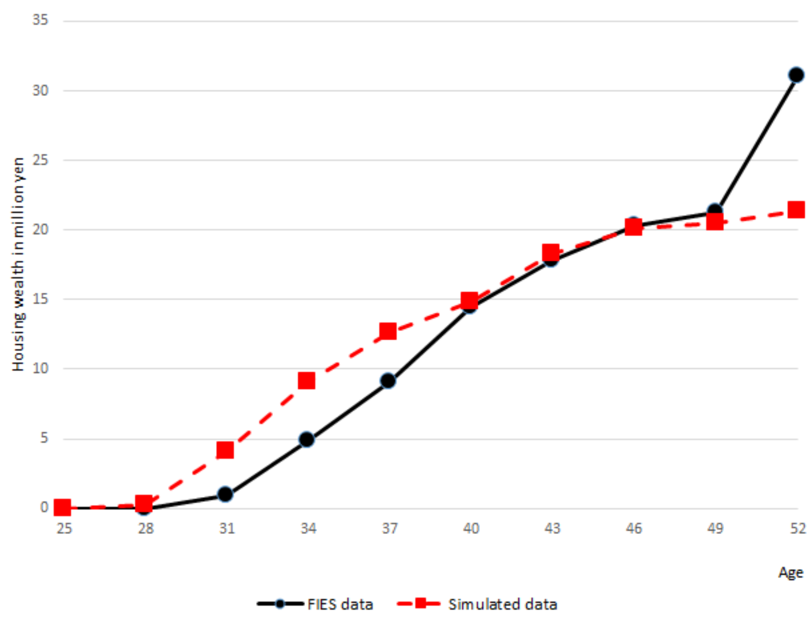


Figure 22 (B). Model fit: housing wealth: younger cohort

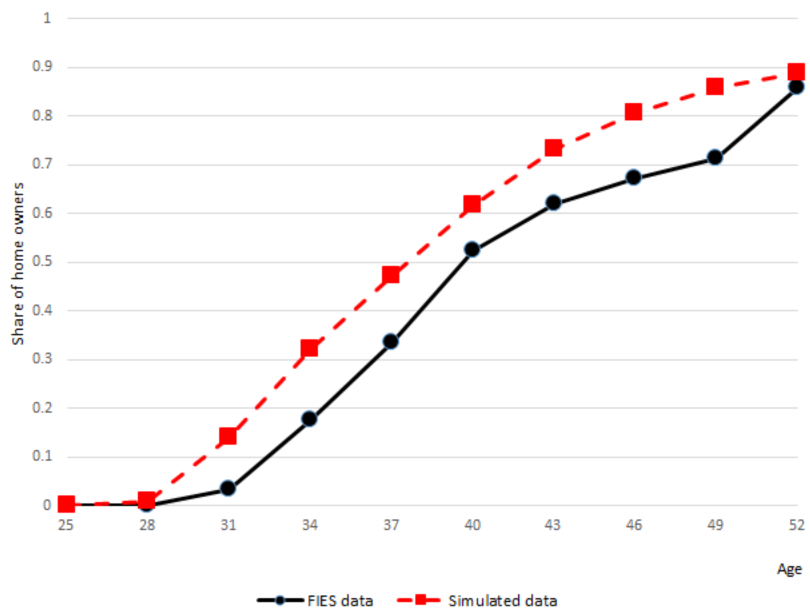


Figure 22 (C). Model fit: homeownership rates: younger cohort

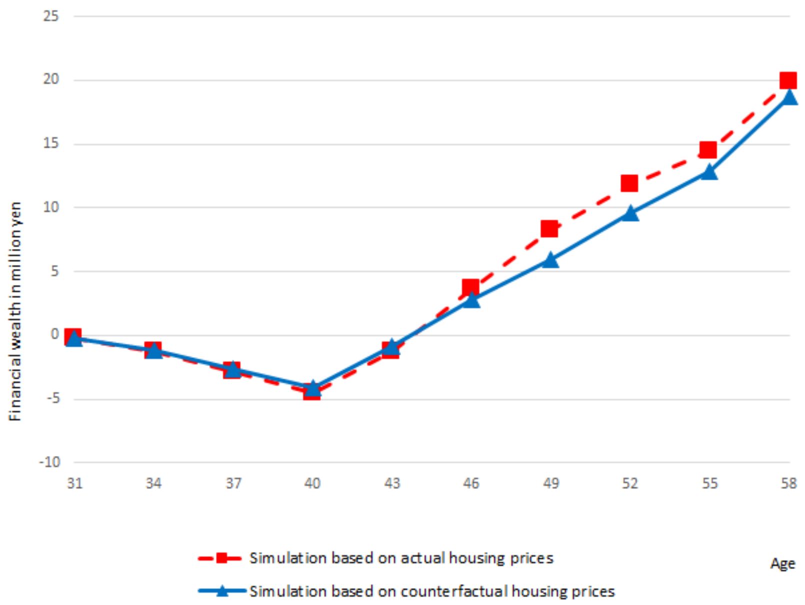


Figure 23 (A). Impact of housing price bubble on older cohort's financial assets

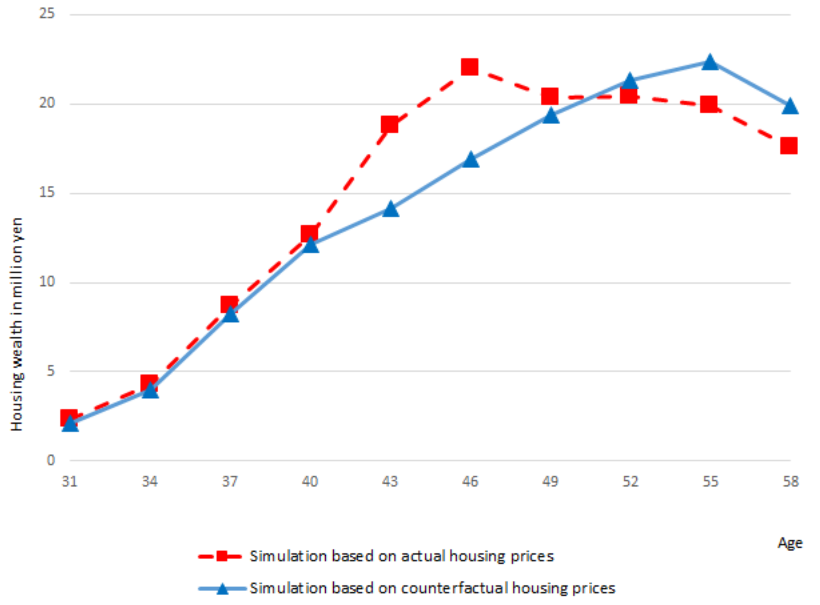


Figure 23 (B). Impact of housing price bubble on older cohort's housing assets

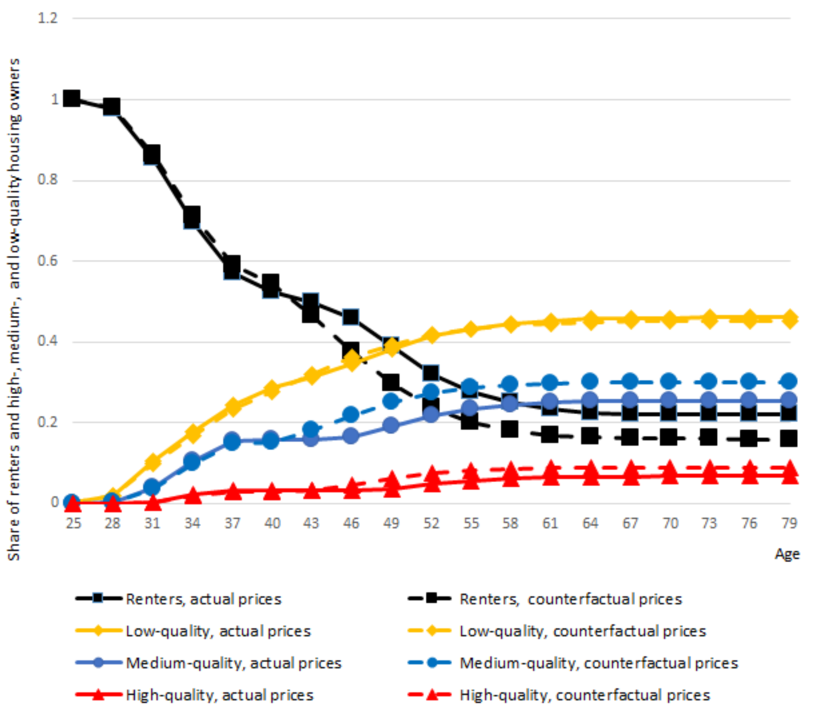


Figure 23 (C). Impact of housing price bubble on older cohort's housing shares

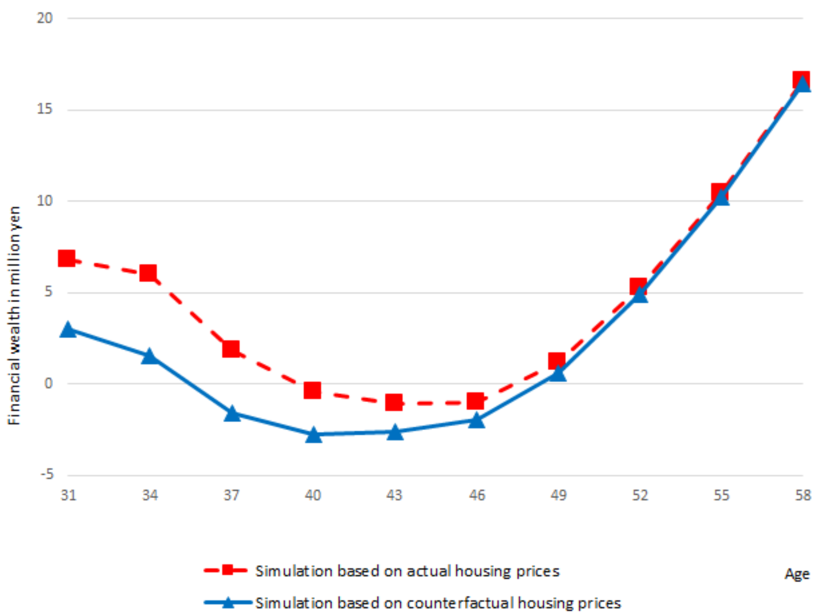


Figure 24 (A). Impact of housing price bubble on younger cohort’s financial assets

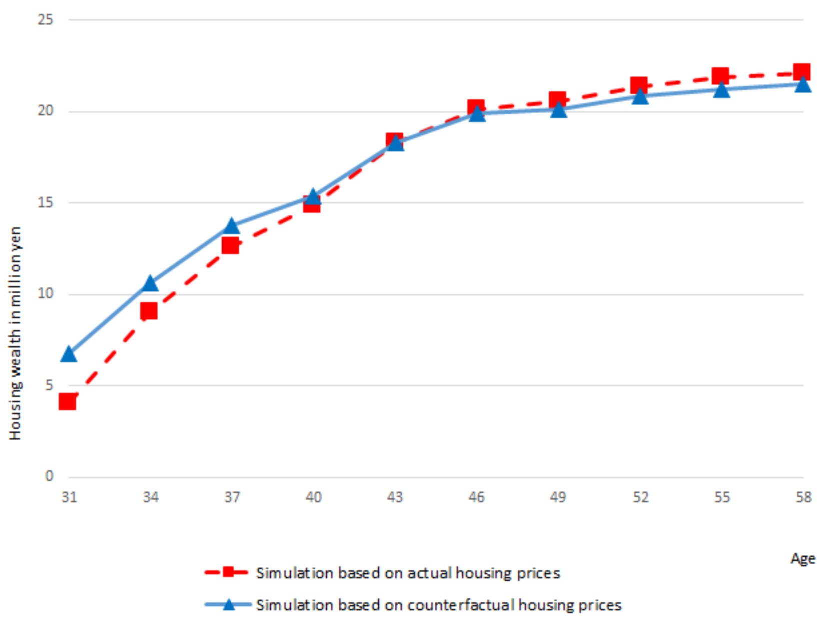


Figure 24 (B). Impact of housing price bubble on younger cohort’s housing assets

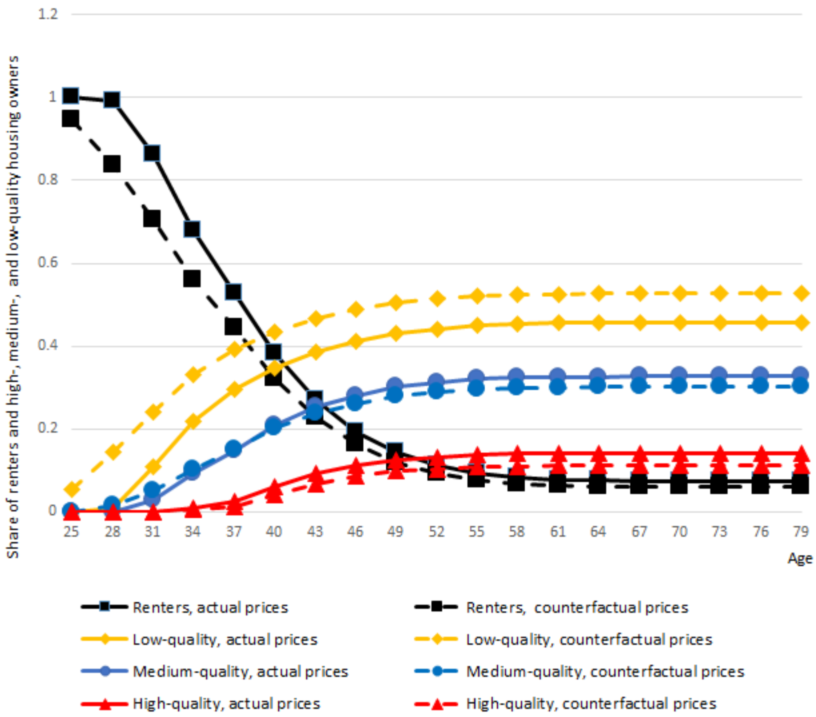


Figure 24 (C). Impact of housing price bubble on younger cohort's housing shares