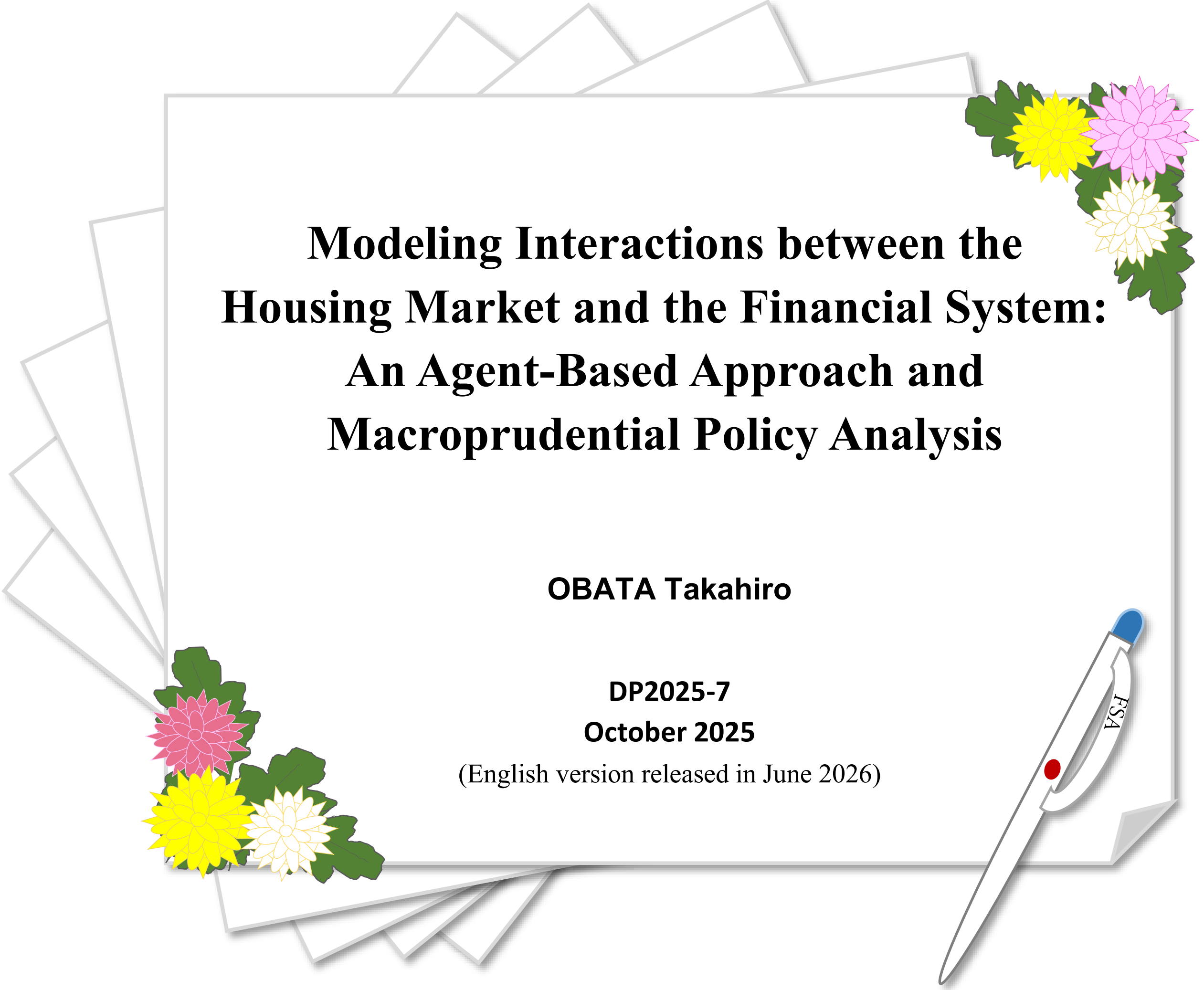
Financial Services Agency

Discussion Paper Series



Modeling Interactions between the Housing Market and the Financial System: An Agent-Based Approach and Macroprudential Policy Analysis

OBATA Takahiro

DP2025-7
October 2025
(English version released in June 2026)

Financial Research Center (FSA Institute)
Financial Services Agency
Government of Japan
3-2-1 Kasumigaseki, Chiyoda-ku, Tokyo 100-8967, Japan

You can download this and other papers at the FSA Institute's website:

https://www.fsa.go.jp/frtc/english/index.html

Do not reprint or reproduce without permission.

The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Financial Services Agency or the FSA Institute.

<FSA Institute Discussion Paper Series DP2025-7 (2025)>

Modeling Interactions between the Housing Market and the Financial System: An Agent-Based Approach and Macroprudential Policy Analysis

OBATA Takahiro[*]

Abstract

Following the Bank of Japan's decision to end its negative interest rate policy in March 2024, Japanese interest rates, which had remained stable at low levels for an extended period, have begun to trend upward. The housing market is one of the markets significantly affected by rising interest rates. While macroprudential regulations are in place to mitigate the adverse effects of rising interest rates on mortgage borrowers in the housing market, it has been difficult to assess their effectiveness empirically in Japan due to the prolonged period of stable, low interest rates. Therefore, this paper develops an analytical framework for the Japanese housing market based on an agent-based model (ABM) and analyzes the impact and effects of regulations on housing-related lending through simulations under rising interest rate scenarios. Specifically, this paper aims at developing a model of the housing market in Tokyo, where housing transactions are particularly concentrated in Japan, and first constructs a baseline housing market ABM. The model is then calibrated, to the greatest extent possible, using relevant data on Tokyo to develop the analytical framework. Simulations are conducted under multiple rising interest rate scenarios to analyze the effects of policies that provide a grace period before mortgage payments actually increase, such as the "5-year rule" and "125% rule". While some of the analytical results confirmed the effectiveness of these policies, challenges remain in the analytical model and methodology.

Keywords: housing market, macroprudential policy analysis, agent-based model.

---

[*] Lecturer, Faculty of Economics, Daito Bunka University (Associate Research Fellow, Financial Research Center)
The author is grateful for helpful comments by MIYAMOTO Takao of the Financial Services Agency.
The views expressed here are those of the author and do not reflect the views of the FSA, the Financial Research Center, or affiliated institutions.

1. Introduction

Following the Bank of Japan’s decision to increase flexibility in its yield curve control policy in July 2023 and to end its negative interest rate policy in March 2024, domestic long-term interest rates have been rising continuously for the first time in about 20 years, and further increase in interest rates is expected in the future. One of the markets significantly affected by rising interest rates is the housing market. Since housing-related loans account for a significant portion of bank lending, and housing-related debt constitutes a major share of household debt, interest rate fluctuations have a substantial impact on the economy through the housing market. Consequently, research into various regulations that could mitigate these effects is crucial.

In this study, we construct an analytical model using an Agent-Based Model (ABM). ABM is a research methodology that aims to elucidate the complex behavior of a macro system by the bottom-up simulation of agents who act based on simple rules. It does this by creating an artificial society composed of autonomous agents and analyzing the emergent phenomena that arise from interactions between agents and between agents and the environment. One of the key features of ABMs is their modeling flexibility. In the context of economic modeling, this allows for the easy incorporation of bounded rationality and heterogeneity among agents. Households, which are core participants in the housing market, exhibit diversity in terms of income and investment preferences. Figure 1 shows the distribution of households based on the Household Survey, while Figure 2 presents the results of a questionnaire on criteria for selecting financial products surveyed on households in Japan with financial assets. These data confirm the diversity of households. Furthermore, no two homes traded in the housing market are identical. Maintaining the diversity of both the homes being traded and the market participants is considered important. In this regard, ABM allows for flexible model specification, making it an effective analytical method.

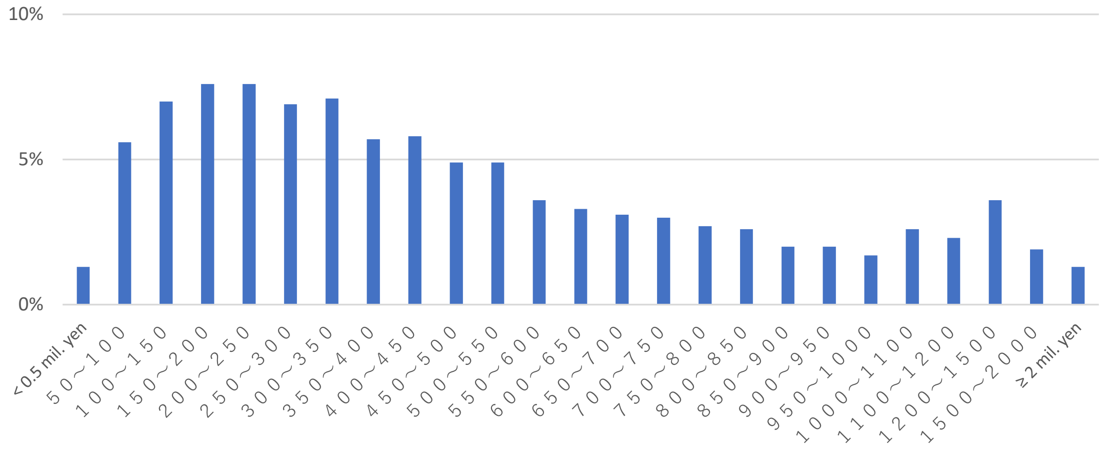


Figure 1: Relative Frequency Distribution of Households by Income Class

(Source) 2023 Basic Survey on National Living Conditions

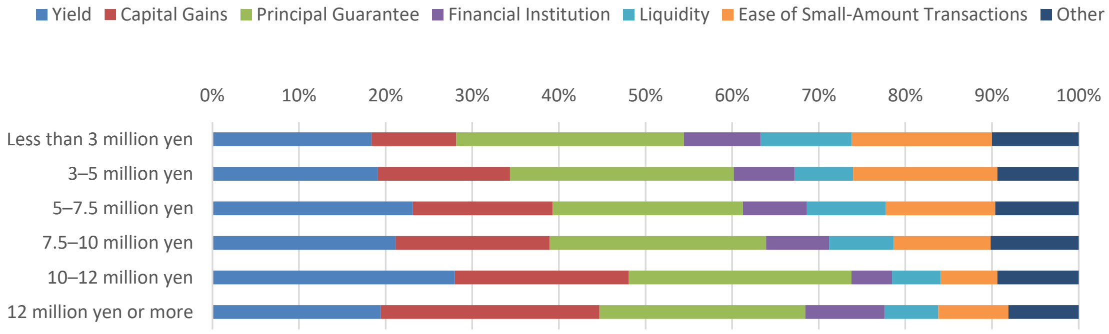


Figure 2: Criteria for Selecting Financial Products (Households Holding Financial Assets)

(Source) Public Opinion Survey on Household Financial Behavior [Households with Two or More Members] (2023)

ABMs that have been constructed for housing market analysis can be broadly classified, based on their model components, into macroeconomic ABMs that encompass the major economic agents and sector-specific ABMs that focus solely on agents closely related to the housing market. The former approach has advantages such as the ability to endogenously create economic conditions and to depict interactions between agents more precisely, but its model tends to be larger, making model construction and execution more difficult. As for the latter approach, it cannot account for interactions with areas outside the model's scope and requires an increase in exogenously specified factors, but it has advantages such as the ability to refine the model more easily by narrowing the scope of the analysis. In this study, as a starting point, we first constructed a relatively small-scale, sector-specific ABM. The housing market ABM we constructed is one modeling Tokyo, which has the most active housing transactions in Japan. We then utilized this model to analyze macroprudential regulations related to the housing market, specifically the "5-year rule" and "125% rule," which are considered regulations distinct to Japan's housing market. In the analysis, recognizing that both rules are intended to mitigate the impact of rising interest rates, we conducted simulations based on rising interest rate scenarios in addition to baseline simulations to analyze the effectiveness of the regulations. Some of the analyses confirmed that these rules are effective.

The structure of this paper is as follows. Chapter 2 introduces prior research that has utilized ABMs for housing market analysis. Chapter 3 explains the mechanism of the model constructed in this paper. Note that details of the model, such as model parameters, are provided in the Appendix; please refer to it as appropriate. Chapter 4 confirms the results of simulations run using the constructed model and verifies the validity of the model. Chapter 5 analyzes macroprudential regulations in the housing market through simulations based on rising interest rate scenarios. Chapter 6 is the conclusion, and Chapter 7 is the Appendix.

2. Previous Research

This chapter reviews major studies that have utilized ABMs for housing market analysis.

Geanakoplos et al. (2012) constructed a housing market-specific ABM based on housing-related and demographic data from Washington, D.C., to analyze the factors influencing housing price fluctuations. Through model simulations, they confirmed that changes in the loan-to-value (LTV) ratio were the primary cause of sharp fluctuations in housing prices and that housing prices would stabilize if the LTV ratio were fixed. Axtell et al. (2014) also focused on the housing market of Washington, D.C., refining household expenditure and purchasing behavior. They constructed a housing market ABM that is scaled 10 to 1 relative to the actual number of households and dwellings, and confirmed that keeping the LTV ratio low could curb fluctuations in housing prices. Baptista et al. (2016) conducted a study analyzing the impact of macroprudential policies on the UK housing market in collaboration with staff from the Bank of England. Since the model by Baptista et al. (2016) serves as the foundation for the model constructed in this paper, we describe its structure in some detail. This model consists of three types of agents: households, banks (mortgage lenders), and the central bank. Households are further subdivided into four categories: renters, first-time homebuyers, homeowners, and buy-to-let (BTL) investors (who own non-residential properties for rental income). Each household possesses attributes such as age, income, and debt levels, and these values vary from household to household. Households borrow mortgages from banks when purchasing homes. The mortgage market is subject to regulation through macroprudential policies implemented by the central bank. Furthermore, as a housing transaction mechanism, the model incorporates a double-auction system in which multiple sellers and buyers each propose their desired prices, and a transaction is concluded if their terms match. The analysis found that an increase in the proportion of BTL investors leads to greater volatility in housing prices, and that introducing loan-to-income (LTI) regulations can help curb housing price volatility. Carro et al. (2023) refined the model proposed by Baptista et al. (2016) by incorporating a segmentation of buyers' evaluation criteria in the transaction market (e.g., housing quality and price for homebuyers, rental yield for rental property buyers) and introducing a dynamic rental market, and analyzed the effects of LTV and LTI regulations.

3. Model

This chapter describes the housing market ABM (hereinafter referred to as "this model") that we have developed. The model parameters were set based on the housing market in Tokyo. Details regarding the model parameters and other components are explained in the Supplementary Notes; refer to them as appropriate. This model is based on the model proposed by Baptista et al. (2016) and its improved version proposed by Carro et al. (2023), and the model descriptions in those papers are also useful references.

This model includes three types of agents: (i) households, (ii) commercial banks, and (iii) the central bank. Although individual housing units are not decision-making entities, they are treated as agents in this paper. The number of agents comprises 5,000 households (note that this number fluctuates slightly during the simulation due to deaths), one commercial bank, one central bank, and 5,628 housing units.[1] Among these, households are the primary agents, interacting with other households through the purchase, sale, and rental of housing. They also interact with commercial banks through mortgage loans. The commercial bank manages mortgage loan screening and supply, as well as adjustments to loan interest rates in response to supply and demand. In this model, the central bank is solely responsible for setting the policy interest rate. Housing units possess a quality that represents their attractiveness, and this quality remains constant throughout the simulation (i.e., housing quality does not deteriorate over time). The number of housing units also remains constant throughout the simulation. Regarding the assumption of constant quality, this setting is adopted from models in prior research that served as a reference. Furthermore, in the Tokyo housing market that this model assumes, land accounts for a significant portion of housing value relative to buildings, and since housing size and location are the primary components of housing value, we determined that the assumption of constant quality is appropriate for this model.

This model incorporates two types of transaction markets: the home sales market and the rental market. Both markets have the same order processing procedures and employ a double-auction system. Each household, as a market participant, possesses one of three residential status attributes—homeownership, rental, or social (defined below)—depending on their housing situation.[2] In addition, a certain proportion of households possess the BTL attribute.[3] “Social” represents housing conditions other than the two types—homeownership and renting—that are the focus of this model; it refers to temporary, rent-free housing while searching for a home to purchase or rent. Specifically, this includes living with parents, living outside a home, and other forms of social assistance. It is important to note that households never voluntarily choose the “social” category; rather, it is assigned to them when they are unable to secure any other form of housing. The BTL attribute indicates whether a household can own rental housing in addition to its primary residence. The transaction markets in which a household can participate and the orders it can place vary depending on the household’s housing status and BTL attribute.

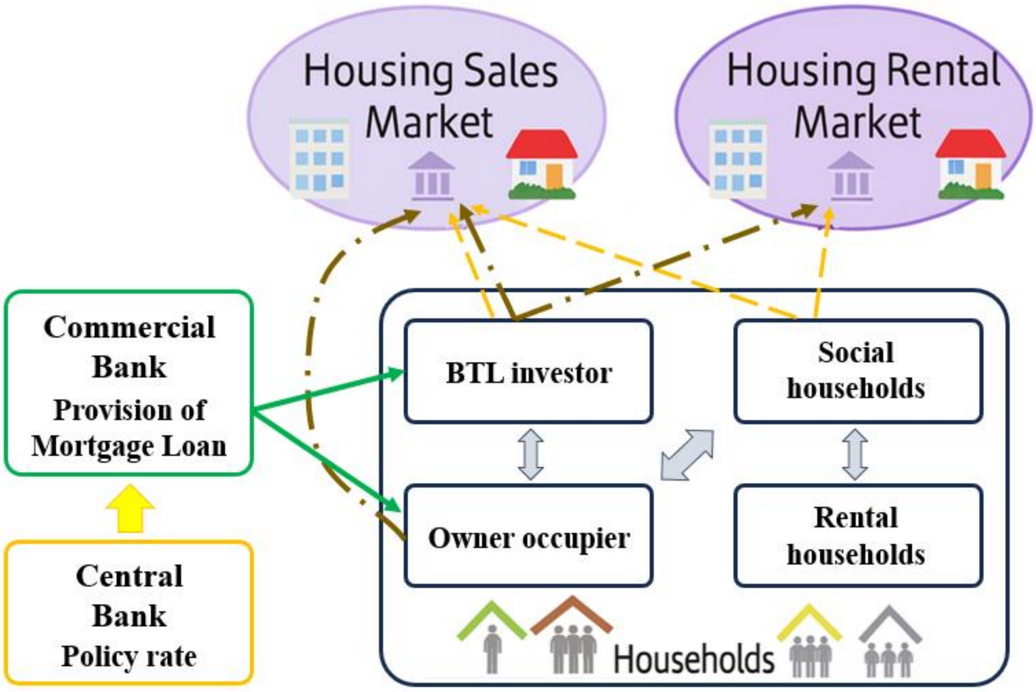
Figure 3 illustrates the overall structure of the model described thus far. The simulation process flow of this model, as well as explanations of each agent and each transaction market, is provided in the following sections. For details on each part of the model, please also refer to the supplementary notes.

---

[1] The number of housings is set by referring to data in Table 1 of the Housing and Land Survey on Tokyo for 2023. Specifically, the number of total housings, total households, persons in the households, housing for each household, and persons in each household.

[2] The initial settings for homeownership and renting among household agents were set to be roughly 6:4. This was based on the ratio of homeownership to renting for households in Tokyo.

[3] The probability of the occurrence of BTL flag was set based on data from Carro et al. (2023) and Table 9 of the 2023 Housing and Land Statistical Survey regarding ownership status of housing other than the current residence.



Households that own multiple properties (including their own home) are classified as "BTL investors," while those owning only their residence are categorized as "owner-occupier households." The residential status of BTL investors corresponds to owner-occupier households.

Figure 3: Overview of the Model

3.1 The Flow of Processing of a Single Step in This Model

This model initializes the model settings at the start of the simulation and then proceeds by iterating steps, with each step representing one month in the real world. During the initialization of model settings, attribute values are assigned to individual agents, such as the age of households and housing quality. The specific details of this process are explained in the following sections of this chapter and in the appendix. The flow of processing within a single step involves executing the sequence of events shown in Table 1.

Table 1: Flow of events within a single step of the model simulation

Step	Event Description
1	Update of household demographics - For each household, advance the ages and determine deaths. - If a household dies, generate a new household that succeeds it and perform inheritance processing.
2	Update of household income, assets, and expenditures - Update rental income, housing-related expenses, disposable income, financial assets, etc., for each active household. - If there is an age change in 10-year increments, update income amounts and target savings amounts.
3	Update of mortgage repayment schedule and lease term - Update the remaining number of mortgage payments and the rental period.
4	Household bankruptcy processing - Identify households in financial distress and process them accordingly.
5	Review of variable-rate mortgages - Review interest rates on variable-rate mortgages every six months (6 steps). - The review applies to variable-rate mortgages with remaining terms of 6 steps or more.
6	Household decisions on home purchase, sale, and rental - For each active household, decisions regarding home purchase or rental are made, and orders are placed in the housing or rental market.
7	Matching of orders in the sales market - Match orders and process transactions in the sales market. - Organize unmatched orders.
8	Matching of orders in the rental market - In the rental market, as in the sales market, perform transaction processing. - Process unmatched orders.
9	Updating Housing Market-Related Indices - Update housing price indices, average prices by housing quality, and related metrics.
10	Update of bank interest rate spreads - Update bank mortgage interest rate spreads in response to mortgage demand.
11	Aggregation of various indicators - Aggregate various indicators, such as the age distribution and income distribution of household agents, as well as loan indicators like LTV.

3.2 Households

3.2.1 Household Income and Expenditures

The primary attributes of a household agent include age, income percentile, and a BTL flag indicating whether the agent owns rental property. These three attributes are values probabilistically assigned when a new household agent is generated and remain constant until the agent dies. Age ranges from 20 to 95 and is assigned such that it approximates the distribution of real-world data[4] when a new household agent is created. The age of each household increases by 1/12 of a year with each simulation step. Income percentiles are assigned from a uniform distribution between 0 and 1, and annual income is set according to the income percentile based on the frequency distribution table[5] prepared for each age group in 10-year increments, ranging from 1 million yen to 30 million yen. In most cases, annual income of agents increases until the age of 50s, begins to decline in their 60s, and drops to an amount reflecting a pension-based lifestyle from their 70s onward. As this setting method indicates, the annual income of household agents changes every 10 years. The probability that the BTL flag is assigned increases with higher annual income; it is assigned when a new agent is generated and remains constant thereafter.

The calculation of total income (which includes rental income) and the amount after deducting taxes (referred to as "net income" in this paper) based on annual income is as follows.

$$\text{Total Income} = \frac{\text{Annual Income}}{12} + \text{Monthly Rental Income} \tag{1}$$

$$\text{Net Income} = \max\left[\left(\frac{\text{AI}}{12} + \text{MRI}\right) \times (1 - \text{IT}), \text{GIS}\right] \times (1 - \text{ENCFR}) \tag{2}$$

AI: annual income, MRI: monthly rental income, IT: income tax, GIS: government income support.

Here, income tax is set at a flat rate of 20%,[6] and government income support is set at 100,000 yen per month.[7] Essential non-housing consumption fraction rate (ENCFR) represents the proportion of essential non-housing consumption and is set at 0.66.[8]

$$\text{Disposable Income} = \text{Net Income} - \text{Housing Costs} \tag{3}$$

Housing costs refer to mortgage payments or rent.

$$\text{Discretionary Consumption} = \max\left[0, \min\left\{\text{DI} + \frac{\text{Savings} - \text{Target Savings}}{2}, \text{DI} \times 0.17\right\}\right] \tag{4}$$

---

[4] The age distribution was set based on the "2020 Census of Japan," Table 43-2 of the Basic Complete Tabulation on Population and Households, data for region 13000_Tokyo Metropolis.

[5] The annual income distribution table was set based on data from the 2022 Comprehensive Survey of Living Conditions: Table 27 on "Income and Savings," Number of Households in Urban Areas (relative to 10,000 households) and Table 26, Number of Households, by Head of Household Age (10-year age groups) and Income Bracket."

[6] The income tax rate applied is the rate corresponding to the average annual income of households in Japan, which is approximately 6 million yen.

[7] While the actual value of monthly public welfare benefit in Japan is 150,000 yen, it has been set at 100,000 yen in this model to balance with the rent settings.

[8] The ratio was set with reference to the breakdown of average household consumption expenditure in Table 2-4 of the Household Income and Expenditure Survey.

Here, DI denotes disposable income. The target amount of savings is determined by annual income and the propensity to save. The propensity to save is set according to a uniform distribution between [0, 1].

$$\text{Savings\_t} = \text{Savings\_(t} - 1) + \text{Disposable Income} - \text{Discretionary Consumption} \tag{5}$$

The amount remaining after subtracting discretionary consumption from disposable income becomes the savings amount for each step.

The amount of savings affects the setting of the down payment when purchasing a home. Note that the ultimate goal of consumption by the household agent in this model is to determine the amount allocated to savings.

3.2.2 Household Decision-Making

Household agents make housing-related decisions based on their housing status. There are three types of housing status: social, rental, and homeownership.

Households with a “social” housing status make decisions regarding whether to rent or purchase a home in order to secure housing. The decision-making process is as follows:

(i) Calculate the desired home purchase price $p'_{desired}$.

$$p_{desired} = \min(\alpha y^{\beta} e^{\varepsilon}, pmax) \tag{6}$$

$$p'_{desired} = \min\,(p_{desired}, \overline{p_{Qmax}}) \tag{7}$$

Here, y is total income; α and β are model parameters for adjusting the desired home purchase price; ε is a random number following a normal distribution; $\varepsilon \sim N(-0.0177,\ 0.4104)$ and $pmax$ represent the maximum amount that can be borrowed; and $\overline{p_{Qmax}}$ represents the average sales price of the highest-quality housing unit.

(ii) Obtain the housing quality Q of the target unit (housing quality is represented by an integer from 1 to 20, where a higher number indicates higher quality).

(iii) For a dwelling with housing quality Q, estimate the following two types of housing costs.

$$\text{Rental Cost : } 12r_Q(1+\lambda) \tag{8}$$

Here, r_Q is the rent for a dwelling with quality Q. λ is a model parameter that adjusts the degree of preference for renting.

$$\text{Owning Cost : } 12m - p'_{desired}\, g \tag{9}$$

m represents monthly mortgage payment, and g is the household’s expectations of housing price appreciation adjusted based on the rate of change in the current housing price index relative to the index two years prior.

(iv) Decision to buy or rent a home based on the probability of home purchase P_{buy} using a sigmoid function.

$$P_{buy} = \sigma(\theta[r_Q(1+\lambda) - (12m - p'_{desired}\, g)]) \tag{10}$$

$\sigma(x)$ is the sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$, and θ is a model parameter for sensitivity adjustment.
(v) Place an order on the trading market according to the choice determined in (iv). The price of order is $p'_{desired}$ when home purchase is selected, and $r_{desired}$ when rental is selected.

$$r_{desired} = \min(\mu y^{\nu},\ Net\ income) \tag{11}$$

ν is a model parameter for adjusting the desired order price for renting

After completing steps (i) through (v) above and placing an order to purchase a home, if the order matches a home sale order in the housing market, the purchase is made entirely with cash if the purchase price is equal to or less than the savings balance; otherwise, the purchase is made using a mortgage and a down payment.

Next, consider households that are currently renting. These households do not make any decisions while they are renting, but once their rental contract expires and their housing status changes to "social," they make decision described above for the "social" housing status.

Finally, there are households with a "homeownership" housing status, but their decision-making process varies depending on whether they have BTL attributes. Households with a "homeownership" housing status and no BTL attributes will not purchase additional non-residential properties; therefore, they only make decisions regarding whether to sell their residential property (this decision corresponds to what is commonly referred to as "moving to a new home"). The decision to sell a residential property is based on the probability of selling a home once every 17 years. For households with BTL attributes (hereinafter referred to as BTL investors), decisions such as the purchase or sale of rental properties (non-residential properties) are made. Note that BTL investors do not sell residential properties. This is because the program becomes too complex if we attempt to model a state where a household owns rental properties but no residential property. When a BTL investor purchases a new rental property, they make decisions based on the expected yield V_{buy} of a home with the same quality as the property under consideration. The calculation formula for V_{buy} is as follows.

$$V_{buy} = \frac{1}{d_{min}}\{(\delta_i g + (1-\delta_i)\bar{s}) * p_{max} - 12m_{max}\} \tag{12}$$

Here, p_{max} is the maximum amount that can be borrowed through a mortgage, and d_{min} is the minimum down payment (10% of the loan amount for BTL investors). δ_i represents the ratio of rental yield and capital gains from price appreciation according to the investment type (see Table 2 for a list of investment types). g represents households' expectations of housing price appreciation, $\bar{s}$ represents the average rental yield for each quality level, and $12m_{max}$ represents the annual repayment value when an agent borrowed the maximum available mortgage amount.

Table 2: Overview of BTL Investor Types

Type	Overview	Proportion
Capital	Priority on capital gains from rising housing prices. Ratio of capital gains to rental yield = 90%:10%	36.15%
Mixed	Priority on both capital gains and rental yields. Ratio of capital gains to rental yield = 50%:50%	14.58%
Income	Priority on rental yield. Ratio of capital gains to rental yield = 10%:90%.	49.27%

The decision to place a bid on a new property is determined probabilistically using the following sigmoid function based on the expected yield V_{buy}.

$$P_{buy}^{BTL} = 1 - \left(1 - \sigma\left(\xi V_{buy}\right)\right)^{1/12} \tag{13}$$

Here, σ (x) denotes the sigmoid function $\sigma(x) = {}^{1}/_{(1 + \exp(-x))}$, and ξ represents the sensitivity adjustment parameter for the expected return in the order probability calculation.

As can be seen from Equations (12) and (13), whether a BTL investor purchases a new property depends on the level of the leveraged expected rate of return.

Regarding the sale of rental properties by BTL investors, decisions are made based on the investment return V_{sell} of the owned properties. The formula for V_{sell} is as follows.

$$V_{sell} = \frac{1}{k}\{(\delta_i g + (1 - \delta_i)s) * \overline{pQ} - 12m\} \tag{14}$$

Here, $\overline{p_Q}$ is the average of transaction prices exponentially smoothed for homes of quality Q over time; k is the equity value of the owned property (the average transaction price for homes of the same quality minus the remaining mortgage principal); and δ_i is the ratio of rental yield to price appreciation rate for the given investment type. g represents expected housing price appreciation; s is the real rental yield of the owned property; and $12m$ represents the annual mortgage repayment amount.

The decision to place a sell order, similar to the decision to purchase a new property, utilizes a sigmoid function.

$$P_{sell}^{BTL} = 1 - \sigma(\xi V_{sell})^{1/12} \tag{15}$$

The expressions σ (x) and ξ are the same as those in Equation (13) used for the decision to purchase a new property. Note that decisions to sell rental properties are made only for properties that are not currently under lease. If the property is retained rather than sold, it is re-listed on the rental market.

The desired rental price r_s when a BTL investor lists a property on the rental market is calculated using the following formula:

$$r_s = \overline{rQ} * \eta_{rent} \tag{16}$$

Here, $\overline{rQ}$ represents the exponential moving average of rental rates for housing of quality Q, and η_{rent} is a random variable representing the markup rate.

If a rental property is vacant, the rent is reduced with a given probability.

3.3 Commercial Banks and the Central Bank

The commercial bank agent offers two types of mortgages to household agents: mortgage with principal and interest repayment plan for the purchase of residential properties, and that with an interest-only repayment plan for BTL investors purchasing rental properties. The maximum term for both types of mortgages is 35 years, and the maturity date cannot be set later than the point at which the household agent reaches the age of 65. Interest rate types include fixed rate and variable rates. For the purposes of analysis in this model, the simulation settings were configured such that either a variable rate or a fixed rate is applied uniformly to all mortgages with principal and interest repayment plans. For interest-only repayment mortgages intended for BTL investors purchasing rental properties, only fixed rates are used. Therefore, unlike in the real world, households cannot choose between variable and fixed rates.

The maximum available mortgage amount is calculated by the commercial bank using indicators such as LTV. In the various calculation formulas, the common symbols are as follow: q represents the maximum available mortgage amount; w represents each household's savings; and y represents annual income. First, LTV is a restriction on how many times the savings amount a mortgage can be granted, and it is calculated using the following formula:

$$q \leq \frac{\varGamma_i}{1 - \varGamma_i} w \tag{17}$$

Here, the value of $\varGamma_i$ varies depending on whether the household has a BTL attribute: it is 0.75 if the household has a BTL attribute and 0.90 if it does not. In other words, households with a BTL attribute can obtain a mortgage amount of up to three times their savings, while those without a BTL attribute can have up to nine times their savings.

Next, LTI is a restriction on the maximum amount of mortgage where up to what multiple of annual income y the household t can borrow, calculated using the following formula.

$$q \leq \varPhi_i * y \tag{18}$$

Here, the value of $\varPhi_i$ varies depending on whether it is a first-time home purchase or a subsequent purchase; it is 7.8 for a first-time purchase and 8.2 for all others.

Debt-service-to-income (DSTI) is a restriction on the ratio of the repayment amount to the income amount y, with the amount repaid calculated based on the principal and interest repayment method.

$$q \leq \varPsi * y \frac{1 - \left(1 + \frac{r}{12}\right)^{-n}}{r} \tag{19}$$

Here, n represents the number of months of mortgage repayment, and r represents the applicable mortgage interest rate. The value of Ψ is set at 0.4, which indicates that the annual mortgage repayment amount is kept within 40% of total income. Interest-coverage-ratio (ICR) is a requirement on safety margin restriction specifying how many times the rental income must exceed the interest payment amount, and is calculated using the following formula.

$$q \leq \frac{w}{\Omega \frac{r}{\bar{s}} - 1} \tag{20}$$

Here, $\bar{s}$ represents the average rental yield for housing of all quality. Ω is set at 1.25, meaning that if the rental yield is 1.25 times the mortgage interest rate or less, the maximum mortgage amount available will be less than the savings balance.

The parameter values for Γ, Φ, and others in the above restriction equations were based on general settings that are said to be used by actual financial institutions.

The four types of restrictions mentioned above do not apply to all mortgages. For mortgages with principal and interest repayments, the LTV, LTI, and DSTI restrictions are applied, while for interest-only mortgages, the LTV and ICR restrictions are applied. The actual mortgage amount is determined by taking the smaller of the applicant’s requested amount and the maximum amount calculated using the respective restriction formulas.

The mortgage interest rate is the sum of the policy rate decided by the central bank and the interest rate spread set by the commercial bank. The interest rate spread is designed to fluctuate in response to changes in total household demand for mortgages, and the initial value of the interest rate spread was set at 1.5%.

For variable-rate mortgages, the mortgage interest rate in effect at that point in time is applied every six steps, and the monthly repayment amount is adjusted accordingly. Interest rate adjustments are not made on a household-by-household basis; instead, they are applied uniformly to all households at the simulation steps corresponding to April and October. This reflects the fact that, in the real world, interest rate adjustments for variable-rate mortgages are typically applied uniformly across all households.

The central bank agent controls only the policy interest rate and plays a purely passive role in this model. The policy interest rate is set at 0.5% and remains constant throughout the simulation unless changed exogenously.

3.4 Housing

Housing units possess a quality attribute that represents their attractiveness. At the start of the simulation, each unit is assigned one of 20 quality levels, which remains constant throughout the simulation period. A higher numerical value indicates higher quality. While in reality housing attractiveness is assessed based on various factors such as building age, number of rooms, and transportation access, this model consolidates these into a single quality attribute. The number of housing units also remains constant throughout the simulation. In other words, within this model, no new housing is constructed, and no old housing is demolished.

3.5 Housing Sales Market and Housing Rental Market

This model features two types of trading markets: the housing sales market and the rental market. Both markets employ a double-auction system for order processing. Each household places orders (bids or offers) for housing sales or rentals in one of these markets based on the results of the housing-related decision-making process described earlier. To process the orders collected in the trading markets, a matching phase takes place first, followed by a selection phase. The order in which orders are processed in the trading markets is such that the housing sales market is processed first, followed by the rental market. The following explanation of the order processing flow uses the housing sales market as an example, but the flow for the rental market is largely the same. The difference is that in the matching phase of the rental market, there is no processing corresponding to buy orders for rental properties placed by BTL investors.

In the matching phase of the residential real estate market, the system selects a matching offer for each bid according to the following process. However, the criteria for selecting offers differ depending on whether the property in question is for owner-occupancy or rental.

<Matching Process for Bids on Residential Properties>

(i) Extract all offers that meet the following conditions

desired purchase price (bids) ≥ desired sale price (offers)

(ii) Among the offers extracted in step (i), the one with the highest quality is designated as the desired residential property quality.

(iii) Match with the offer that has the lowest asking price among those that meet the desired quality. If multiple offers match at this point, select one offer at random from among them.

<Matching Process for Bids on Rental Properties>

(i) Same process as for bids from households without BTL attributes

(ii) Match with the offer with the highest expected yield among the offers extracted in step ①. If there are multiple matching offers at this point, select one offer at random from among them.

Next, the selection phase follows. At the conclusion of the matching phase, it is possible that multiple bids have been matched to a single offer. For offers matched to multiple bids, the asking price set by the offer is slightly increased, and one bid is randomly selected from among those that meet the new asking price. If there are no bids that meet the adjusted asking price, one bid is randomly selected from among those that meet the original asking price (i.e., all matched bids). For offers with only one matched bid, that bid is selected as is. The household that submitted the bid selected during the selection phase is eligible to purchase the property.

If unmatched bids and offers remain after the above double-auction process, the process is repeated as long as further matches are possible. The double auction process stops when there is no longer a possibility of a match, such as when the desired purchase prices of all remaining bids fall below the lowest desired selling price of the remaining offers. For bids that did not match, the orders are withdrawn, and bidders must submit new bids in the next step. On the other hand, offers that did not match until the end of the process are pooled in the trading market and carried over to the next step. While in the pool, the asking prices of these offers are subject to probabilistic downward adjustments. Additionally, there are cases where a property that had an offer in the home sales market is re-listed in the rental market, or conversely, where an offer from the rental market is re-listed in the home sales market.

3.6 Inheritance and Bankruptcy Procedures

Households die probabilistically according to mortality rates set for each age group.[9] However, all household agents die upon reaching the age of 96. When a household agent dies, a new household agent who is the inheritor is generated, and the inheritance process is executed. During the inheritance process, the housing and savings held by the deceased household (the decedent) are inherited by the new household agent. While savings are inherited by the full amount, the number of homes that can be inherited is limited to two. If the decedent owned three or more homes, a fire sale is conducted to sell the homes, and the proceeds are transferred to the inheritor. In the fire sale, the sale price is set at 50% of the average market price for homes of the same quality as that being sold. The purchaser in the fire-sale process is randomly selected from households that have savings exceeding the sales price and are in a position to purchase a home. However, the system is configured to give priority to BTL investors if any are available. If any of the deceased's homes have outstanding mortgages, the system assumes that group insurance is applied, and all mortgage repayments are treated as fully settled.

Household bankruptcy is triggered when a household's savings balance becomes negative. Causes of a negative savings balance include cases where monthly housing-related expenses—such as mortgage payments or rent—exceeded net income, or where the principal repayment due at the end of a mortgage term exceeded the savings balance. For households that own homes, all properties with outstanding mortgages are sold through the fire sale process. If all owned properties are sold, the housing status of the bankrupt household is changed to "social." Furthermore, if the proceeds from the fire sale are insufficient to cover the negative savings balance, the savings balance is reset to 1. For households with a "rental" housing status, the bankrupt household vacates the rental property, and the housing status is changed to "social." The savings balance is reset to 1.

4. Simulation Results and Validation of the Model

This chapter reports the results of a 1,000-step simulation conducted based on the model parameters described in Chapter 3. Hereinafter, "base simulation" refers to the simulation conducted using the settings

---

[9] Set with reference to Table 2-20, "Deaths and Mortality Rates by Age" (2019) from Japan's Vital Statistics.

explained in the preceding chapters. Figure 4 shows the trends in the House Price Index (HPI) for each of the 10 runs of the base simulation.

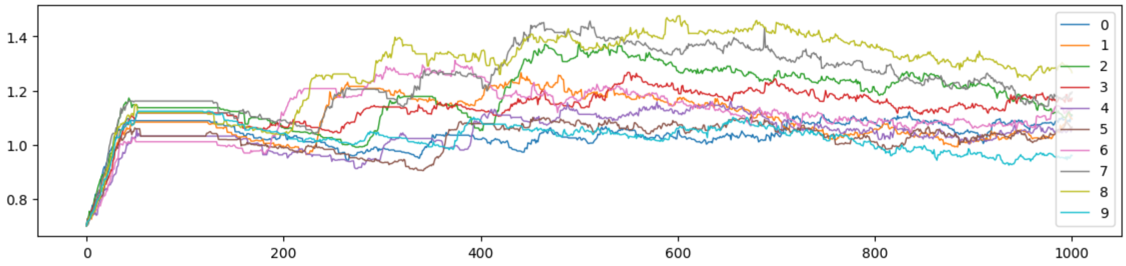


Figure 4: Trends in the HPI for Each Run of the Base Simulation

As can be seen in Figure 4, although there are some differences in the individual trial results, the trends are generally similar. Since ABM simulations incorporate randomness, variations are inevitable in individual trial results. Therefore, it is common practice to run multiple simulations and base the analysis on the average values, and this paper also follows that approach. Figure 5 shows the trends in the HPI, interest rate spreads, and the number of completed housing transactions, calculated as the average of each trial for every simulation step.

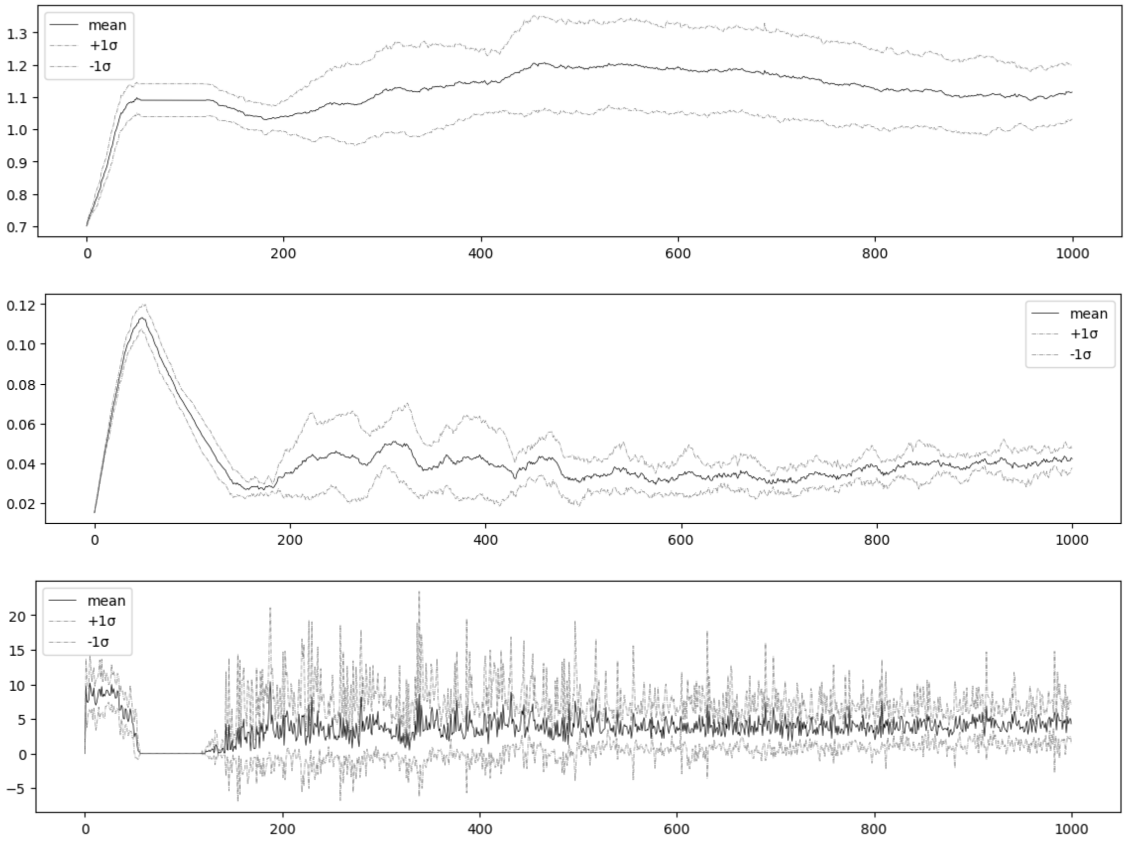


Figure 5: Trends in Average Values of Key Indicators in the Base Simulation

(Note) Top panel: HPI; Middle panel: Interest rate spread; Bottom panel: Number of settled home sales

As shown in the top graph of Figure 5, the HPI surged sharply at the beginning of the simulation. This was due to a concentration of home purchase orders immediately after the simulation began, as many of the households generated by the initial settings had sufficient savings. As shown in the middle graph of Figure 5, the interest rate spread also surged in response to this movement. Subsequently, as the interest rate spread widened, the number of housing transactions concluded declined, and at around step 100 there was a period when no housing transactions were concluded at all. Afterward, as the interest rate spread returned to its pre-spike level, housing transactions began to recover, and the HPI trended upward between steps 200 and 400. During this period, there is significant variation between trials, resulting in a wider range of one standard deviation. While the standard deviation for interest rate spreads and the number of housing transactions concluded is also large during this period, the graphs show that the standard deviation narrows around steps 500 to 600 and remains stable thereafter. The period of unstable behavior at the beginning of the simulation is referred to as the burn-in period or warm-up period. For the analysis in this chapter, the first 600 steps of the simulation are treated as the burn-in period, and movements from step 601 onward are the subject of analysis. Figure 6 shows the trends in the indicator values from step 601 onward, excluding the burn-in period, for the same indicators as in Figure 5.

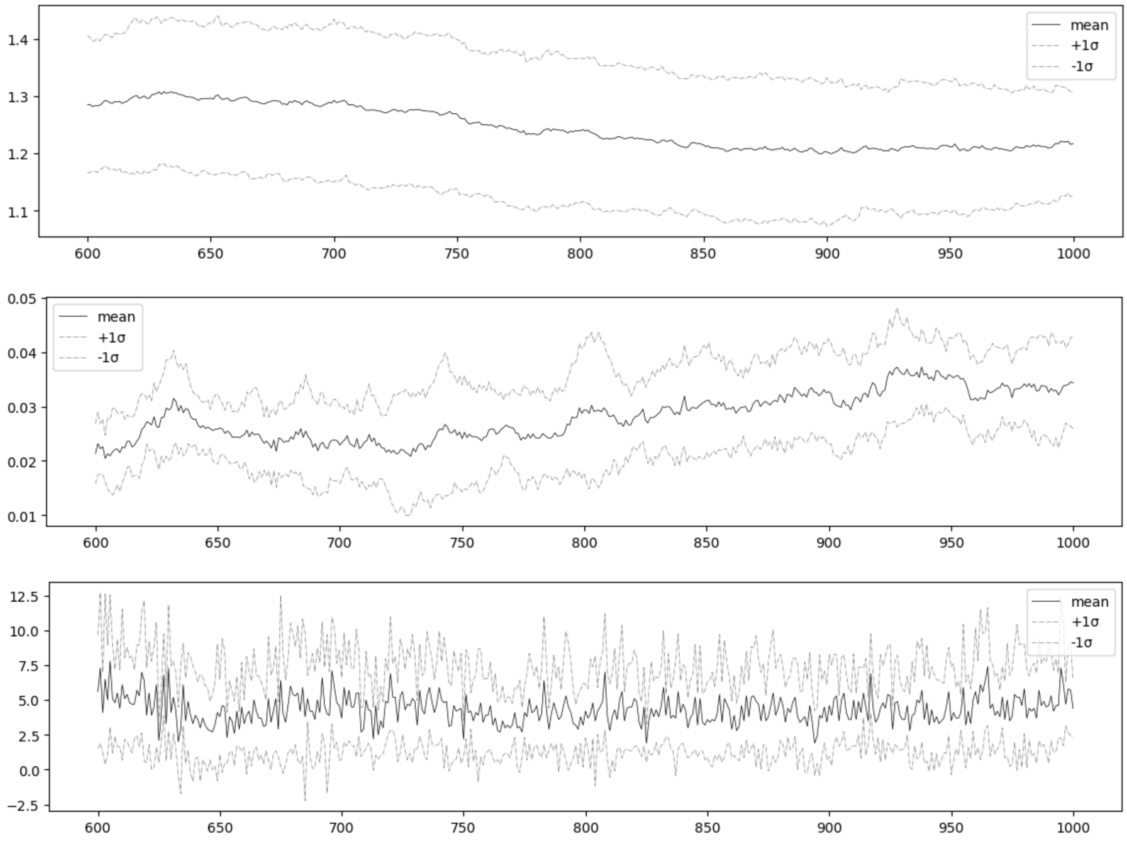


Figure 6: Trends in the average values of each indicator from step 601 onward in the base simulation

(Note) Top row: HPI; Middle row: Interest rate spread; Bottom row: Number of settled housing sales

Next, we will verify the validity of this model by comparing the trends in the value of each indicator with actual data. Figure 7 plots the Tokyo's index of the JREI Housing Price Index, calculated by the Japan Real Estate Institute (JREI), covering the period from June 1993 to May 2025, going back as far as data is available.

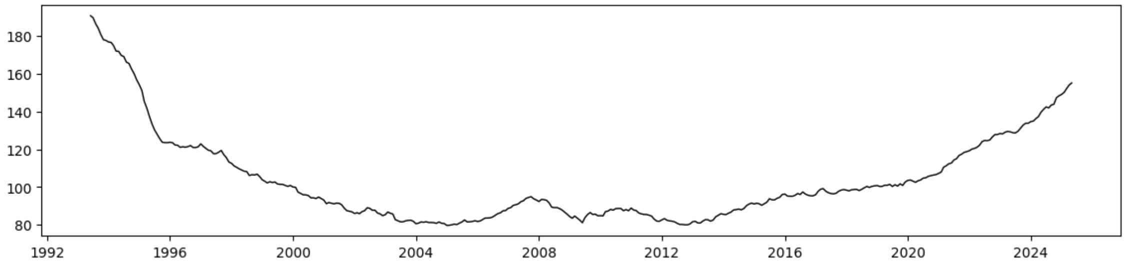


Figure 7: Trends in the Tokyo index of the JREI Housing Price Index

As can be seen, after the decline in house prices continued in the 1990s due to the bursting of the bubble economy, the trend remained largely flat throughout the 2000s and 2010s, before picking up in the 2020s. When comparing the results of this model with actual data, the question arises as to data of which period should be used for comparison. To compare with a period characterized by the prolonged low-interest-rate environment, data from 2000 onward is used, excluding data from the 1990s when the effects of the bubble collapse were still evident. Table 3 summarizes the mean and standard deviation of the month-over-month HPI. The values from this model were calculated by first computing the month-over-month HPI for every 10 trials, then calculating the average of those 10 trials for each step, and finally deriving the overall mean and standard deviation. The overall mean for the actual data is 15 bps, while that for this model is -1 bps, indicating that they are generally at similar levels. Note that the average calculated for the period from 2000 to 2020, excluding the period of rising housing prices in the 2020s in the actual data, was 0.0003. Regarding the standard deviation, while the model's value of 0.0020 is slightly smaller than the actual data's standard deviation of 0.0093, since the model's value is the average of 10 trials, the standard deviation of each simulation trial can be considered to be approximately $\sqrt{10}$ times the standard deviation of the model shown in the table, indicating that it is at a level close to the actual data.

Table 3 Comparison of HPI Month-over-Month Changes

	Mean	**Standard Deviation**
Actual Data	0.0015	0.0093
Model	-0.0001	0.0020

Figure 8 shows the autocorrelation of the HPI calculated over a lag of 40. The blue line in the figure represents the autocorrelation of the JREI Housing Price Index (Tokyo) data from 2000 onward, while the box-and-whisker plot summarizes the autocorrelation of the HPI for each of the 10 trials of this model. Both the actual data and this model show similar trends in autocorrelation values: positive autocorrelation is observed up to around lag 10, after which negative autocorrelation gradually strengthens until around lag 22, and then the autocorrelation begins to fade.

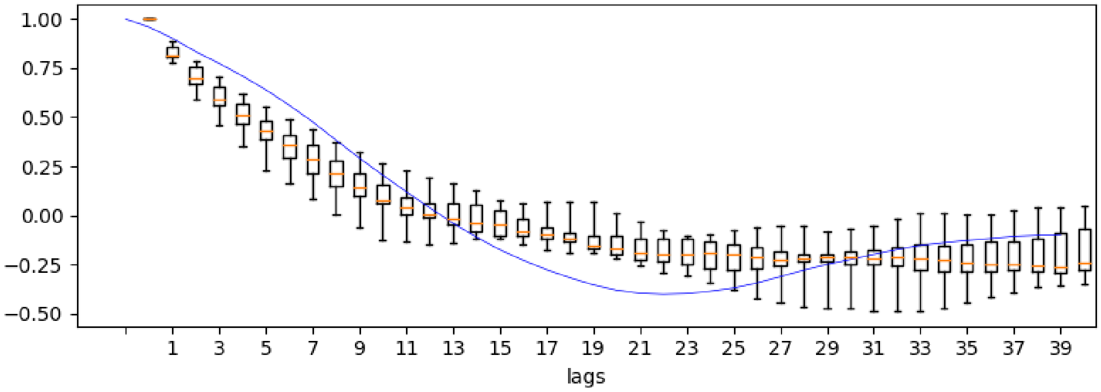


Figure 8: Trends in Autocorrelation of the HPI

(Note) Box-and-whisker plot: Aggregated autocorrelation calculated from the results of each trial; Blue line: Autocorrelation based on actual data

Regarding the number of residential property transactions concluded, the average in this model has remained stable at approximately 4.1 transactions per step. As for actual data, the number of households in Tokyo was approximately 7.5 million as of January 2025. According to the “Trends in the Greater Tokyo Area Real Estate Market” published by the East Japan Real Estate Distribution Organization, the number of transactions for pre-owned condominiums and single-family homes in 2024 was approximately 25,000 and the number of new condominium units sold in Tokyo, as compiled by the Real Estate Economic Research Institute, was approximately 10,000. Therefore, in terms of the 5,000 households in this model, the number of transactions per month comes to approximately 1.94. Compared to actual data, the number of housing sales transactions in this model is approximately twice as high. One reason for verifying this is that parameters have been adjusted to facilitate housing sales transactions for the purpose of macroprudential policy, which is the main focus of this paper. Figure 9 shows the trend in the number of sales transactions by housing quality in this model. For clarity, the graph is divided into five categories of housing quality. Higher numerical values indicate higher housing quality. Figure 9 shows that the density of data points is higher for lower-quality homes compared to higher-quality homes, indicating that sales are more active in the lower-quality segment. It should be noted that the scale of the vertical axis differs across the graphs in Figure 9.

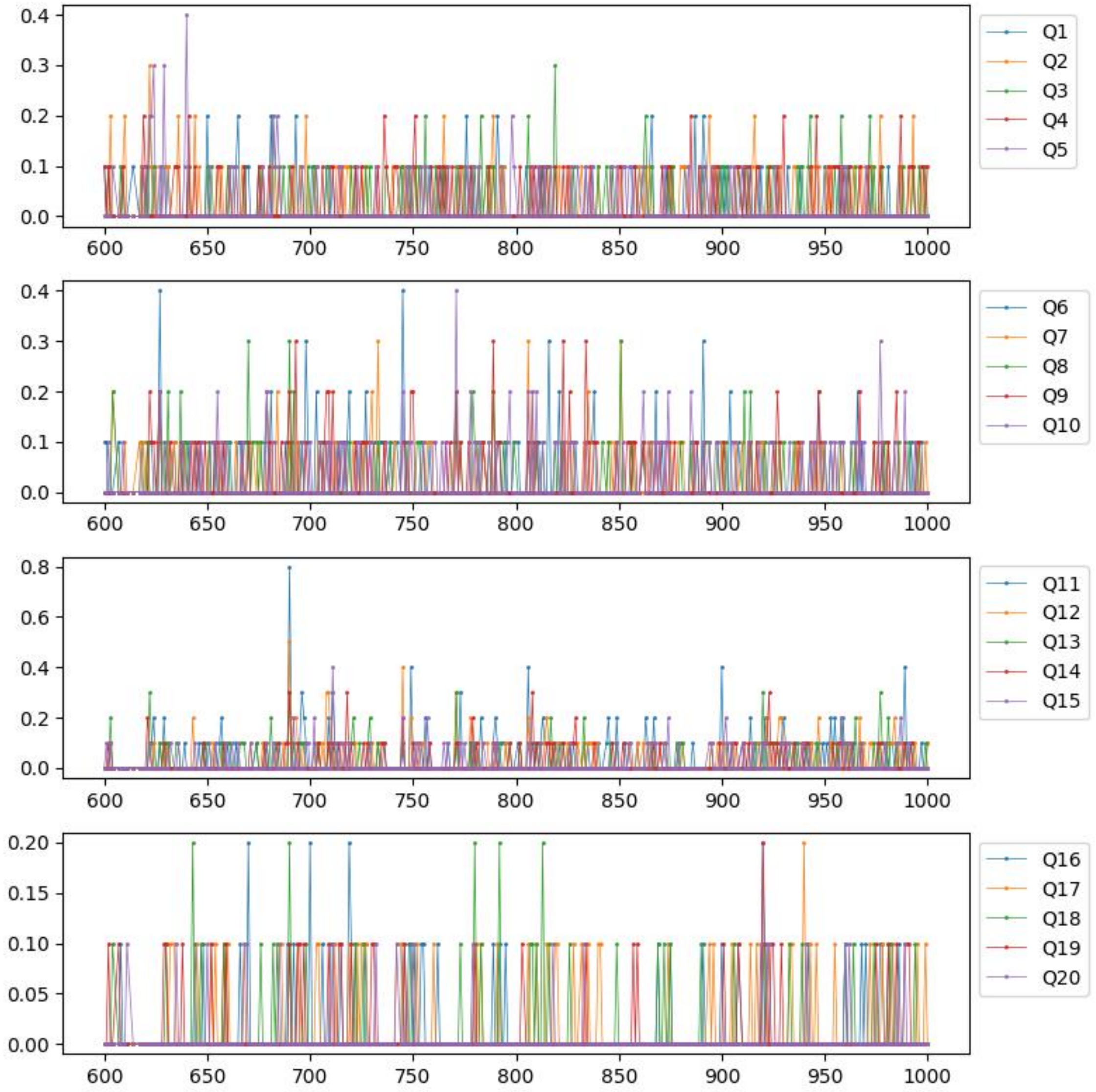


Figure 9: Trends in Average Number of Sales by Housing Quality Across 10 Trials

(Note 1) For clarity, the graph has been divided into five housing quality categories

(Note 2) For housing quality Q, a higher numerical value indicates higher quality.

Next, we will examine the number of cases in which mortgage borrowers defaulted on their loans. In this model, a borrower is deemed in default when the savings balance turns negative. Mortgage-related defaults include (i) cases where monthly mortgage payments exceeded net income, and (ii) cases where the principal repayment at the end of the mortgage term exceeded savings. (There are also cases of default related to rent payments.) Figure 10 shows the trend in the number of mortgage-related defaults, with the top panel displaying the results for BTL investors and the bottom panel showing figures for homeowner households without BTL attributes. Looking at the average number of defaults per step, BTL investors account for approximately 0.32 cases, while homeowner households account for approximately

0.47 cases; combined, this results in approximately 0.79 defaults per step. The actual rate of mortgage default is said to be less than 1% of all mortgage loans, and so the number of defaults is clearly high relative to the average transactions concluded in this model, which is approximately 4.1 . While in reality various measures are taken before a default occurs, this model mechanically classifies the situation as default once savings turn negative. Reducing the number of defaults is a key challenge for this model. Furthermore, among the defaults generated by this model, most cases involving BTL investors stemmed from insufficient savings to repay the principal at the mortgage maturity date, whereas all cases involving homeowner households without BTL attributes resulted from insufficient income to cover monthly repayments. In the case of BTL investors, when the mortgage maturity approaches and savings are insufficient to repay the principal, we consider it effective to sell the owned home at a fire-sale price to prepare as much savings as possible.

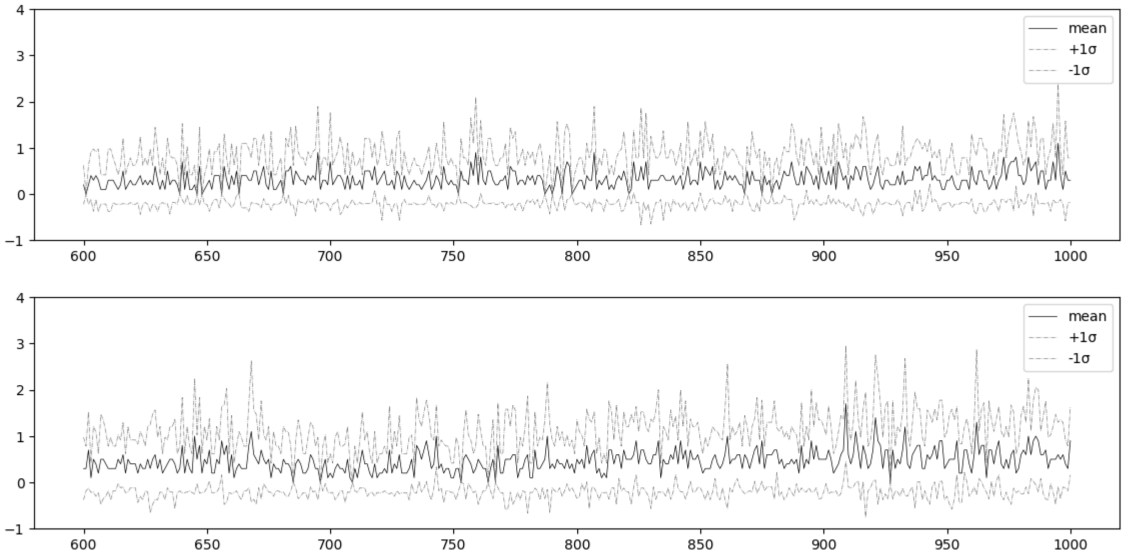


Figure 10: Trends in the Average Number of Defaults Across 10 Simulations

(Note) Top row: Number of cases for BTL investors; Bottom row: Number of cases for homeowner households without BTL attributes

Figure 11 shows the trend in LTV, one of the indicators of mortgage borrower soundness, broken down by BTL investors and households without BTL attributes. Figure 12 shows the trend in LTI, a different indicator of mortgage borrower soundness from that shown in Figure 11.

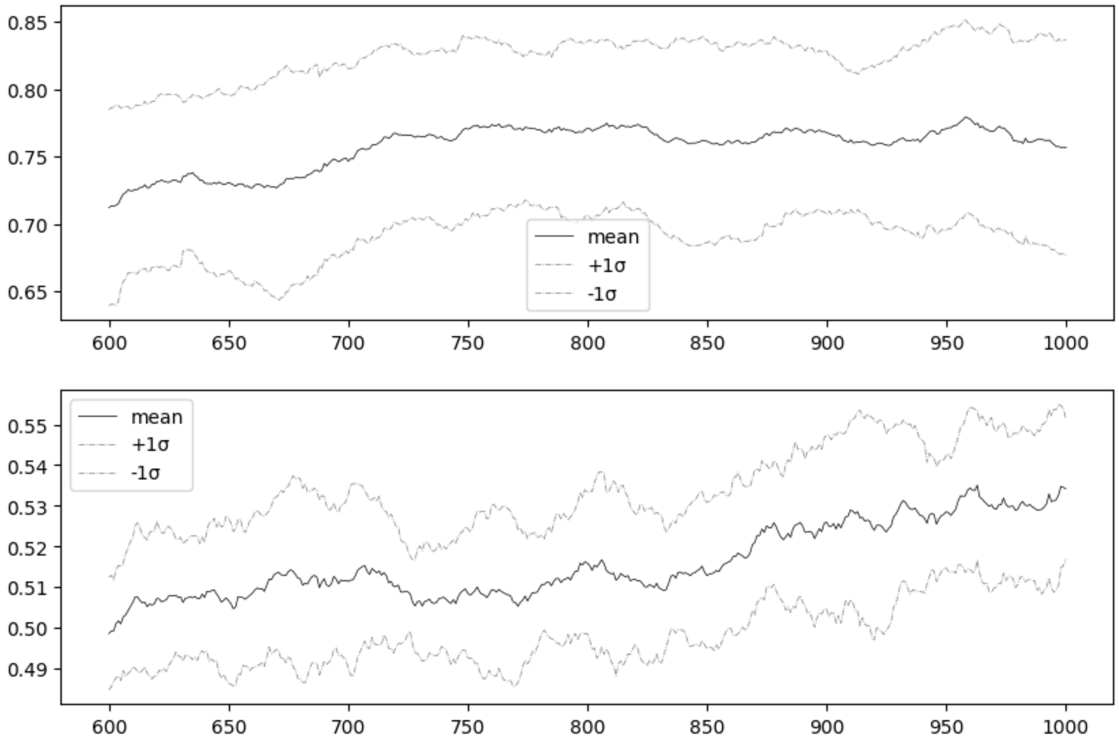


Figure 11: Trends in Average LTV Across 10 Simulations

(Note) Top panel: LTV for BTL investors; Bottom panel: LTV for households without BTL attributes

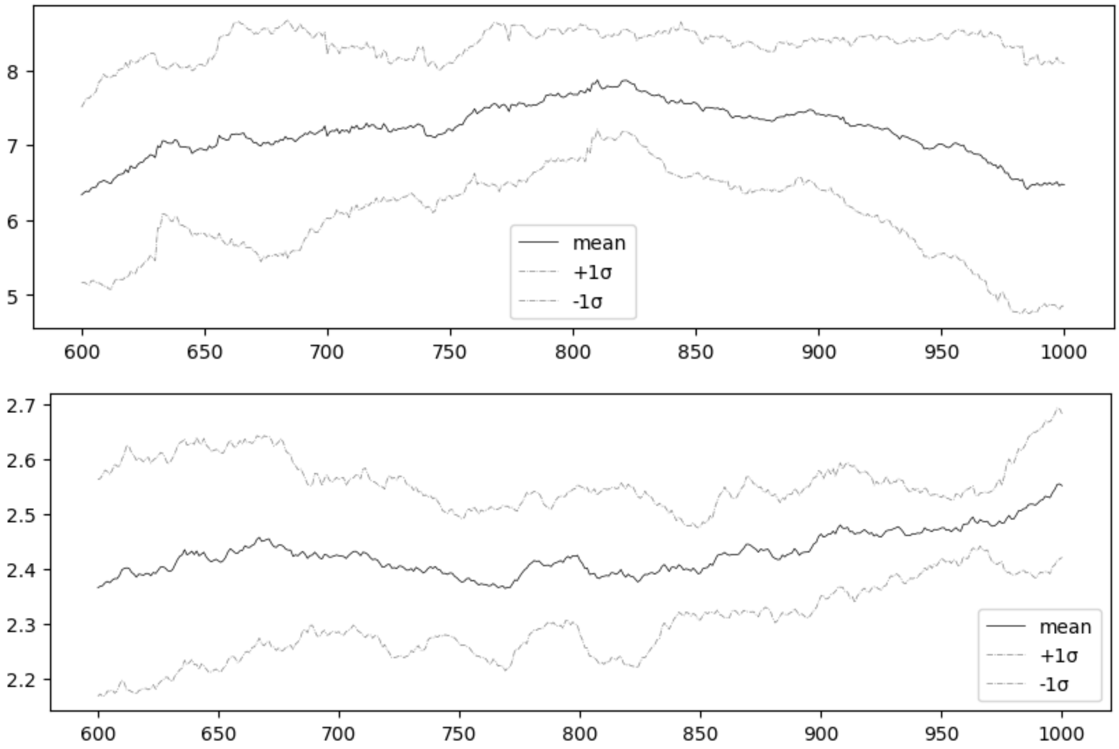


Figure 12: Trends in Average LTI Over 10 Simulations

(Note) Top panel: LTI for BTL investors; Bottom panel: LTI for households without BTL attributes

The data shows that the average LTV remains stable at around 0.75 for BTL investors and around 0.50 for households without BTL attributes. The average LTI stands at around 7.0 for BTL investors and around 2.5 for households without BTL attributes. The disparity in LTI values between households with and without BTL attributes stems from the fact that BTL investors often utilize mortgages with leverage of nearly 9 times when acquiring rental properties. The LTV and LTI values shown in Figures 11 and 12 are considered to be at standard levels.

Thus far, we have verified the validity of this model based on the results of the baseline simulation. While some indicators show deviations from actual data, most values are reproduced at levels close to the actual data. In the next chapter, we carry out the analysis of macroprudential regulations using this model.

5. Analysis of the Effects of Macroprudential Regulations

In this chapter, we examine the effects of the “5-Year Rule” and “125% Rule,” which are macroprudential regulations widely applied to domestic mortgage interest rates. The 5-Year Rule requires that “mortgage repayment amounts must be reviewed every five years” and the 125% Rule sets “the upper limit for the revised interest repayment amount at 125% of the previous repayment amount.” These two rules are applied in combination to many mortgage loans in Japan at variable-rate, with principal and interest repayment plan. Note that these rules apply to the repayment amount; the mortgage interest rate itself is reviewed every six months, and the breakdown of principal and interest within the repayment amount changes accordingly. However, in this model, for programming purposes, the timing that mortgage interest rate is reviewed is set at every five years for mortgages to which the 5-Year Rule is applied.

In the simulations based on the baseline scenario examined in the previous chapter, neither the 5-year rule nor the 125% rule was applied. We now conduct new simulations applying both rules together and analyze their combined effects by comparing the results.

When running the simulation with these macroprudential regulations in place, instead of applying the rules from step 1, we loaded and used the results of 10 runs of the baseline scenario up to step 600, and then conducted the simulation with both rules applied starting from step 601. This is because we believe it is easier to compare and evaluate the results when the initial state at the start of the evaluation is the same, rather than running completely separate simulations. Note that because simulations involve randomness, the trends in each trial after step 601 will not be identical.

To measure the effects of both rules, with and without their application, we focused on two points: (i) whether the proportion of defaults among existing mortgages changes at the end of step 600 (immediately after the burn-in period), and (ii) whether the proportion of defaults among newly originated mortgages increases or decreases. Table 4 summarizes the differences resulting from the case with and without the application of both rules regarding the former, and Table 5 summarizes the results regarding the latter.

Table 4: Subsequent Number of Defaults on Existing Mortgages at Step 600

No.	Existing Loans	No Macroprudential Regulation		With Macroprudential Regulation	
		Defaults	Default Rate	Defaults	Default Rate
1	372	16	4.3%	16	4.3%
2	350	11	3.1%	12	3.4%
3	336	16	4.8%	5	1.5%
4	381	20	5.2%	20	5.2%
5	409	7	1.7%	10	2.4%
6	409	23	5.6%	22	5.4%
7	359	8	2.2%	12	3.3%
8	308	13	4.2%	9	2.9%
9	360	12	3.3%	12	3.3%
10	421	22	5.2%	13	3.1%
		Mean	**4.0%**	Mean	**3.5%**
		Std.	1.3%	Std.	1.2%

Table 5: Number of defaults on newly originated mortgages from step 601 onwards

No.	No Macroprudential Reg.			With Macroprudential Reg.		
	New Loans	Defaults	Default Rate	New Loans	Defaults	Default Rate
1	372	60	16.1%	389	58	14.9%
2	311	43	13.8%	272	43	15.8%
3	183	25	13.7%	160	19	11.9%
4	256	42	16.4%	327	56	17.1%
5	302	41	13.6%	350	41	11.7%
6	314	46	14.6%	326	44	13.5%
7	297	32	10.8%	190	27	14.2%
8	200	20	10.0%	226	38	16.8%
9	192	37	19.3%	158	29	18.4%
10	284	36	12.7%	241	36	14.9%
		Mean	**14.1%**		Mean	**14.9%**
		Std.	2.7%		Std.	2.2%

Looking at the results in Table 4, the number of defaults and the default rate for existing mortgages at step 600 are at similar levels regardless of whether the macroprudential regulation is in place or not. The average default rate is also similar, at 3.5% with the regulation compared to 4.0% without it. A Welch's t-test is conducted to test the difference in the average default rates. The p-value is 0.41, and we cannot reject the null hypothesis that there is no difference between the two averages. The results in Table

5 are similar: the default rates and their averages for newly originated mortgages are at similar levels regardless of the presence or absence of regulations, and the p-value from the Welch's t-test is 0.46, so the null hypothesis is not rejected.

In the base scenario of this model, the model parameters have been adjusted so that the HPI and mortgage interest rates remain flat. Hence, simply extending the simulation period is unlikely to increase the range of interest rate fluctuations, and it would be difficult to see what influence these macroprudential regulations have, which are effective during periods of rising interest rates. Therefore, we attempt to verify the impact of the regulation by raising interest rates deliberately at a specific point in the simulation and analyzing the state of mortgage loans before and after that point. Regarding the means of applying the interest rate shock, we tested two types of interest rate rise scenarios: one in which interest rates rise over a short period and then remain high (Interest Rate Rise Scenario 1), and another in which interest rates rise over a longer period (Interest Rate Rise Scenario 2). Table 6 summarizes the settings for each interest rate rise scenario.

Table 6: Interest Rate Rise Scenario Settings

Item	Scenario 1	Scenario 2
The start of rising interest rates	Step 637 (3 years after simulation with the rules started)	Step 601 (Immediately after simulation with the rules started)
Period of interest rate rise	2 years (24 steps)	10 years (120 steps)
Range of interest rate increase	2% interest rate increase	4% interest rate increase
Frequency of interest rate increases	Every 3 months	Every 3 months
Period for maintaining interest rate	7 years	2 years

In the interest rate rise scenario, we use the policy rate as the target to raise interest rates, rather than the spread on mortgage interest rates. The extent of the rate increases was maintained at 2% and 4% because, for the 125% rule to effectively curb the rise in repayment amounts, an interest rate increase of approximately 2% is necessary compared to the rate at the time of the previous interest rate review. On the other hand, if the interest rate increase is too large, home purchases will stagnate, so we did not allow interest rates to rise indefinitely. Therefore, the interest rate increase in each scenario was set so that the total increase over the five years since the previous interest rate review would be within 2%.The interest rate maintenance period was established because, in this model, unless we deliberately maintain the level of the interest rate spread , the spread would immediately narrow to a level equivalent to the previous interest rate level, making it difficult to discern the effectiveness of this macroprudential regulation. Figure 13 shows the trend of the interest rate spread during the interest rate increase period and the interest rate maintenance period for both scenarios.

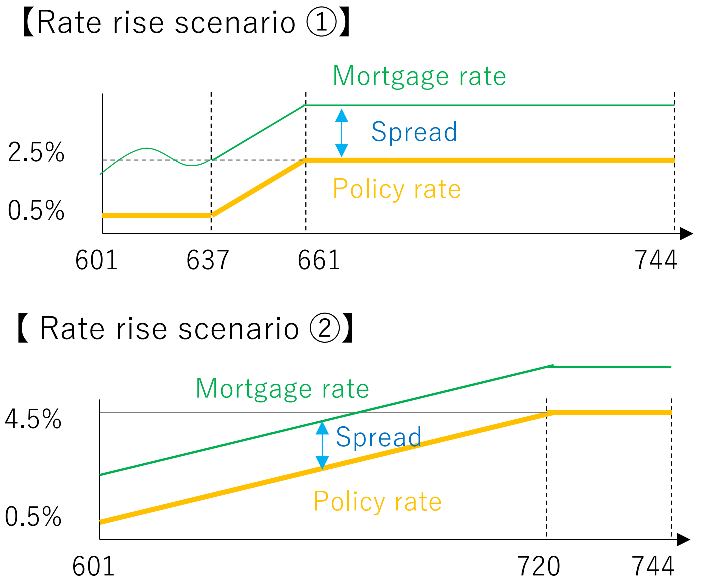


Figure 13: Illustration of Interest Rate Changes in the Interest Rate Rise Scenario

As described above, the interest rate rise scenarios have been designed with the intention to ensure that home purchases would not cease even after interest rates rose. However, looking at the actual trends in home sales, the number of transactions decreased as interest rates rose, and once rates reached close to 2%, there were virtually no transactions thereafter. Figure 14 shows the trend in the average number of home sales transactions across 10 trials of Rising Rate Scenarios 1 and 2. Given this pattern of transactions in home sales, it is important to note when reviewing the analysis results that the mortgages concluded in the rising rate scenario simulations are likely to have been arranged at times when interest rates were relatively low before the rate began to increase, and thus may be significantly affected by subsequent interest rate increases.

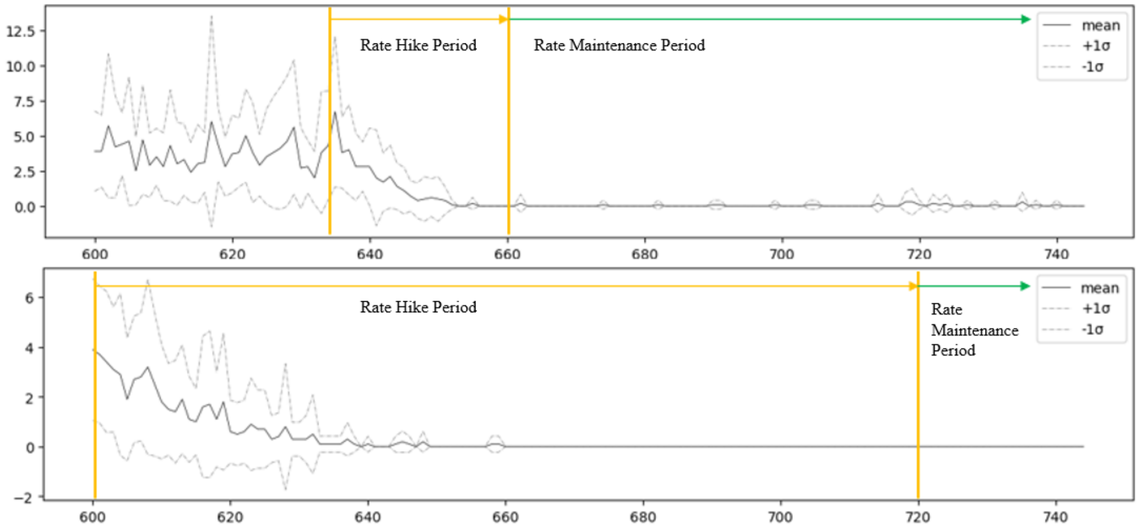


Figure 14: Trends in the Number of Housing Transactions Under Rising Rate Scenarios

(Note) Top: Values for Rising Rate Scenario 1; Bottom: Values for Rising Rate Scenario 2

Table 7 summarizes the number of defaults on existing mortgages at the end of the 600th step in the Rising Rate Scenario 1, while Table 8 summarizes the number of defaults on new mortgages originated during the simulation period.

Table 7: Number of defaults on existing mortgages at the 600th step under Rising Rate Scenario 1

No.	Existing Loans	No Macroprudential Regulation		With Macroprudential Regulation	
		Defaults	Default Rate	Defaults	Default Rate
1	372	26	7.0%	24	6.5%
2	350	24	6.9%	14	4.0%
3	336	23	6.8%	17	5.1%
4	381	35	9.2%	41	10.8%
5	409	27	6.6%	19	4.6%
6	409	35	8.6%	33	8.1%
7	359	16	4.5%	17	4.7%
8	308	28	9.1%	15	4.9%
9	360	30	8.3%	29	8.1%
10	421	28	6.7%	23	5.5%
		Mean	**7.4%**	Mean	**6.2%**
		Std.	1.4%	Std.	2.1%

Table 8: Number of defaults on new mortgages originated from Step 601 onwards under Rising Rate Scenario 1

No.	No Macroprudential Reg.			With Macroprudential Reg.		
	New Loans	Defaults	Default Rate	New Loans	Defaults	Default Rate
1	94	33	35.1%	86	17	19.8%
2	117	31	26.5%	82	14	17.1%
3	14	6	42.9%	61	13	21.3%
4	124	22	17.7%	105	19	18.1%
5	120	26	21.7%	97	16	16.5%
6	135	22	16.3%	120	24	20.0%
7	62	19	30.6%	79	14	17.7%
8	95	21	22.1%	104	16	15.4%
9	77	19	24.7%	58	13	22.4%
10	87	8	9.2%	88	19	21.6%
		Mean	**24.7%**		Mean	**19.0%**
		Std.	9.7%		Std.	2.4%

Table 7 shows that the average proportion of defaulted mortgages is 7.4% when the macroprudential regulations are not applied, and 6.2% when they are applied. Table 8 also shows that the average proportion of defaulted mortgages is 24.7% without the application of the macroprudential regulations and 19.0% with their application. Both sets of results suggest that the application of these macroprudential regulations has an effect to curb default. Therefore, we performed a Welch's t-test to test the difference in means. The p-value from the Welch's t-test for Table 7 was 0.19, and for Table 8 it was 0.10; in both cases, the results did not allow us to reject the null hypothesis.

Next, we examine the results of Interest Rate Rise Scenario 2. Table 9 summarizes the number of defaults on existing mortgages at the end of Step 600 under Interest Rate Rise Scenario 2, and Table 10 summarizes the number of defaults on new mortgages originated from Step 601 onward.

Table 9: Number of defaults on existing mortgages at the 600th step under Interest Rate Rise Scenario 2

No.	Existing Loans	No Macroprudential Regulation		With Macroprudential Regulation	
		Defaults	Default Rate	Defaults	Default Rate
1	372	45	12.1%	35	9.4%
2	350	26	7.4%	16	4.6%
3	336	25	7.4%	18	5.4%
4	381	45	11.8%	34	8.9%
5	409	19	4.6%	18	4.4%
6	409	72	17.6%	44	10.8%
7	359	23	6.4%	17	4.7%
8	308	40	13.0%	25	8.1%
9	360	71	19.7%	51	14.2%
10	421	64	15.2%	33	7.8%
		Mean	**11.5%**	Mean	**7.8%**
		Std.	5.0%	Std.	3.2%

Table 10: Number of defaults on new mortgages originated from Step 601 onwards under Interest Rate Rise Scenario 2

No.	No Macroprudential Reg.			With Macroprudential Reg.		
	New Loans	Defaults	Default Rate	New Loans	Defaults	Default Rate
1	95	31	32.6%	15	3	20.0%
2	23	3	13.0%	145	31	21.4%
3	5	1	20.0%	8	0	0.0%
4	23	6	26.1%	21	4	19.0%
5	20	2	10.0%	21	5	23.8%
6	3	0	0.0%	4	1	25.0%
7	22	7	31.8%	23	3	13.0%
8	76	28	36.8%	20	3	15.0%
9	37	12	32.4%	48	11	22.9%
10	52	16	30.8%	75	17	22.7%
		Mean	**23.4%**		Mean	**18.3%**
		Std.	12.1%		Std.	7.5%

As with Interest Rate Rise Scenario 1, Tables 9 and 10 show that, under Interest Rate Rise Scenario 2, the average proportion of defaulted mortgages across each indicator is lower when the macroprudential regulations are applied. A Welch's t-test revealed that for the proportion of defaulted mortgages among existing loans in Table 9, the p-value was 0.07, allowing us to reject the null hypothesis that there is no difference in the average at the 10% significance level. On the other hand, for the proportion of defaulted mortgages among newly originated loans in Table 10, the p-value was 0.28, and the null hypothesis could not be rejected.

As described above, regarding the proportion of defaults for each indicator, the results showed that while some analyses allowed us to reject the null hypothesis that there is no difference in the mean values when applying the macroprudential regulations, others did not allow us to reject the null hypothesis. Regarding the cases where the null hypothesis could not be rejected, a common factor observed in both interest rate increase scenarios 1 and 2 is that the standard deviation of the default rate for newly originated mortgage loans increased significantly. As shown in Table 10, the number of newly originated mortgage loans varied widely across trials, ranging from single-digit figures to nearly 100 cases. One contributing factor to the increased standard deviation is that, within this range, the proportion of defaults deviated significantly from the others in trials with a small number of originated loans. By refining this model and setting more appropriate interest rate rise scenarios, we can expect to mitigate the variability in the results of each simulation. If simulations are then rerun under such conditions and a test is conducted on the differences in the mean values of each indicator, the likelihood of rejecting the null hypothesis is likely to increase.

6. Conclusion

In this paper, we constructed an ABM for Tokyo's housing market and examined the effects of macroprudential regulations on mortgage interest rates during periods of rising interest rates. Although the constructed housing market ABM showed some discrepancies from actual data—such as a higher frequency of loan defaults—we assess that we have built a valid model, as the output results were close to actual data in many respects. Next, using the ABM, we conducted simulations based on rising interest rate scenarios and analyzed the effects of the "5-year rule" and "125% rule"—macroprudential regulations distinct to the Japanese housing market—by focusing on differences in the number of mortgage defaults. Through this analysis, some results confirmed that both rules are effective in curbing mortgage defaults.

Given that low interest rates have persisted for an extended period in Japan, it is difficult to empirically analyze the effectiveness of macroprudential regulations in the housing market during periods of rising interest rates. We believe that presenting a framework to analyze the impact of various regulations in such a market environment in Japan is one of the contributions of this study. The second contribution is that we have confirmed the effectiveness of the 5-year rule and the 125% rule, albeit based on partial analysis of the results. Given the prospect of rising interest rates in Japan's financial markets, it is significant that we confirmed the intended effects of regulations designed to mitigate the adverse impacts of rising interest rates.

Despite these contributions, challenges remain for improving this study. The first challenge is to address the discrepancy between the constructed model and real-world behavior. Areas requiring improvement include reducing the frequency of defaults in the simulation, the fact that the proportion of renting households gradually declines as the simulation progresses, making it impossible to maintain a 4:6 ratio of homeownership to renting. The second challenge for this paper concerns improving the methodology for verifying the impact of macroprudential regulations. In this study, we conducted simulations based on a scenario of gradually rising policy interest rates and assessed the effectiveness of the regulations by analyzing differences in the number of mortgage defaults depending on whether macroprudential regulations were applied or not. However, due to the decline in housing transactions and mortgage demand caused by rising policy interest rates, we were unable to generate a sufficient number of mortgages within the simulation. Consequently, the proportion of defaults among the originated mortgages varied significantly across simulation runs, leaving some uncertainty regarding the measurement of the macroprudential regulations' effectiveness. In addition to improving the model's accuracy, which refers to the first challenge mentioned above, establishing a highly accurate method for measuring effectiveness remains a major challenge for the future. We expect that as data is accumulated in the phase of rising interest rates, it will become easier to improve both the model's accuracy and the effectiveness of measurement methods.

Other areas we intend to address in the future include analyzing the effects of other macroprudential regulations that we did not address in this study, comparing the effects of various regulations, and constructing housing market models for regions outside the Tokyo market. We also recognize the importance of expanding the scale of the model to analyze the impact of macroprudential regulations at a finer granularity. The use of ABM makes it possible to conduct analyses at the individual household level. The ABM constructed in this paper consists of 5,000 household agents and represents a model that reproduces economic agents such as households in the real world at a coarse granularity; however, housing market ABMs developed overseas have models that correspond one-to-one with economic agents in the real world. By increasing the granularity of this model, we expect to improve the precision of the policies that can be examined. We intend to proceed to resolve these challenges one by one.

7. Supplementary Discussion

7.1 Model Details

The details of the model constructed in this paper are described below. First, Table 11 lists the model parameters.

Table 11: List of Model Parameters for the Model of This Study

scope	model parameters	symbols	values	notes
General	Share of Renting Households		0.6	
	Number of Household Agents		5,000	
	Number of Bank Agents		1	
	Number of Central Bank Agents		1	
	Number of Housing Units		5,628	
	Number of Housing Markets		1	
Households	Minimum Age		20	
	Maximum Age		95	
	Government Income Support (Monthly)		100,000	Eq.(2)
	Non-housing Essential Consumption Ratio	ENCFR	0.66	Eq.(2)
	Max Share of Discretionary Consumption in Disposable Income		0.17	Eq.(5)
	Income Tax Rate		0.2	Eq.(2)
	Desired House Price Parameter	α	42.9036	Eq.(6)
	Desired House Price Parameter	β	0.89	Eq.(6)
	Desired House Price Parameter (mean of ε)	μ_{ε}	-0.0177	Eq.(6)
	Desired House Price Parameter (std of ε)	σ_{ε}	0.4104	Eq.(6)
	Rental Cost Adjustment in Purchase Probability	λ	-0.025	Eq.(8),(10)
	Cost Sensitivity in Purchase Probability	θ	0.001	Eq.(10)
	Rental Price Adjustment Parameter	μ	15	Eq.(11)
	Rental Price Adjustment Parameter	ν	0.68	Eq.(11)
	Capital Gain Preference in Household Investment Preference i	δ_i	{'income': 0.1, 'capital': 0.9, 'mixed': 0.5}	Eq.(12)
	Distribution of Household Investment Preferences (3 types)	i	{'income': 0.4927, 'capital': 0.1458, 'mixed': 0.3615}	Eq.(12)
	Expected Return Adjustment for BTL Investors (Buy Orders)	ξ	500	Eq.(13)
	Price Reduction Probability for Unsold Housing Offers		0.0703	
	Price Reduction Probability for Unsold Rental Offers		0.1057	
	Fire-sale Discount Rate for Housing Transactions		0.5	
	Max Number of Inheritable Properties		2	

Table 11: Continued List of Model Parameters

scope	model parameters	symbols	values	notes
Banks	Initial Mortgage Interest Rate Spread		0.015	
	LTV-based Loan Limit Parameter (Non-BTL Households)	Γ_{nonbtl}	0.9	Eq.(17)
	LTV-based Loan Limit Parameter (BTL Investors)	Γ_{btl}	0.75	Eq.(17)
	LTI-based Loan Limit Parameter (First-time Buyers)	Φ_{ftb}	7.8	Eq.(18)
	LTI-based Loan Limit Parameter (Repeat Buyers)	Φ_{hm}	8.2	Eq.(18)
	DSTI-based Loan Limit Parameter	ψ	0.4	Eq.(19)
	ICR-based Loan Limit Parameter	Ω	1.25	Eq.(20)
	Maximum Mortgage Term (Months)		420	
	Upper Bound of Monthly Change in Interest Rate Spread		0.003	
	Lower Bound of Monthly Change in Interest Rate Spread		-0.003	
Central Bank	Initial Policy Rate		0.005	
Housing	Number of Housing Quality Classes	Q	20	
Market	Initial Housing Price Index		0.7	
	Initial Rental Price Index		0.8	
	Initial Average Rental Yield		0.04	
	Reference Price Initialization Parameter by Housing Quality		{'loc': 3.1, 'scale': 1.3}	
	Purchase Probability Adjustment Parameter γ (Non-BTL Households)		0.44	Eq.(22)
	Purchase Probability Adjustment Parameter ζ (Non-BTL Households)		0.023	Eq.(22)
	Average Holding Period of Owner-Occupied Housing (Years)		17	
	Vacancy Rate in Expected Return Calculation		0.89	
	Minimum Rental Contract Length (Months)		12	
	Maximum Rental Contract Length (Months)		36	

Table 12 shows the age distribution for the initial settings. For ages 20 to 84, the percentages listed in the table are distributed evenly across each one-year interval within the five-year age ranges. For ages 85 and above, the distribution is weighted by one-year increments. If a household agent dies during a simulation step, the age probability is set so the age of the household agent generated for replacement is approximate to the age distribution immediately after the simulation's initial setup. Specifically, the difference between the age distribution immediately after the initial setup and the age distribution at the time the replacement household is generated is calculated, and the age probability is adjusted so that it increases for ages that have less agent distribution.

Table 12: Age Distribution at Initial Setup

Age Group	Share
20 - 24	5.04%
25 - 29	7.99%
30 - 34	7.79%
35 - 39	8.17%
40 - 44	8.64%
45 - 49	9.73%
50 - 54	9.16%
55 - 59	7.94%
60 - 64	6.33%
65 - 69	6.26%
70 - 74	7.36%
75 - 79	6.01%
80 - 84	4.74%
85+	4.84%

The mortality rate for each age of a household is calculated using the following equation, based on Carro et al. (2023).

$$A * \exp(k * age) \tag{21}$$

Here, A and k are parameters for adjusting the mortality rate level, with A = 7.576 $\times 10^{-9}$ and k = 0.148.

Figure 14 plots mortality rates on the vertical axis and age on the horizontal axis. As shown in Figure A1, the mortality rate begins to rise steeply around age 70, particularly after age 85. This is the result of setting higher mortality rates for older age groups to maintain the initial age distribution as much as possible.

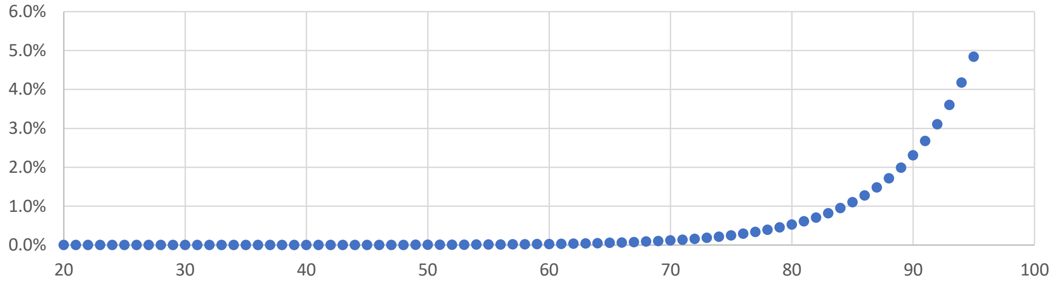


Figure 15: Probability of Death by Age

(Note) The model is set so that households die when they reach the age of 96.

Table 13 shows the percentile distribution of annual income by the age of household agents. Annual income percentiles are set at the time of household creation using a uniform distribution between 0 and 1 and remain constant until the household dies. As shown in Table 13, while the annual income percentile for each household is fixed, the corresponding column in the age-income percentile table changes as age increases, so the actual annual income amount changes in 10-year increments.

Table 13: Age and Annual Income Percentile Distribution Table

Annual Income(JPY)		Distribution by Age Group						
Lower	Upper	20 - 29	30 - 39	40 - 49	50 - 59	60 - 69	70 - 79	80 - 95
1,000,000	1,500,000	23.7%	4.6%	5.3%	7.4%	11.4%	17.1%	24.3%
1,500,000	2,000,000	28.7%	6.4%	7.1%	10.0%	16.9%	25.5%	34.9%
2,000,000	2,500,000	33.5%	9.6%	10.6%	14.3%	23.7%	35.9%	47.5%
2,500,000	3,000,000	41.8%	13.1%	13.1%	17.8%	30.0%	46.2%	57.1%
3,000,000	3,500,000	53.2%	17.2%	16.7%	21.1%	35.9%	55.0%	66.6%
3,500,000	4,000,000	61.4%	21.7%	20.4%	25.0%	42.2%	62.1%	73.1%
4,000,000	4,500,000	69.8%	28.2%	24.3%	29.0%	47.8%	67.9%	78.0%
4,500,000	5,000,000	74.1%	34.7%	28.3%	32.5%	52.9%	72.2%	80.7%
5,000,000	5,500,000	77.2%	42.4%	33.6%	36.5%	57.0%	75.9%	83.0%
5,500,000	6,000,000	79.9%	51.0%	37.9%	40.5%	61.8%	79.3%	85.1%
6,000,000	6,500,000	83.9%	58.0%	43.8%	44.3%	65.5%	82.2%	87.0%
6,500,000	7,000,000	87.0%	64.3%	48.9%	48.1%	68.8%	84.9%	88.3%
7,000,000	7,500,000	88.6%	69.5%	54.5%	52.5%	71.8%	86.5%	89.4%
7,500,000	8,000,000	90.6%	73.9%	59.4%	56.2%	74.3%	88.2%	90.5%
8,000,000	8,500,000	92.1%	77.5%	64.0%	60.9%	77.0%	89.7%	91.5%
8,500,000	9,000,000	92.7%	79.9%	67.3%	64.3%	79.0%	90.9%	92.2%
9,000,000	9,500,000	94.6%	83.2%	72.0%	68.9%	80.7%	92.2%	93.3%
9,500,000	10,000,000	95.2%	85.2%	74.4%	71.4%	82.2%	92.9%	93.8%
10,000,000	11,000,000	97.7%	90.1%	80.9%	77.6%	85.3%	94.5%	94.9%
11,000,000	12,000,000	98.8%	92.6%	85.3%	81.3%	88.2%	95.5%	95.9%
12,000,000	15,000,000	99.6%	97.1%	92.5%	90.2%	93.3%	97.7%	97.6%
15,000,000	20,000,000	100.0%	99.4%	97.4%	96.4%	96.5%	98.7%	99.0%
20,000,000	30,000,000	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Table 14 shows the distribution of asset values by annual income bracket. The initial target savings amount is set based on this table.

Table 14: Asset Distribution by Income Class

Assets		Annual Income (JPY 10,000; top: lower, bottom: upper)											
(Unit: JPY 10,000)		0	150	200	250	300	350	400	450	500	550	600	650
Lower	Upper	150	200	250	300	350	400	450	500	550	600	650	700
0	25	0.17	0.17	0.14	0.14	0.10	0.10	0.09	0.09	0.09	0.09	0.06	0.06
25	50	0.19	0.19	0.15	0.15	0.12	0.12	0.10	0.10	0.09	0.09	0.07	0.07
50	100	0.22	0.22	0.17	0.17	0.13	0.13	0.10	0.10	0.09	0.09	0.07	0.07
100	150	0.23	0.23	0.19	0.19	0.15	0.15	0.12	0.12	0.10	0.10	0.08	0.08
150	200	0.25	0.25	0.20	0.20	0.16	0.16	0.12	0.12	0.11	0.11	0.08	0.08
200	300	0.29	0.29	0.23	0.23	0.18	0.18	0.14	0.14	0.12	0.12	0.10	0.10
300	450	0.32	0.32	0.26	0.26	0.21	0.21	0.18	0.18	0.15	0.15	0.12	0.12
450	600	0.36	0.36	0.31	0.31	0.24	0.24	0.20	0.20	0.18	0.18	0.14	0.14
600	750	0.39	0.39	0.34	0.34	0.28	0.28	0.24	0.24	0.20	0.20	0.17	0.17
750	900	0.43	0.43	0.38	0.38	0.31	0.31	0.27	0.27	0.23	0.23	0.20	0.20
900	1,200	0.49	0.49	0.45	0.45	0.37	0.37	0.33	0.33	0.30	0.30	0.26	0.26
1,200	1,500	0.54	0.54	0.52	0.52	0.43	0.43	0.39	0.39	0.35	0.35	0.31	0.31
1,500	2,000	0.60	0.60	0.59	0.59	0.51	0.51	0.47	0.47	0.43	0.43	0.40	0.40
2,000	3,000	0.73	0.73	0.72	0.72	0.64	0.64	0.62	0.62	0.58	0.58	0.53	0.53
3,000	4,000	0.81	0.81	0.79	0.79	0.75	0.75	0.74	0.74	0.68	0.68	0.64	0.64
4,000	5,000	0.85	0.85	0.85	0.85	0.82	0.82	0.81	0.81	0.75	0.75	0.74	0.74
5,000	7,500	0.93	0.93	0.94	0.94	0.93	0.93	0.93	0.93	0.88	0.88	0.87	0.87
7,500	10,000	0.97	0.97	0.96	0.96	0.96	0.96	0.97	0.97	0.93	0.93	0.92	0.92
10,000	20,000	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.98
20,000	40,000	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 14: Continued: Asset Distribution by Income Class

Assets (Unit: JPY 10,000)		Annual Income (JPY 10,000; top: lower, bottom: upper)										
		700	750	800	850	900	950	1,000	1,100	1,200	1,500	2,000
Lower	Upper	750	800	850	900	950	1,000	1,100	1,200	1,500	2,000	3,000
0	25	0.06	0.06	0.07	0.07	0.07	0.07	0.04	0.02	0.06	0.06	0.00
25	50	0.07	0.07	0.07	0.07	0.07	0.07	0.04	0.03	0.06	0.06	0.00
50	100	0.07	0.07	0.08	0.08	0.08	0.08	0.04	0.03	0.06	0.06	0.00
100	150	0.08	0.08	0.08	0.08	0.08	0.08	0.05	0.03	0.06	0.06	0.00
150	200	0.08	0.08	0.08	0.08	0.08	0.08	0.05	0.03	0.06	0.06	0.00
200	300	0.10	0.10	0.09	0.09	0.09	0.09	0.07	0.04	0.06	0.06	0.00
300	450	0.12	0.12	0.10	0.10	0.10	0.10	0.08	0.04	0.13	0.13	0.06
450	600	0.14	0.14	0.12	0.12	0.12	0.12	0.11	0.05	0.13	0.13	0.06
600	750	0.17	0.17	0.14	0.14	0.14	0.14	0.11	0.05	0.14	0.14	0.07
750	900	0.20	0.20	0.16	0.16	0.16	0.16	0.13	0.06	0.14	0.14	0.08
900	1,200	0.26	0.26	0.20	0.20	0.20	0.20	0.16	0.08	0.16	0.16	0.09
1,200	1,500	0.31	0.31	0.25	0.25	0.25	0.25	0.20	0.11	0.18	0.18	0.11
1,500	2,000	0.40	0.40	0.33	0.33	0.33	0.33	0.27	0.16	0.21	0.21	0.14
2,000	3,000	0.53	0.53	0.45	0.45	0.45	0.45	0.40	0.29	0.25	0.25	0.18
3,000	4,000	0.64	0.64	0.58	0.58	0.58	0.58	0.50	0.38	0.35	0.35	0.26
4,000	5,000	0.74	0.74	0.66	0.66	0.66	0.66	0.60	0.46	0.44	0.44	0.34
5,000	7,500	0.87	0.87	0.82	0.82	0.82	0.82	0.78	0.61	0.53	0.53	0.43
7,500	10,000	0.92	0.92	0.89	0.89	0.89	0.89	0.88	0.70	0.63	0.63	0.53
10,000	20,000	0.98	0.98	0.97	0.97	0.97	0.97	0.97	0.92	0.91	0.91	0.77
20,000	40,000	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Since the calculation method for price indices is the same for both the housing price index and the rental price index, we describe the calculation method using housing as an example here. First, we collect the transaction prices of housing sales contracts concluded in the current step for each of the 20 housing quality classes and calculate the average housing price for that quality. Next, an exponentially smoothed moving average is calculated for each average housing price level over time. In addition, besides the exponentially smoothed moving average, a weighted average housing price is calculated using the number of properties in that quality category as a weight, and the current Housing Price Index (HPI) is determined by taking the ratio of this value to the corresponding value at the start of the simulation.

Households' expectations of housing price increases (g) are calculated using the following formula.

$$g = \frac{\gamma(HPI_t + HPI_{t-1} + HPI_{t-2})}{HPI_{t-24} + HPI_{t-25} + HPI_{t-26}} + \zeta \tag{22}$$

γ is the weight adjustment parameter for the HPI growth rate, and ζ is the parameter for adjusting the level of expected house price growth

The markup rates used by households when making an offer to sell a home, and by BTL investors when calculating rental prices for rental properties, are determined probabilistically according to the distribution table in Table 15.

Table 15 Distribution Table for Housing Sale Price Markup Rates

Markup Rate (η)		Prob.	Markup Rate (η)		Prob.	Markup Rate (η)		Prob.
Lower	Upper		Lower	Upper		Lower	Upper	
0.5	0.525	0.007%	1	1.025	41.129%	1.5	1.525	0.038%
0.525	0.55	0.005%	1.025	1.05	12.325%	1.525	1.55	0.031%
0.55	0.575	0.005%	1.05	1.075	8.756%	1.55	1.575	0.025%
0.575	0.6	0.005%	1.075	1.1	6.016%	1.575	1.6	0.021%
0.6	0.625	0.006%	1.1	1.125	4.071%	1.6	1.625	0.018%
0.625	0.65	0.008%	1.125	1.15	2.766%	1.625	1.65	0.015%
0.65	0.675	0.009%	1.15	1.175	1.936%	1.65	1.675	0.014%
0.675	0.7	0.012%	1.175	1.2	1.255%	1.675	1.7	0.012%
0.7	0.725	0.014%	1.2	1.225	0.869%	1.7	1.725	0.011%
0.725	0.75	0.022%	1.225	1.25	0.618%	1.725	1.75	0.009%
0.75	0.775	0.031%	1.25	1.275	0.446%	1.75	1.775	0.008%
0.775	0.8	0.041%	1.275	1.3	0.321%	1.775	1.8	0.007%
0.8	0.825	0.060%	1.3	1.325	0.235%	1.8	1.825	0.007%
0.825	0.85	0.081%	1.325	1.35	0.181%	1.825	1.85	0.006%
0.85	0.875	0.112%	1.35	1.375	0.131%	1.85	1.875	0.006%
0.875	0.9	0.161%	1.375	1.4	0.103%	1.875	1.9	0.006%
0.9	0.925	0.244%	1.4	1.425	0.081%	1.9	1.925	0.004%
0.925	0.95	0.403%	1.425	1.45	0.067%	1.925	1.95	0.003%
0.95	0.975	0.997%	1.45	1.475	0.053%	1.95	1.975	0.005%
0.975	1	16.125%	1.475	1.5	0.044%	1.975	2	0.005%

Table 16: Distribution Table for Housing Sale Price Markup Rates

Markup Rate (η)		Prob.	Markup Rate (η)		Prob.	Markup Rate (η)		Prob.
Lower	Upper		Lower	Upper		Lower	Upper	
0.5	0.525	0.011%	1	1.025	37.395%	1.5	1.525	0.020%
0.525	0.55	0.008%	1.025	1.05	7.551%	1.525	1.55	0.012%
0.55	0.575	0.008%	1.05	1.075	7.025%	1.55	1.575	0.009%
0.575	0.6	0.008%	1.075	1.1	3.488%	1.575	1.6	0.009%
0.6	0.625	0.012%	1.1	1.125	2.223%	1.6	1.625	0.008%
0.625	0.65	0.014%	1.125	1.15	1.384%	1.625	1.65	0.006%
0.65	0.675	0.017%	1.15	1.175	0.836%	1.65	1.675	0.006%
0.675	0.7	0.023%	1.175	1.2	0.532%	1.675	1.7	0.006%
0.7	0.725	0.028%	1.2	1.225	0.425%	1.7	1.725	0.004%
0.725	0.75	0.041%	1.225	1.25	0.246%	1.725	1.75	0.004%
0.75	0.775	0.063%	1.25	1.275	0.212%	1.75	1.775	0.004%
0.775	0.8	0.090%	1.275	1.3	0.124%	1.775	1.8	0.004%
0.8	0.825	0.147%	1.3	1.325	0.099%	1.8	1.825	0.003%
0.825	0.85	0.220%	1.325	1.35	0.078%	1.825	1.85	0.002%
0.85	0.875	0.340%	1.35	1.375	0.049%	1.85	1.875	0.003%
0.875	0.9	0.573%	1.375	1.4	0.042%	1.875	1.9	0.002%
0.9	0.925	1.055%	1.4	1.425	0.035%	1.9	1.925	0.002%
0.925	0.95	1.782%	1.425	1.45	0.027%	1.925	1.95	0.002%
0.95	0.975	3.048%	1.45	1.475	0.019%	1.95	1.975	0.002%
0.975	1	30.596%	1.475	1.5	0.014%	1.975	2	0.002%

For the initial housing price distribution in the simulation, we referenced data on the prices of pre-owned condominiums sold in “Tokyo” between October 2023 and September 2024, taken from individual property price data provided by the Real Estate Information Library. The Real Estate Information Library contains two types of price data: one is real estate transaction price information by a survey on real estate transaction parties conducted by the Ministry of Land, Infrastructure, Transport and Tourism; the other is closed transaction price information based on real estate transaction price data held by the Real Estate Information Network System (REINS). Upon comparing the two types of price data for the aforementioned period, the real estate transaction price information showed a high number of transactions in the 20 million yen range or lower, giving the impression that the price distribution was skewed toward lower prices; therefore, we referred the transaction price information. In the transaction price information, 99.8% of the price distribution falls within the 400 million yen range or lower, and 98.5% falls within the 200 million yen range or lower, accounting for the vast majority. As shown in Table 13, which presents the age and annual income percentile distributions, households with annual incomes exceeding 15 million yen account for only about 3% of the total. Considering that the general guideline for home purchase prices is approximately 5 to 7 times the annual income, this model focused its analysis on price data where the transaction price was 200 million yen or less. To approximate this price distribution, we used a gamma distribution with a location parameter of 3.1 and a scale parameter of 1.3 to set the average price and upper limit of the price range for each initial housing quality level in this model. Note that the location and scale parameters referred to here correspond to the loc and scale arguments of the gamma class in the stats module of the Python numerical analysis library scipy. Figure 15 shows, in the upper left, the price distribution of transaction data for properties priced at 400 million yen or less; in the upper right, the same distribution for properties priced at 200 million yen or less; in the lower left, the probability density function of the gamma distribution with the aforementioned location and scale parameters; and in the lower right, a superimposed plot of the price distribution for properties priced at 200 million yen or less and the gamma distribution. Note that the gamma distribution in the lower right graph has its x-axis scaled by a factor of 10 million to align with the x-axis of the price distribution of transaction data.

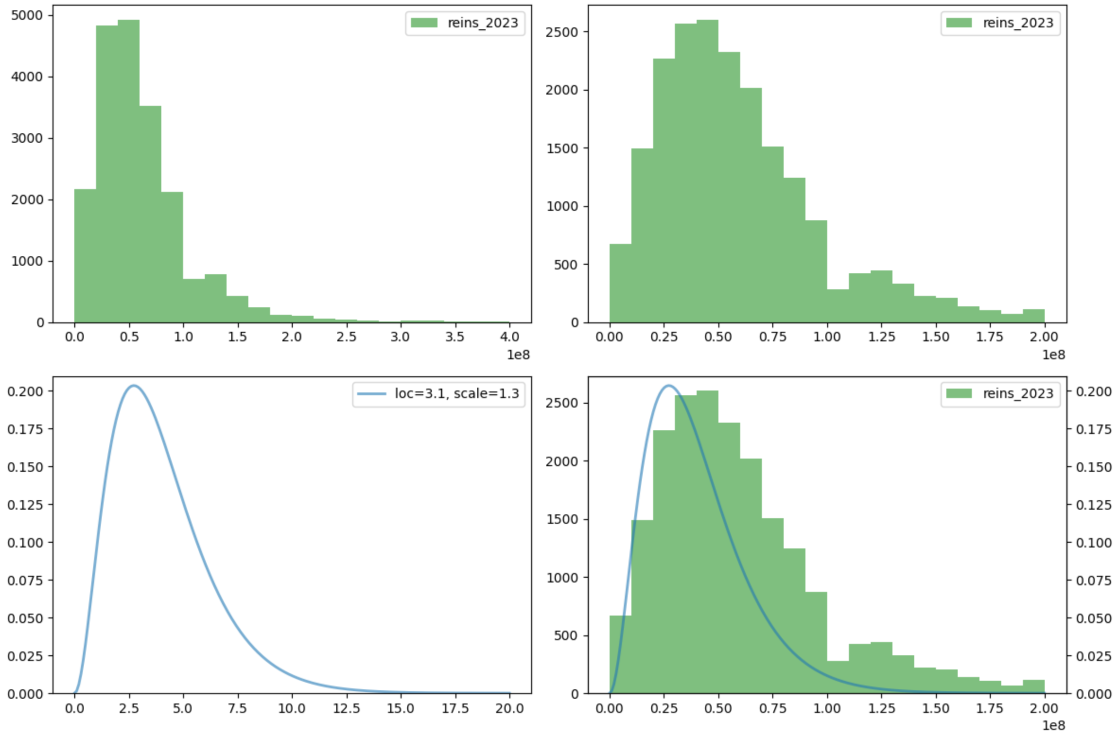


Figure 15: Price distribution based on actual data from Tokyo and the corresponding probability distribution

In the initial step of this model, the average housing price for each housing quality is calculated by multiplying the value at the corresponding percentile point of the inverse of the cumulative distribution function of the above-mentioned gamma distribution by the initial HPI value. The average rental price for each housing quality is calculated by multiplying the average housing price for that quality by the initial rental yield of 4%.

References

Axtell, R., D. Farmer, J. Geanakoplos, P. Howitt, E. Carrella, B. Conlee, J. Goldstein, M. Hendrey, P. Kalikman, D. Masad, N. Palmer, and C.Y. Yang. (2014). "An Agent-Based Model of the Housing Market Bubble in Metropolitan Washington, DC," a write up based on presentation at Deutsche Bundesbank's Spring Conference on "Housing Markets and the Macroeconomy: Challenges for Monetary Policy and Financial Stability." June 5–6, 2014.

Baptista, R., J. D. Farmer, M. Hinterschweiger, K. Low, D. Tang, and A. Uluc. (2016). "Macroprudential policy in an agent-based model of the UK housing market," Staff Working Paper No. 619, Bank of England.

Carro, A., Hinterschweiger, M., Uluc, A., and J. D. Farmer. (2023). "Heterogeneous effects and spillovers of macroprudential policy in an agent-based model of the UK housing market," *Industrial and Corporate Change*, Volume 32, Issue 2, pp. 386–432.

Geanakoplos, J., R. Axtell, J. D. Farmer, P. Howitt, B. Conlee, J. Goldstein, M. Hendrey, N. M. Palmer, and C.Y. Yang. (2012). "Getting at Systemic Risk via an Agent-Based Model of the Housing Market," *American Economic Review*, Volume 102, No.3, pp. 53–58.

Financial Research Center（FSA Institute）
Financial Services Agency
Government of Japan

3-2-1 Kasumigaseki, Chiyoda-ku, Tokyo 100-8967, Japan

TEL：03-3506-6000
URL：https://www.fsa.go.jp/frtc/english/index.html