A Study on the Application of Weighted Average Land Prices to Macroeconomic Analysis

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1. Introduction

Empirical analyses of the interactions among macroeconomic variables and the effects of monetary policy typically employ the vector autoregression (VAR) model proposed by Sims (1980). The VAR framework is well-suited for dynamically analyzing interdependencies among variables over time and identifying potential causal relationships without requiring strong theoretical assumptions. The estimated parameters of the VAR model allow for a range of derivative analyses. A representative example, the impulse response function, visually and temporally illustrates how a shock to one variable affects other variables, facilitating an intuitive understanding of the dynamic relationships. Furthermore, complementary tools often accompany VAR models, such as the Granger causality test, a statistical hypothesis test used to determine whether one time series can help predict another. Variance decomposition and historical decomposition are also commonly included because they help identify the sources of fluctuations in each variable and trace the historical contributions of structural shocks to the observed time series.[i]

The primitive form of the VAR model (also called a reduced-form VAR) has been criticized for its inability to identify restrictions among endogenous variables, making interpreting the estimated parameters difficult and limiting the results to mere statistical correlations. Various methodological refinements have been developed in response to such criticisms. Among the most prominent advancements, the structural VAR (SVAR) model incorporates theory-driven restrictions to identify structural shocks. Notable examples include Christiano, Eichenbaum, and Evans (1999) and Blanchard and Quah (1989), whose SVAR models gained widespread adoption from the late 1980s through the early 1990s.[ii] Therefore, this study also uses the SVAR model.

Researchers can choose various approaches depending on the analytical objective in identifying restrictions. These include short-run restrictions, such as imposing a recursive structure on the contemporaneous coefficient matrix, as well as long-run restrictions that constrain the long-term effects of structural shocks on the economy; however, the term "structural" in this context refers to the dependence structure among variables being explicitly derived from economic theory. It does not imply a stronger notion of structural invariance because the structural parameters remain constant across different policy regimes or periods.

In addition to the structural VAR (SVAR) model, various VAR extensions have been actively developed to suit specific research objectives and the characteristics of the available data. These include the time-varying parameter VAR (TVP-VAR), which allows estimated parameters to evolve; the Bayesian VAR (BVAR), which enhances stability through Bayesian estimation; the stochastic volatility VAR (SV-VAR), which permits time-varying shock variances; the local projection VAR (LP-VAR), which directly estimates impulse responses without relying on the complete VAR system; the nonlinear VAR, which accommodates nonlinear relationships among variables; the global VAR (GVAR), which incorporates cross-country interdependencies; and the panel VAR, which applies the VAR framework to panel data settings.

For Japan-specific empirical applications, many studies have employed structural VAR models. For example, Fueki and Kawamoto (2009) and Kitagawa et al. (2022) decomposed oil price fluctuations into demand- and supply-driven components to examine their differential effects. Furthermore, Nishi (2011) adopted a post-Keynesian perspective to analyze the dynamic interactions among capital accumulation, income distribution, and debt. Moreover, Kimura and Nakajima (2013) attempted to identify conventional and unconventional monetary policy shocks, while Urasawa (2013) investigated deflationary pressures, focusing on wage costs. Nakanishi (2021) assessed the effectiveness of the Bank of Japan's quantitative and qualitative monetary easing policy. Iwaisako and Nakata (2015) evaluated the relative importance of exchange rate fluctuations and foreign demand shocks on Japan's exports. Finally, Tamekawa (2022) examined how monetary base expansion impacts bank lending, differentiated by type of financial institution. These studies illustrate the breadth of empirical VAR applications in the context of the Japanese economy.

One key feature of this paper is including asset prices — specifically land prices — among the endogenous variables in the structural VAR model to quantitatively assess and examine how asset effects impact the macroeconomy. Representative asset prices such as stocks, bonds, and commodities are readily available as macro-level time series data at the national level. In contrast, land price data — such as official land prices and land value survey data typified by appraised land values — are primarily used for micro-level purposes, such as reference indicators in individual real estate transactions or as the basis for tax assessments.[iii] This study examines whether such land price statistics can provide meaningful insights when applied to macroeconomic analysis.

Recently, land prices have been rising throughout Japan. The 2025 Official Land Price Survey (a representative appraised land price index) found that the average prices for all land use—residential, commercial, and overall — have increased for four consecutive years, with the increase accelerating. Focusing on residential land, housing demand has remained robust, partly due to the continued low interest rate environment. In particular, areas with high levels of transportation accessibility and convenience for daily life, attracting many new residents, have experienced relatively strong and sustained increases in residential land prices, supported by solid housing demand.

Rising land prices lead to increases in asset values, such as owner-occupied housing, and these asset effects have wide-ranging influences on the macroeconomy, including consumption, employment, and bank lending. SVAR models are commonly used to empirically analyze relationships among macroeconomic variables; however, such models primarily use flow variables, and the use of stock variables remains relatively limited. Therefore, this paper focuses on land prices — a stock variable — as a proxy for asset effects, incorporating them into a structural VAR model. However, land prices are diverse, often referred to as having "five different prices for a single property[iv]"; thus, they require methodological adjustments to be suitable for macro-level time series analysis. This paper explains the procedures for deriving a weighted average land price based on processed statistics and its dynamic behavior.

2. Weighted average land price

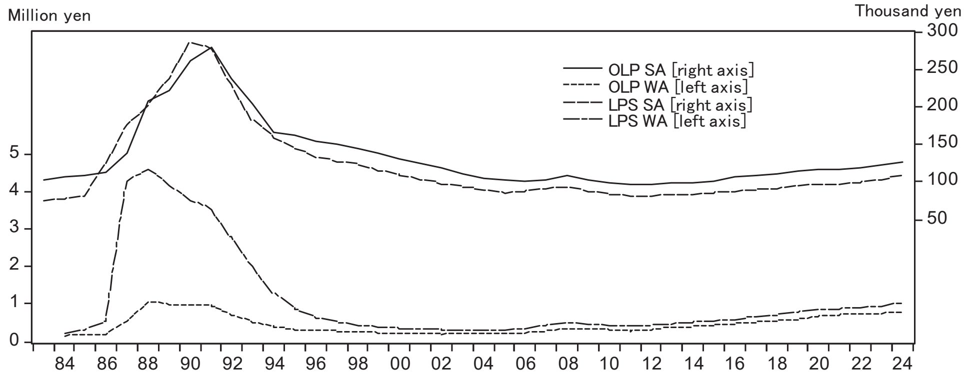
The land price variable used in this paper is a weighted average of appraised land prices, namely, the Official Land Prices and the Prefectural Land Value Survey. This average is calculated using the previous year's value of each surveyed site as weights, following the methodology of Saida et al. (2004) and Nakamura and Saida (2007).

$$P_{S,t} = \sum \frac{V_{j,t-1}}{\sum V_{j,t-1}} P_{jt}. \quad (1)$$

Here, P_{jt} denotes the land price at location j at time t, and $V_{j,t-1}$ represents the previous year's value for the same site, calculated as the product of the site area and the unit land price (per square meter). Thus, the weighted average land price, $P_{S,t}$, is the average of current land prices weighted by their respective values from the previous year. When aggregating point-based data, such as the more than 20,000 appraisal sites nationwide, a simple average would assign equal weight to both high- and low-priced locations. This approach can lead to overestimating the impact of price changes in low-value areas, particularly during periods of significant fluctuation. The analysis in this paper examines the relationship between land prices and macroeconomic indicators. A land price index that reflects differences in price levels is more appropriate in such analyses, and the weighted average land price serves this purpose.

To investigate the effects of household consumption, this study focuses on sites where the current land use includes residential purposes. In 2024, the Official Land Price Survey covers 17,968 sites nationwide, while the Prefectural Land Value Survey includes 17,049 sites. For both datasets, some survey locations have continuous records dating back to 1983. Using equation (1), the annual time series data were calculated and converted into quarterly data through linear interpolation. Simple average values from both datasets were also computed and interpolated for comparison. Figure 1 shows the trends in these land price data. The fluctuations in land prices are more pronounced in the weighted averages. In the case of the Land Value Survey, the peak value (1988) is more

Figure 1: Land price trends



Note: Created by the author based on appraisal land price data — official land price (Chika kōji) (OLP), Land Price Survey (Chika chōsa) (LPS).
SA = Simple average; WA = Weighted average.

than four times higher than that of the Official Land Price Survey. Furthermore, the weighted average land price peak appears earlier than the simple average (three years earlier in the Official Land Price Survey and two years in the Land Value Survey), indicating a sharper and earlier rise during the bubble period.

3. Characteristics of the structural VAR model

The SVAR model employed in this study is a generalized economic structural model with minimal restrictions; the current and lagged values of all variables included are used as explanatory variables. An SVAR model comprising four variables (x_{1t} to x_{4t}) with two lags can be expressed without matrix notation, as shown in equation (2).

$$
\begin{aligned}
x_{1t} + a_{12,0}x_{2t} + a_{13,0}x_{3t} + a_{14,0}x_{4t} &= c_1 + a_{11,1}x_{1,t-1} + a_{12,1}x_{2,t-1} + a_{13,1}x_{3,t-1} + a_{14,1}x_{4,t-1} \\
&\quad + a_{11,2}x_{1,t-2} + a_{12,2}x_{2,t-2} + a_{13,2}x_{3,t-2} + a_{14,2}x_{4,t-2} + \varepsilon_{1t} \\
a_{21,0}x_{1t} + x_{2t} + a_{23,0}x_{3t} + a_{24,0}x_{4t} &= c_2 + a_{21,1}x_{1,t-1} + a_{22,1}x_{2,t-1} + a_{23,1}x_{3,t-1} + a_{24,1}x_{4,t-1} \\
&\quad + a_{21,2}x_{1,t-2} + a_{22,2}x_{2,t-2} + a_{23,2}x_{3,t-2} + a_{24,2}x_{4,t-2} + \varepsilon_{2t} \\
a_{31,0}x_{1t} + a_{32,0}x_{2t} + x_{3t} + a_{34,0}x_{4t} &= c_3 + a_{31,1}x_{1,t-1} + a_{32,1}x_{2,t-1} + a_{33,1}x_{3,t-1} + a_{34,1}x_{4,t-1} \\
&\quad + a_{31,2}x_{1,t-2} + a_{32,2}x_{2,t-2} + a_{33,2}x_{3,t-2} + a_{34,2}x_{4,t-2} + \varepsilon_{3t} \\
a_{41,0}x_{1t} + a_{42,0}x_{2t} + a_{43,0}x_{3t} + x_{4t} &= c_4 + a_{41,1}x_{1,t-1} + a_{42,1}x_{2,t-1} + a_{43,1}x_{3,t-1} + a_{44,1}x_{4,t-1} \\
&\quad + a_{41,2}x_{1,t-2} + a_{42,2}x_{2,t-2} + a_{43,2}x_{3,t-2} + a_{44,2}x_{4,t-2} + \varepsilon_{4t}
\end{aligned} \tag{2}
$$

Here, ci denotes the constant term, $a_{ij,k}$ represents the coefficients, and ε_{it} is the error term, where $i, j = 1,\cdots,4$, and $k = 0, 1, 2$. The SVAR model is a simultaneous equation model in which the current values of endogenous variables are included as explanatory variables, distinguishing it from a primitive or standard VAR model. Therefore, each equation reflects a distinct underlying economic structure, and the error terms (ε_{it}) can be interpreted as structural shocks that independently affect each economic structure, as represented in equation (3).

$$
\varepsilon_{it} \overset{\text{i.i.d.}}{\sim} i.i.d.\left(0, \sigma_i^2\right) \qquad \left(i = 1, \cdots, 4\right) \tag{3}
$$

Equation (4) presents the equation (2) matrix notation, which tends to be cumbersome when expressed in scalar form.

$$
\begin{aligned}
&\mathbf{A}_0\mathbf{x}_t = \mathbf{c} + \mathbf{A}(L)\mathbf{x}_t + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim i.i.d.(\mathbf{0}, \textstyle\sum_\varepsilon) \\
&\mathbf{x}_t = \begin{bmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \\ x_{4t} \end{bmatrix}, \quad \boldsymbol{\varepsilon}_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}, \quad \mathbf{c} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix}, \\
&\textstyle\sum_\varepsilon = E(\boldsymbol{\varepsilon}_t\ \boldsymbol{\varepsilon}_t') = \begin{bmatrix} \sigma_{\varepsilon 1}^2 & 0 & 0 & 0 \\ 0 & \sigma_{\varepsilon 2}^2 & 0 & 0 \\ 0 & 0 & \sigma_{\varepsilon 3}^2 & 0 \\ 0 & 0 & 0 & \sigma_{\varepsilon 4}^2 \end{bmatrix}
\end{aligned} \tag{4}
$$

$$\mathbf{A}_0 = \begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} \\ a_{21} & 1 & a_{23} & a_{24} \\ a_{31} & a_{32} & 1 & a_{34} \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix}, \quad \mathbf{A}_k = \begin{bmatrix} a_{11,k} & a_{12,k} & a_{13,k} & a_{14,k} \\ a_{21,k} & a_{22,k} & a_{23,k} & a_{24,k} \\ a_{31,k} & a_{32,k} & a_{33,k} & a_{34,k} \\ a_{41,k} & a_{42,k} & a_{43,k} & a_{44,k} \end{bmatrix} \quad (k = 1, 2)$$

Here, $\mathbf{x}_t$ denotes the vector of the endogenous variables. $\mathbf{A}_0$ is the contemporaneous coefficient matrix with the ones on the diagonal. $\mathbf{A}_k$ represents the coefficient matrices at each lag, and c is the vector of the constant terms. L is the lag operator, and with up to two lags, the expression takes the form $\mathbf{A}(L) = \mathbf{I}_4 - \mathbf{A}_1 L - \mathbf{A}_2 L^2$.[v] $\boldsymbol{\varepsilon}_t$ is the vector of error terms; however, in the subsequent impulse response analysis context, it is more appropriately interpreted as a vector of structural shocks specific to the underlying economic structure. For this reason, $\boldsymbol{\varepsilon}_t$ is referred to as the innovation vector. Each element is assumed to be completely independent and not contemporaneously correlated, meaning that the structural shocks do not affect each other simultaneously. Accordingly, the variance–covariance matrix, $\sum_{\varepsilon}$, of $\boldsymbol{\varepsilon}_t$ is assumed to be diagonal.

The SVAR model is a simultaneous equations model that includes current-period endogenous variables as explanatory variables. Therefore, if, for example, the first equation of the model shown in equation (2) were estimated directly using ordinary least squares (OLS), simultaneous equation bias would arise; thus, the resulting estimators would be neither unbiased nor consistent.

$$\begin{aligned} x_{1t} &= c_1 - a_{12}x_{2t} - a_{13}x_{3t} - a_{14}x_{4t} \\ &\quad + a_{11,1}x_{1,t-1} + a_{12,1}x_{2,t-1} + a_{13,1}x_{3,t-1} + a_{14,1}x_{4,t-1} \\ &\quad + a_{11,2}x_{1,t-2} + a_{12,2}x_{2,t-2} + a_{13,2}x_{3,t-2} + a_{14,2}x_{4,t-2} + \varepsilon_{1t} \end{aligned}$$

To address this, we first transform the model into a reduced-form VAR that excludes contemporaneous variables; OLS estimation is then applied to this reduced form. Then, by imposing minimal identification restrictions on the estimated results, the structural parameters of the VAR model are recovered. Specifically, both sides of equation (4) are premultiplied by the inverse of the contemporaneous coefficient matrix: $\mathbf{A}_0^{-1}$. To simplify the model representation, the vectors for the constant term, coefficients, and error terms are replaced by $\mathbf{k}, \mathbf{B}_k, \mathbf{u}_t$, respectively. This approach provides the following reduced-form expression.

$$\begin{aligned} &\mathbf{x}_t = \mathbf{k} + \mathbf{B}(L)\mathbf{x}_t + \mathbf{u}_t, \quad \mathbf{u}_t \sim i.i.d.(\mathbf{0}, \textstyle\sum_u) \\ &\qquad \mathbf{k} = \mathbf{A}_0^{-1}\mathbf{c}, \quad \mathbf{B}_k = \mathbf{A}_0^{-1}\mathbf{A}_k \quad (k = 1, 2) \\ &\qquad \mathbf{u}_t = \mathbf{A}_0^{-1}\boldsymbol{\varepsilon}_t \Rightarrow E(\mathbf{u}_t\, \mathbf{u}_t') = \textstyle\sum_u = \mathbf{A}_0^{-1}E(\boldsymbol{\varepsilon}_t\, \boldsymbol{\varepsilon}_t')(\mathbf{A}_0^{-1})' = \mathbf{A}_0^{-1}\textstyle\sum_{\varepsilon}(\mathbf{A}_0^{-1})' \end{aligned} \tag{5}$$

In the reduced form, the innovation vector ($\mathbf{u}_t = [u_{1t} \quad u_{2t} \quad u_{3t} \quad u_{4t}]'$) is a linear function of the structural innovation vector ($\boldsymbol{\varepsilon}_t$); therefore, it is no longer mutually independent but is typically correlated. Consequently, the variance–covariance matrix ($\sum_u$) becomes a symmetric, nondiagonal matrix, where the off-diagonal elements are generally non-zero, as shown in equation (6).

$$\sum_u = E(\mathbf{u}_t\,\mathbf{u}_t') = \begin{bmatrix} \sigma_{u11}^2 & \sigma_{u12}^2 & \sigma_{u13}^2 & \sigma_{u14}^2 \\ \sigma_{u12}^2 & \sigma_{u22}^2 & \sigma_{u23}^2 & \sigma_{u24}^2 \\ \sigma_{u13}^2 & \sigma_{u23}^2 & \sigma_{u33}^2 & \sigma_{u34}^2 \\ \sigma_{u14}^2 & \sigma_{u24}^2 & \sigma_{u34}^2 & \sigma_{u44}^2 \end{bmatrix} \tag{6}$$

Estimating the reduced-form VAR model in equation (5) using OLS provides parameters no longer subject to simultaneous equation bias.

Estimating the contemporaneous coefficient matrix ($\mathbf{A}_0$) is the key to identifying the structural parameters. Once $\mathbf{A}_0$ is estimated, we can derive the remaining coefficient parameters of the structural VAR model from equation (5) using the OLS estimates $\hat{\mathbf{k}}, \hat{\mathbf{B}}_k, \hat{\Sigma}_u$ from the reduced-form VAR. $\mathbf{A}_0$ and $\sum_\varepsilon$ contain 16 unknown parameters[vi]; however, the matrix $\sum_\varepsilon$ is symmetric and contains only 10 independent elements.[vii] Therefore, at least six additional restrictions are required to identify $\mathbf{A}_0$.[viii]

Following Sims (1980), this study imposes the additional identifying restrictions using a fully recursive contemporaneous restriction, which assumes a sequential expansion of the contemporaneous dependence among variables. The Cholesky decomposition is employed for this purpose, as presented below.[ix]

The variance–covariance matrix ($\sum_u$) of the reduced-form innovation vector (assumed to be a 4 × 4 positive definite symmetric matrix) has a unique lower triangular matrix — $\mathbf{P}$ (the Cholesky factor)—that satisfies $\sum_u = \mathbf{PP}'$. Assuming $\mathbf{P} = \mathbf{A}^{-1}\sum_\varepsilon^{\frac{1}{2}}$, and using the variance–covariance matrix ($\sum_\varepsilon$) of the structural innovation vector, a diagonal matrix with positive elements, $\sum_u$ can be decomposed into three components: $\sum_u = \mathbf{PP}' = \mathbf{A}^{-1}\sum_\varepsilon\left(\mathbf{A}^{-1}\right)'$. Here, $\mathbf{A}^{-1}$ is a lower triangular matrix with ones on the diagonal; thus, interpreting $\mathbf{A}_0^{-1}$ in equation (4) as $\mathbf{A}^{-1}$ implies that the six identifying restrictions required for identifying $\mathbf{A}_0$ are satisfied.

When estimating a VAR model, we must select the lag order. Ideally, this selection should be based on various information criteria, such as the Akaike information criterion or the Schwarz Bayesian information criterion; however, an indiscriminate increase in variables or lag order can lead to a severe loss of degrees of freedom. The reduced-form VAR model shown in equation (5) can be transformed into the infinite vector moving average (VMA) representation with the reduced-form shocks (u), as expressed in equation (7).

$$\begin{aligned} \mathbf{x}_t &= \mathbf{k} + \mathbf{B}(L)\mathbf{x}_t + \mathbf{u}_t \\ \left[\mathbf{I} - \mathbf{B}(L)\right]\mathbf{x}_t &= \mathbf{k} + \mathbf{u}_t \\ \mathbf{x}_t &= \mathbf{k}\left[\mathbf{I} - \mathbf{B}(1)\right]^{-1} + \left[\mathbf{I} - \mathbf{B}(L)\right]^{-1}\mathbf{u}_t \\ &= \tilde{\mathbf{k}} + \mathbf{\Phi}_0\mathbf{u}_t + \mathbf{\Phi}_1\mathbf{u}_{t-1} + \mathbf{\Phi}_2\mathbf{u}_{t-2} + \cdots \\ &= \tilde{\mathbf{k}} + \mathbf{\Phi}(L)\mathbf{u}_t \end{aligned} \tag{7}$$

Here, $\tilde{\mathbf{k}}\left(= \mathbf{k}\left[\mathbf{I} - \mathbf{B(1)}\right]^{-1} = \mathbf{k}\left[\mathbf{I} - \mathbf{B}_1 - \mathbf{B}_2\right]^{-1}\right)$ is the vector of the constant terms. $\mathbf{\Phi}_s$ (s = 0, 1, 2, ⋯) is the matrix of the coefficient parameters representing the response of each variable s periods after a one-unit reduced-form shock (hereafter referred to as the shock coefficient matrix). Therefore, $\mathbf{\Phi}_0 = \mathbf{I}$. From equation (7), the endogenous variables $\mathbf{x}_t$ can be decomposed into the constant ($\tilde{\mathbf{k}}$) and the stochastic — $\mathbf{\Phi}(L)\mathbf{u}_t$ — components. The latter can be interpreted as a systematic dynamic mechanism originating from the error terms.

Here, we define the effect of the reduced-form shock (du_j) of the j-th variable on the i-th variable x_i after s periods as the lowercase $\phi_{ij,s}$ corresponding to the uppercase $\mathbf{\Phi}_0$. Thus, this effect ($\phi_{ij,s}$) can be expressed as in equation (8).

$$\phi_{ij,s} = dx_{it+s} = \frac{\partial x_{it+s}}{\partial u_{jt}} du_{jt} = [\mathbf{\Phi}_s]_{i,j}\, du_{jt} \tag{8}$$

The impulse response function quantifies the changes in each endogenous variable over time resulting from the interdependencies mediated by an exogenous shock. Examining equation (8) reveals that when a unit shock is applied solely to the first endogenous variable (x_1), the contemporaneous values of the other endogenous variables x_2, x_3, and x_4 are assumed to be unaffected by x_1. The same assumption applies when shocks are applied exclusively to the second, third, or fourth endogenous variables. The model captures interdependencies among endogenous variables; however, analyses that contradict these assumptions would be inappropriate as empirical tools.

Equations (7) and (8) represent the infinite VMA representation and the impulse responses of each variable to the reduced-form shocks, u_t. However, multiple structural shocks are embedded within the reduced-form shocks; thus, the direct use of these equations makes economic interpretation difficult. The relationship between the reduced-form and structural representations, $\mathbf{u}_t = \mathbf{A}_0^{-1}\boldsymbol{\varepsilon}_t$, is utilized to address this issue. This approach allows us to transform equations (7) and (8) into the infinite VMA representation and impulse response functions based on structural shocks (ε_t).

$$\begin{aligned}\mathbf{x}_t &= \mathbf{A}_0^{-1}\mathbf{c}[\mathbf{I} - \mathbf{B}(1)]^{-1} + [\mathbf{I} - \mathbf{B}(L)]^{-1}\mathbf{A}_0^{-1}\boldsymbol{\varepsilon}_t \\ &= \tilde{\mathbf{c}} + \mathbf{\Phi}_0\mathbf{A}_0^{-1}\boldsymbol{\varepsilon}_t + \mathbf{\Phi}_1\mathbf{A}_0^{-1}\boldsymbol{\varepsilon}_{t-1} + \mathbf{\Phi}_2\mathbf{A}_0^{-1}\boldsymbol{\varepsilon}_{t-2} + \cdots \\ &= \tilde{\mathbf{c}} + \mathbf{\Gamma}_0\boldsymbol{\varepsilon}_t + \mathbf{\Gamma}_1\boldsymbol{\varepsilon}_{t-1} + \mathbf{\Gamma}_2\boldsymbol{\varepsilon}_{t-2} + \cdots \\ &= \tilde{\mathbf{c}} + \mathbf{\Gamma}(L)\boldsymbol{\varepsilon}_t\end{aligned} \tag{9}$$

Furthermore, unlike the uppercase matrix $\mathbf{\Gamma}_0$, we define the effect of a structural shock of magnitude $d\varepsilon_j$ in the j-th variable on the i-th variable x_{it} after s periods as $\gamma_{ij,s}$. This effect ($\gamma_{ij,s}$) can be expressed as shown in equation (10).

$$\gamma_{ij,s} = dx_{it+s} = \frac{\partial x_{it+s}}{\partial \varepsilon_{jt}} d\varepsilon_{jt} = [\mathbf{\Gamma}_s]_{i,j}\, d\varepsilon_{jt} \tag{10}$$

Equation (9) now represents the endogenous variables in the model solely in terms of exogenous structural shocks. This adjustment makes equation (9) more useful than equation (7) for direct policy analysis and forecasting applications.

4. Estimation

4.1. Four-Variable AD-AS model

Consider the following aggregate demand–aggregate supply (AD-AS) model: the four endogenous variables are income y, price level p, interest rate r, and asset price p_w.

$$\begin{cases} y = c(y) + i\left(y, r - \overline{\pi}^e\right) + \overline{g} \\ y = F\left(L^D\left(\overline{w}/p\right)\right) \\ r = r\left(y - \overline{y}^*, \pi - \overline{\pi}^*\right) \\ \overline{m}^* / p = m^D\left(y, r, p_w\right) \end{cases} \tag{11}$$

The first equation represents the IS curve for the goods market, and the second is the AS curve incorporating the production function. The third denotes a policy reaction function based on the Taylor rule, and the fourth corresponds to the LM curve, which accounts for the asset market. Here, $\overline{\pi}^e$ denotes expected inflation, $\overline{g}$ represents other components of demand, and $\overline{w}$ indicates wages. The variables $\overline{y}^*$, $\overline{\pi}^*$, and $\overline{m}^*$ refer to the desired levels of income, inflation, and money stock, respectively; they are treated as exogenous variables for convenience. Furthermore, the LM curve is rearranged by isolating p_w on the left-hand side to obtain an explicit functional form, referred to as the asset price equation. Increasing land prices raises the value of owned real estate, which may lead to higher consumption expenditure — thereby increasing the gross domestic product (GDP)—through the wealth effect. A rise in interest rates is expected to lower asset prices through higher bank borrowing costs, decrease the present discounted value of future returns, and shift funds toward bonds. When prices rise, real estate investment tends to increase as a hedge against inflation, boosting the demand for land and potentially raising asset prices. Incorporating stochastic disturbances, ε_i (where $i = y, p, r, p_w$), and omitting the exogenous variables allows us to express the resulting stochastic model as equation (12). The plus and minus signs above the endogenous variables on the right-hand side indicate the expected signs of the partial effects.

$$\begin{cases} y = y^D(\overset{-}{r}) + \varepsilon_y \\ y = y^S(\overset{+}{p}) + \varepsilon_{y^s} \Rightarrow p = p(\overset{+}{y}) + \varepsilon_p \\ r = r(\overset{+}{y}, \overset{+}{\pi}) + \varepsilon_r \\ p_w = p_w(\overset{+}{y}, \overset{+}{p}, \overset{-}{r}) + \varepsilon_{pw} \end{cases} \tag{12}$$

We then reformulate the static model represented by equation (12) as a dynamic structural VAR model by explicitly incorporating lags. Equation (13) presents the resulting matrix form analogous to equation (4).

$$\mathbf{A}_0\mathbf{x}_t = \begin{bmatrix} 1 & 0 & a_{yr} & 0 \\ -a_{py} & 1 & 0 & 0 \\ -a_{ry} & -a_{rp} & 1 & 0 \\ -a_{p_w y} & -a_{p_w p} & a_{p_w r} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ p_t \\ r_t \\ p_{w,t} \end{bmatrix} = \mathbf{c} + \mathbf{A}(\mathbf{L}) \begin{bmatrix} y_t \\ p_t \\ r_t \\ p_{w,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_y \\ \varepsilon_p \\ \varepsilon_r \\ \varepsilon_{pw} \end{bmatrix} \tag{13}$$

$$= \mathbf{c} + \mathbf{A}(L)\mathbf{x}_t + \boldsymbol{\varepsilon}_t$$

Note: Assuming $a_i > 0$ ($i = py, ry, \ldots, p_w r$)

Here, we assume that investment does not respond contemporaneously to interest rates (i.e., $a_{yr} = 0$); thus, the contemporaneous coefficient matrix in equation (13) becomes a lower triangular matrix, allowing the model to be expressed as a fully recursive VAR. Based on the estimated parameters, the impulse response functions derived from equation (13) should satisfy the following sign restrictions concerning contemporaneous relationships.

$$\begin{bmatrix} dy \\ dp \\ dr \\ dp_w \end{bmatrix} = \begin{bmatrix} + & - & - & 0 \\ + & ? & - & 0 \\ ? & + & + & 0 \\ 0 & 0 & - & + \end{bmatrix} \begin{bmatrix} d\varepsilon_y \\ d\varepsilon_p \\ d\varepsilon_r \\ d\varepsilon_{pw} \end{bmatrix} \tag{14}$$

The estimation period is based on quarterly data from 1983 to 2024. From a priori considerations, lag lengths of two and four quarters are selected, corresponding to the inclusion of information from approximately half a year to one year prior in the case of quarterly data. Real GDP is used for the income variable. The price variable employs three types of the consumer price index (CPI): the headline CPI, the core CPI (excluding fresh food), and the core-core CPI (excluding both fresh food and energy). Three types of average contracted interest rates on loans (stock/long-term) are used for the interest rate variable, corresponding to city banks, regional banks, and second-tier regional banks. As for the asset price variable, land prices are represented by the simple and weighted averages of the official land prices (Chika kōji) and land price surveys (Chika chōsa) discussed in the previous section. Since land prices are stock variables at a given time, a one-period lag is applied to the official land prices. At the same time, both no lag and a one-period lag are used for the land price surveys, resulting in six variations.

Estimation was conducted for 108 cases (2 × 1 × 3 × 3 × 6). Log-differencing is applied to income, price level, and asset price variables to avoid spurious regression due to non-stationary time series data while differencing is applied to interest rates.[1] Table 1 summarizes a portion of the results. For details regarding the data and sources, refer to the appendix.

Among the six parameters of the contemporaneous coefficient matrix ($\hat{\mathbf{A}}_0$), estimations matching up to five parameters were obtained in 6 cases for the 2-lag model and 11 cases for the 4-lag model. Regarding price indices, most sign conditions were satisfied in cases using the overall CPI and core CPI; however, many cases using the core-core CPI failed to meet these conditions. No significant differences occurred across any groups of lending contract average interest rates. In terms of asset prices, sign condition conformity was observed in many cases using the weighted average land price survey data, demonstrating the usefulness of this data in macroeconomic

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1） The unit root tests are hypothesis tests used to determine whether time series variables are stationary. The results are omitted here; however, the variables were generally difference-stationary.

Table 1: Contemporaneous Coefficient Matrix ($\hat{\mathbf{A}}_0$) of the Four-variable AD-AS Structural VAR Model

Lag 2

case06

Model [y, p1, r1, pa2w]			
1	0	0	0
−0.001	1	0	0
0.507	−1.575	1	0
−0.465	−2.713 *	0.205 *	1

case12

Model [y, p1, r2, pa2w]			
1	0	0	0
−0.001	1	0	0
0.475	−1.164	1	0
−0.460	−2.634 *	0.202 *	1

case18

Model [y, p1, r3, pa2w]			
1	0	0	0
−0.002	1	0	0
0.369	−0.997	1	0
−0.461	−2.546 *	0.188 *	1

case24

Model [y, p2, r1, pa2w]			
1	0	0	0
−0.002	1	0	0
0.517	−1.198	1	0
−0.492	−1.493	0.195 *	1

case30

Model [y, p2, r2, pa2w]			
1	0	0	0
−0.002	1	0	0
0.484	−1.029	1	0
−0.484	−1.485	0.194 *	1

case36

Model [y, p2, r3, pa2w]			
1	0	0	0
−0.001	1	0	0
0.372	−0.772	1	0
−0.486	−1.424	0.181 *	1

Lag 4

case02

Model [y, p1, r1, pa1w]			
1	0	0	0
−0.012	1	0	0
0.354	−2.056	1	0
−0.260	−0.768	0.104 *	1

case06

Model [y, p1, r1, pa2w]			
1	0	0	0
−0.014	1	0	0
0.417	−2.452 *	1	0
−0.409	−3.560 *	0.251 *	1

case08

Model [y, p1, r2, pa1w]			
1	0	0	0
−0.012	1	0	0
0.354	−1.738	1	0
−0.266	−0.732	0.087 *	1

case12

Model [y, p1, r2, pa2w]			
1	0	0	0
−0.013	1	0	0
0.412	−2.079	1	0
−0.412	−3.451 *	0.223 *	1

case14

Model [y, p1, r3, pa1w]			
1	0	0	0
−0.011	1	0	0
0.245	−1.813	1	0
−0.274	−0.692	0.078 *	1

case17

Model [y, p1, r3, pa2a]			
1	0	0	0
−0.005	1	0	0
0.216	−2.057	1	0
−0.003	−0.088	0.008	1

case18

Model [y, p1, r3, pa2w]			
1	0	0	0
−0.013	1	0	0
0.290	−2.121 *	1	0
−0.421	−3.324 *	*	1

case24

Model [y, p2, r1, pa2w]			
1	0	0	0
−0.012	1	0	0
0.399	−2.626	1	0
−0.477	−1.607	0.228 *	1

case30

Model [y, p2, r2, pa2w]			
1	0	0	0
−0.012	1	0	0
0.392	−1.919	1	0
−0.478	−1.468	0.198 *	1

case35

Model [y, p2, r3, pa2a]			
1	0	0	0
−0.006	1	0	0
0.190	−1.470	1	0
−0.004	−0.150	0.009	1

case36

Model [y, p2, r3, pa2w]			
1	0	0	0
−0.012	1	0	0
0.265	−1.611	1	0
−0.480	−1.376	0.181 *	1

Note: Y = Real GDP; p1 = General CPI index; p2 = Core CPI index; r1 = Interest rate (city banks); r2 = Interest rate (regional banks); r3 = Interest rate (second-tier regional banks); pa1w = Official land price (Chika kōji, weighted); pa2w = Land Price Survey (Chika chōsa, weighted). Italicized values indicate that the sign does not match the expected direction; * denotes statistical significance at the 5% level.

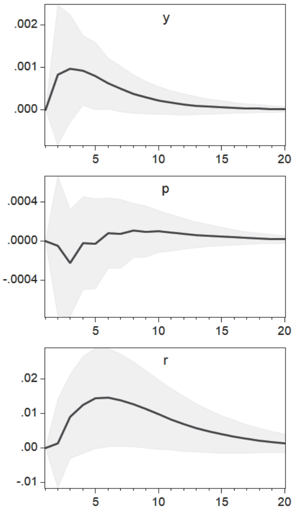
model analysis. Notably, the income parameter ($-a_{ry}$) in the policy reaction function was positive in all cases. This outcome may be related to the zero lower bound constraint, which prevents sufficiently lowering interest rates in response to income decreases. Figure 2 shows the impulse response functions to asset price shocks for 5 cases (among those presented in Table 1) with many parameters significant at the 5% level.

The weighted average land price represents asset price shocks; they consistently induced a positive response in income across all cases, peaking at around one year and sustaining for approximately three years. Regarding prices (inflation rate), an initial decline occurs, dissipating after about one year, followed by a slight positive response. Interest rates generally exhibit a positive overall reaction; however, cases using data from regional and second-tier regional banks show a slight initial decline. The magnitude of this decline is somewhat larger for the second-tier regional banks. This difference may reflect variations in the information-gathering capabilities of financial institutions or possibly the economic conditions prevailing in their respective localities. Regardless, the differing responses by the banking sector are noteworthy. Conversely, this situation suggests that when adverse shocks occur (such as unintended declines in asset prices exemplified by a bubble burst), immediate interest rate reductions may not be feasible. Instead, rate increases could exacerbate economic downturns in the banks' operational regions.

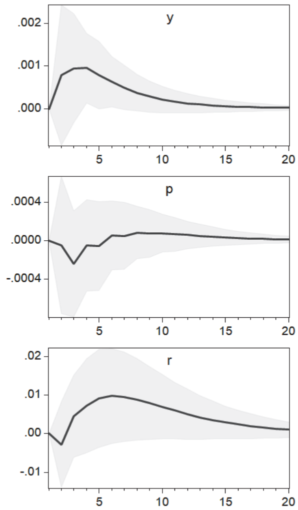
Figure 2: Impulse Response Functions of the Four-Variable VAR Model (Asset Price Shock)

Lag 2

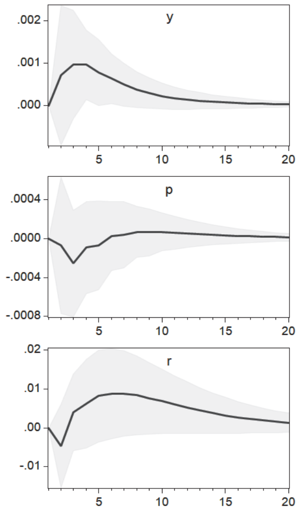
Case 06
Model [y, p1, r1, pw2w]



Case 12
Model [y, p1, r2, pw2w]

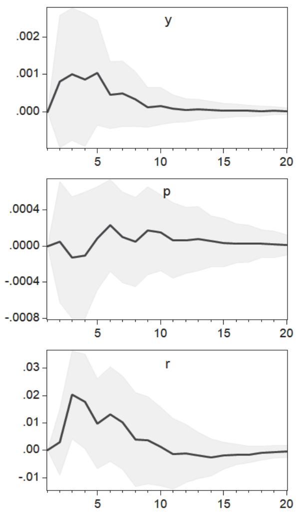


Case 18
Model [y, p1, r3, pw2w]

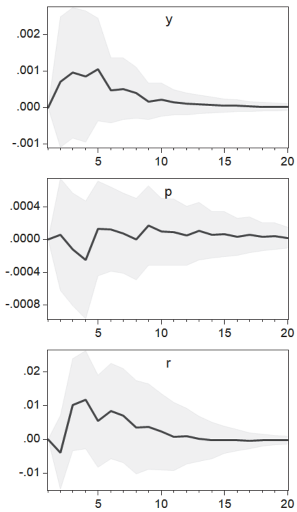


Lag 4

Case 06
Model [y, p1, r1, pw2w]



Case 18
Model [y, p1, r3, pw2w]



y : Real GDP
p1: General CPI index
r1: Interest rate (city banks)
r2: Interest rate (regional banks)
r3: Interest rate (second-tier regional banks)
p_w2w: Land Price Survey (Chika chōsa, weighted)

Note: The solid line represents the point estimates of the impulse responses. The horizontal axis shows the time horizon up to 20 quarters. The shaded area indicates the 90% confidence interval.

4.2. Five -Variable AD-AS model

Next, we extend the four-variable model from the previous section by adding the exchange rate, which is considered on the transmission pathway, thereby formulating the five-variable AD-AS model shown in equation (15).

$$\begin{cases} y = y^D(\overset{-}{r}) + \varepsilon_y \\ y = y^S(\overset{+}{p}) + \varepsilon_{y^s} \Rightarrow p = p(\overset{+}{y}) + \varepsilon_p \\ r = r(\overset{+}{y}, \overset{+}{\pi}) + \varepsilon_r \\ p_w = p_a(\overset{+}{y}, \overset{+}{p}, \overset{-}{r}) + \varepsilon_{pw} \\ ex = ex(\overset{\pm}{y}, \overset{\pm}{p}, \overset{\mp}{r}, \overset{\mp}{p_w}) + \varepsilon_{ex} \end{cases} \tag{15}$$

Note: For the sign restrictions on exchange rates, the upper row refers to the JPY–USD exchange rate, and the lower row refers to the real effective exchange rate.

The exchange rate responded with a domestic currency depreciation during economic expansions due to increased imports. During periods of rising prices, it also depreciates due to a decline in the purchasing power of the domestic currency. Investors seek high-yield currencies when interest rates rise, appreciating the domestic currency. During asset price increases, capital inflows from foreign investors tend to cause an appreciation of the domestic currency. The exchange rate reacts contemporaneously to various variables in this manner and is positioned in the lowest row of the contemporaneous coefficient matrix, as shown in equation (16).

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ -a_{py} & 1 & 0 & 0 & 0 \\ -a_{ry} & -a_{rp} & 1 & 0 & 0 \\ -a_{p_w y} & -a_{p_w p} & a_{p_w r} & 1 & 0 \\ \mp a_{exy} & \mp a_{exp} & \pm a_{exr} & \pm a_{exp_w} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ p_t \\ r_t \\ p_{w,t} \\ ex_t \end{bmatrix} = \mathbf{c} + \mathbf{A}(\mathbf{L}) \begin{bmatrix} y_t \\ p_t \\ r_t \\ p_{w,t} \\ ex_t \end{bmatrix} + \begin{bmatrix} \varepsilon_y \\ \varepsilon_p \\ \varepsilon_r \\ \varepsilon_{pw} \\ \varepsilon_{ex} \end{bmatrix} \tag{16}$$

Note: Assuming $a_i > 0$ ($i = py, ry, \dots, exy$)
The upper part of the fifth row represents the JPY–USD exchange rate; the lower part represents the real effective exchange rate.

The estimation period, model lag order, and variables used are the same as in the previous section. Two types of exchange rates were prepared: the JPY–USD rate and the real effective exchange rate. Estimations were conducted for 216 cases (2 × 1 × 3 × 3 × 6 × 2). Differencing was applied to the interest rate data, while logarithmic differencing was applied to all other data. Table 2 summarizes a portion of the results.

Among the cases in Table 2, Figure3 presents the impulse response functions to weighted average land price shocks as asset prices for the three lag-2 models, showing many parameters significant at the 5% level. The only difference among the models lies in the type of interest rate used — city banks, regional banks, or second-tier regional banks. Income, prices (overall CPI), land prices (weighted average of land price survey), and the real effective exchange rate are identical across all three models.

Table 2: Contemporaneous Coefficient Matrix $\hat{\mathbf{A}}_0$ of the Five-Variable AD-AS Structural VAR Model

Lag 2

case04 — Model [y, p1, r1, pa1w, ex2]

1	0	0	0	0
0.018	1	0	0	0
0.597	−0.669	1	0	0
−0.310	−0.643	0.097 *	1	0
0.429	−0.551	*0.020*	−0.120	1

case12 — Model [y, p1, r1, pa2w, ex2]

1	0	0	0	0
0.015	1	0	0	0
0.618	−0.787	1	0	0
−0.507	−2.730 *	0.241 *	1	0
0.498 *	*−0.511*	*0.024*	−0.061	1

case16 — Model [y, p1, r2, pa1w, ex2]

1	0	0	0	0
0.018	1	0	0	0
0.584	−0.217	1	0	0
−0.308	−0.611	0.093 *	1	0
0.445	*−0.539*	*0.018*	−0.127 *	1

case24 — Model [y, p1, r2, pa2w, ex2]

1	0	0	0	0
0.015	1	0	0	0
0.606	−0.309	1	0	0
−0.506	−2.616 *	0.238 *	1	0
0.515 *	*−0.486*	*0.020*	−0.067	1

case28 — Model [y, p1, r3, pa1w, ex2]

1	0	0	0	0
0.018	1	0	0	0
0.471	−0.054	1	0	0
−0.311	−0.577	0.090 *	1	0
0.437	*−0.507*	*0.011*	−0.130	1

case36 — Model [y, p1, r3, pa2w, ex2]

1	0	0	0	0
0.015	1	0	0	0
0.502	−0.152	1	0	0
−0.509	−2.533 *	0.223 *	1	0
0.510 *	*−0.458*	*0.014*	−0.068	1

case40 — Model [y, p2, r1, pa1w, ex2]

1	0	0	0	0
0.018	1	0	0	0
0.612	−0.315	1	0	0
−0.307	−0.014	0.095 *	1	0
0.439	*−0.665*	*0.017*	−0.129	1

case48 — Model [y, p2, r1, pa2w, ex2]

1	0	0	0	0
0.015	1	0	0	0
0.633	−0.462	1	0	0
−0.506	−1.522	0.234 *	1	0
0.506 *	*−0.619*	*0.022*	−0.064	1

case52 — Model [y, p2, r2, pa1w, ex2]

1	0	0	0	0
0.018	1	0	0	0
0.593	−0.095	1	0	0
−0.303	−0.011	0.093 *	1	0
0.455	*−0.678*	*0.016*	−0.136	1

case59 — Model [y, p2, r1, pa2w, ex1]

1	0	0	0	0
0.003	1	0	0	0
0.539	−0.41	1	0	0
−0.535	−1.678	0.218 *	1	0
−0.006	*0.333*	*−0.019*	0.032	1

case60 — Model [y, p2, r1, pa2w, ex2]

1	0	0	0	0
0.015	1	0	0	0
0.615	−0.209	1	0	0
−0.502	−1.481	0.235 *	1	0
0.523 *	*−0.623*	*0.018*	−0.069	1

case71 — Model [y, p2, r1, pa2w, ex1]

1	0	0	0	0
0.004	1	0	0	0
0.431	−0.157	1	0	0
−0.538	−1.621	0.202 *	1	0
−0.008	*0.319*	*−0.015*	0.034	1

Lag 4

case45 — Model [y, p2, r1, pa2a, ex1]

1	0	0	0	0
−0.002	1	0	0	0
0.279	−1.639	1	0	0
−0.008	−0.299	0.027 *	1	0
0.184	−0.783	0.020	0.283	1

case46 — Model [y, p2, r1, pa2a, ex2]

1	0	0	0	0
0.010	1	0	0	0
0.429	−0.94	1	0	0
−0.002	−0.239	0.027 *	1	0
0.394	0.381	−0.024	−0.454	1

case47 — Model [y, p2, r1, pa2w, ex1]

1	0	0	0	0
−0.012	1	0	0	0
0.444	−1.829	1	0	0
−0.460	−2.530	0.245 *	1	0
−0.042	−0.199	*−0.007*	0.006	1

case57 — Model [y, p2, r2, pa2a, ex1]

1	0	0	0	0
−0.001	1	0	0	0
0.388	−0.823	1	0	0
−0.003	−0.272	0.016	1	0
0.186	−0.746	0.039	0.325	1

case59 — Model [y, p2, r2, pa2w, ex1]

1	0	0	0	0
−0.012	1	0	0	0
0.450	−1.068	1	0	0
−0.474	−2.366	0.207 *	1	0
−0.065	−0.129	*−0.009*	0.007	1

case69 — Model [y, p2, r3, pa2a, ex1]

1	0	0	0	0
−0.001	1	0	0	0
0.278	−0.327	1	0	0
−0.015	−0.261	0.005	1	0
0.188	−0.697	0.051	0.320	1

case71 — Model [y, p2, r3, pa2w, ex1]

1	0	0	0	0
−0.012	1	0	0	0
0.335	−0.638	1	0	0
−0.482	−2.284	0.177 *	1	0
−0.068	−0.086	*−0.003*	0.005	1

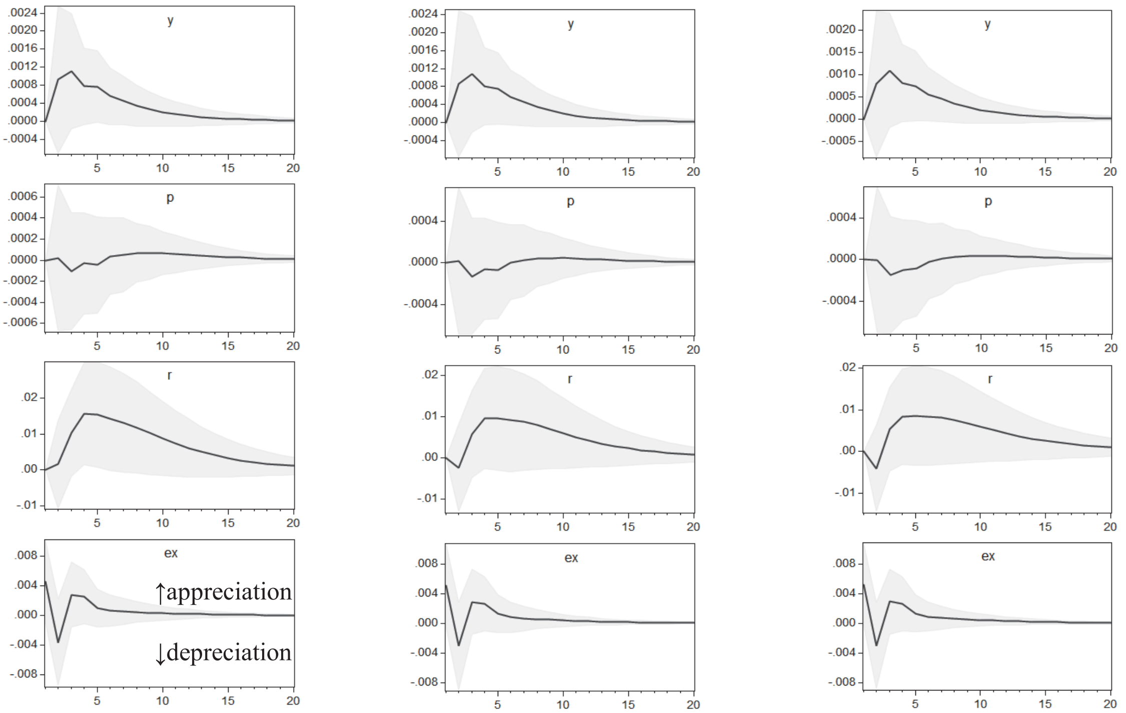
Note: Y = Real GDP; p1 = General CPI index; p2 = Core CPI index; r1 = Interest rate (city banks); r2 = Interest rate (regional banks); r3 = Interest rate (second-tier regional banks); pa1w = Official land price (Chika kōji, weighted); pa2w = Land Price Survey (Chika chōsa, weighted); ex1 = JPY–USD exchange rate; ex2 = real effective exchange rate. Italicized values indicate that the sign does not match the expected direction; * denotes statistical significance at the 5% level.

A consistent positive response to income occurred in all cases, peaking at around one year and persisting for approximately three years. Prices (inflation rate) initially exhibit a negative response, dissipating within about one year, followed by a slight positive effect. Interest rates generally show a positive response, peaking at around one year; however, cases using data from regional banks and second-tier regional banks initially display a slight decline, with the latter experiencing a larger decrease. These responses closely resemble those in the four-variable model in Figure 2. The exchange rate is the real effective exchange rate; thus, the initial positive response indicates an appreciation (the yen strengthening). Although the exchange rate temporarily depreciates afterward, it reverses to appreciation, exhibiting a somewhat complex movement but reflecting an appreciation response overall.

Figure 3: Impulse Response Functions of the Five-Variable VAR Model (Asset Price Shock)

Lag 2

Case 12	Case 24	Case 36
Model [y, p1, r1, pw2w, ex2]	Model [y, p1, r2, pw2w, ex2]	Model [y, p1, r3, pw2w, ex2]



Note 1: Y = real GDP; p1 = general CPI index; r1 = Interest rate (city banks); r2 = Interest rate (regional banks); r3 = Interest rate (second-tier regional banks); pw2w = The land price survey (Chika chōsa, Weighted); ex2 = the real effective exchange rate.

Note 2: The solid line represents the point estimates of the impulse responses. The horizontal axis shows the time horizon up to 20 quarters. The shaded area indicates the 90% confidence interval.

4.3. Supplementary analysis

The previous section analyzed each variable's dynamic response to asset price shocks using impulse response functions. As a derivative analysis based on the structural VAR model, forecast error variance decomposition (FEVD) defines each variable's unexpected fluctuations as forecast error variances and measures the contribution of various shocks to these variances. This approach provides information on the relative importance of each structural shock to the endogenous variables within the model. Another approach, historical decomposition, breaks down the fluctuations during the sample period of the time series data into the cumulative effects of each shock. This method allows us to analyze the extent and timing of each factor's contribution to the overall variation. This section conducts these decomposition analyses in addition to the previous impulse response analysis. The results

Table 3: Forecast Error Variance Decomposition

Four-variable Lag4 model (Case 06)

Variable y	Shock			
Quarters	y	p	r	pw
1	100.00	0.00	0.00	0.00
4	97.43	0.13	1.07	1.37
12	95.65	0.51	1.58	2.26
20	95.61	0.55	1.58	2.26

Variable p	Shock			
Quarters	y	p	r	pw
1	0.13	99.87	0.00	0.00
4	9.06	88.15	2.69	0.10
12	11.85	85.09	2.64	0.42
20	11.88	85.06	2.62	0.45

Variable r	Shock			
Quarters	y	p	r	pw
1	0.31	1.83	97.85	0.00
4	1.02	5.21	89.99	3.79
12	1.67	5.28	87.94	5.11
20	1.81	5.47	87.57	5.14

Variable pw	Shock			
Quarters	y	p	r	pw
1	0.75	3.04	7.10	89.11
4	0.62	2.05	9.28	88.05
12	1.41	2.12	8.97	87.51
20	1.56	2.26	8.94	87.24

Four-variable model [y, p1, r1, pa2w]
Five-variable model [y, p1, r1, pa2w, ex2]

Five-variable Lag2 model (Case 12)

Variable y	Shock				
Quarters	y	p	r	pw	ex
1	100.00	0.00	0.00	0.00	0.00
4	94.56	0.25	1.48	1.60	2.10
12	93.55	0.38	1.59	2.39	2.08
20	93.54	0.38	1.59	2.41	2.08

Variable p	Shock				
Quarters	y	p	r	pw	ex
1	0.14	99.86	0.00	0.00	0.00
4	5.25	87.07	1.45	0.03	6.18
12	6.76	84.68	2.16	0.10	6.30
20	6.76	84.66	2.16	0.12	6.30

Variable r	Shock				
Quarters	y	p	r	pw	ex
1	0.70	0.19	99.11	0.00	0.00
4	0.96	0.12	88.26	1.90	8.76
12	1.10	0.49	81.64	6.47	10.31
20	1.11	0.50	81.32	6.78	10.28

Variable pw	Shock				
Quarters	y	p	r	pw	ex
1	0.92	2.74	7.95	88.38	0.00
4	0.87	1.69	10.55	86.25	0.64
12	1.23	1.76	9.92	86.44	0.64
20	1.25	1.77	9.89	86.44	0.65

Variable ex	Shock				
Quarters	y	p	r	pw	ex
1	1.68	0.60	0.68	1.11	95.93
4	1.65	2.12	1.84	2.27	92.13
12	1.71	2.19	1.84	2.37	91.88
20	1.71	2.19	1.84	2.38	91.88

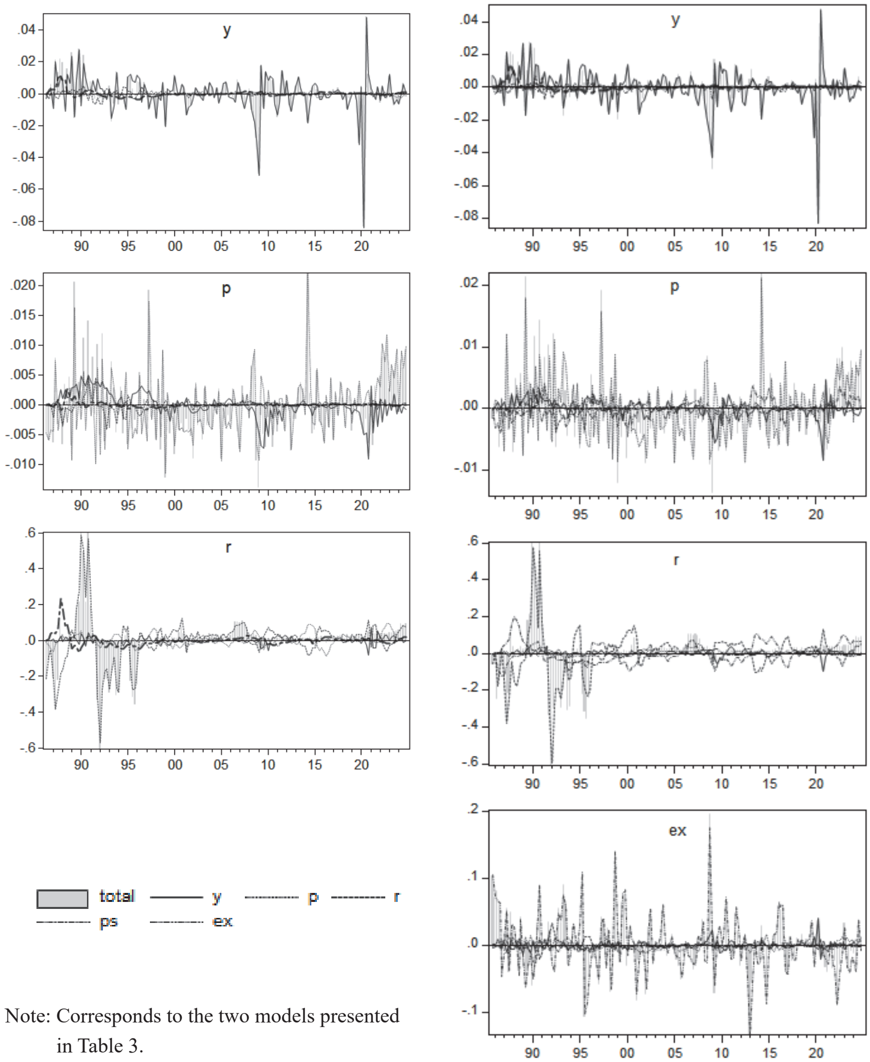
of the forecast error variance decomposition are presented first. FEVD was performed for each of the five models shown in Figure 2; however, no substantial differences were observed. Table 3 presents the results for two cases—the four-variable lag-4 model (Case 06) and the five-variable lag-2 model (Case 12).

Many studies on forecast error variance decomposition have shown that shocks originating from each variable explain approximately 90% of the forecast error over the 20-quarter (5-year) evaluation period. Within the four-variable model, GDP shocks contributed about 12% to price fluctuations, while interest rate shocks accounted for roughly 9% of land price variations, making relatively substantial contributions. In the five-variable model, with the addition of the exchange rate, GDP shocks contributed approximately 7% to price fluctuations, and interest rate shocks contributed about 10% to land price fluctuations; these are also relatively large values. Although comparative figures are not presented, the influence of lending interest rates was greater for city banks than regional banks and regional banks than for second-tier regional banks. This outcome indicates that the lending behavior of larger or higher loan-volume banks more strongly affects land price fluctuations. The contributions of own shocks to real GDP and the real effective exchange rate fluctuations exceeded 90%, higher than those for other variables. This result confirms that the impacts of monetary policy and asset price shocks on income and exchange rates are relatively limited.

Figure 4 presents the results of the historical decomposition, focusing on the contribution of asset price shocks by displaying the variations of variables other than asset prices. The bar graphs represent the total impact of all shocks combined; the lines indicate the contribution of each variable's shocks. For clarity, the asset price contributions are shown with thicker lines than the others. A notable contribution appears during the late 1980s

Figure 4: Historical Decomposition

Four-variable model　　　　Five-variable model



Note: Corresponds to the two models presented in Table 3.

bubble period, but the subsequent impact seems limited. Overall, these findings corroborate the results from the variance decomposition analysis.

5. Conclusion

Examples of introducing residential land prices as asset prices into structural VAR models as endogenous variables are rare. This study processed and organized appraisal land price data (primarily used for microlevel applications) into simple average land price data and weighted average land price data through statistical manipulation. Furthermore, we incorporated the weighted average land price data as an endogenous variable in the structural VAR model. Our estimation using the four-variable and five-variable AD-AS models revealed that several cases (including the weighted average land price) exhibited significant relationships with the macroeconomic variables.

The response of interest rates to an upward shock in the weighted average land price was initially misjudged by relatively smaller banks, sometimes resulting in a decline instead of an appropriate increase. Conversely, in the case of a negative shock represented by an unintended decline in asset prices, such as a bubble collapse, an immediate lowering of interest rates may not be implemented. Instead, interest rates may be raised, potentially worsening economic conditions in the banks' regional bases. Concerns arise in areas where small-scale banks are concentrated that economic fluctuations may be amplified beyond necessity. Establishing a system for timely collection of land price information and expanding information analysis capabilities through capital and business alliances, management integration, or mergers with neighboring banks would be sensible.

This study's SVAR model has the advantage of analyzing interactions and causal relationships among variables over time and assessing the effects of various economic shocks; however, it also has the undeniable limitation of being unable to account for differences across individual entities. Prior studies noted that analysis can be conducted nationally for Japan, but it becomes difficult at the prefectural or municipal levels. In contrast, panel data analysis allows us to consider heterogeneity across entities by reflecting differences among local governments. As Kitamura (2003, 2006) highlighted, with the increasing availability of microlevel data, analysis utilizing such data is expected to advance further in the future.

This paper confirmed the usefulness of calculating the weighted average land prices at the national level and incorporating these prices into an SVAR model for analysis. However, the appraisal land price data comprise approximately 17,000 locations (Chika kōji and Chika chōsa); therefore, they might be better utilized as weighted average land prices at the prefectural or even more granular municipal levels. In other words, treating the data as panel rather than time series data would vastly increase the information available, potentially leading to improved estimation accuracy. Furthermore, estimating previously unobservable latent variables may become possible, thereby enhancing the understanding of the dynamic fluctuations of economic agents.

Regarding the variables used in this study, income variables are available as taxable income by the municipality from the "Survey on Municipal Taxation Status" conducted by the Ministry of Internal Affairs and Communications. Price variables are provided as price indices for cities hosting prefectural government offices from the Ministry's "Mid-level Classification Index by City." For interest rates, statistics on lending income and outstanding loan balances are maintained for ordinary banks (city banks, regional banks, and second-tier regional banks), making it possible to approximate lending yields by bank headquarters location. Thus, a comparative analysis between the current time-series estimation results and panel estimations disaggregated by local governments is feasible. Focusing on sudden asset price fluctuations and monetary policy effects, employing the structural VAR model for time-series analysis and the fixed-effects model for panel data could reveal distinct policy implications. This topic is intriguing and warrants comparative analyses.

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Note

i　Examples of historical decomposition studies include Dungey et al. (2013) and Parkyn and Vehbi (2013).

ii　The error correction model (ECM), which focuses on cointegration relationships and allows for the simultaneous analysis of long-run equilibrium and short-run dynamics, also gained widespread use around the same period.

iii　Although real estate investment trusts (REITs) have been utilized in some cases for macroeconomic analysis, the accumulation of research in this area remains relatively limited.

iv　The five representative types of land prices are official land prices (as of January 1), land value survey prices (as of July 1), inheritance tax roadside land prices (early July), fixed asset tax roadside land prices (around April to June), and actual market transaction prices. The roadside land prices are generally based on the official land prices as a benchmark. Thus, within the framework of the official land valuation system, the two most representative forms of appraised land prices are the official land prices and the land value survey prices. Both surveys cover over 20,000 locations nationwide, with more than 80% of the surveyed sites classified as "residential" or including residential land.

v　To ensure that the VAR process is stationary and that the matrix $\mathbf{A}(L)^{-1}$ exists, all the roots of the characteristic equation — that is, all eigenvalues λ_j — must lie inside the unit circle.

vi　Refers to the 16 elements of $\left[a_{12}, a_{13}, a_{14}, a_{21}, a_{23}, a_{24}, a_{31}, a_{32}, a_{34}, a_{41}, a_{42}, a_{43}, \sigma^2_{\varepsilon 1}, \sigma^2_{\varepsilon 2}, \sigma^2_{\varepsilon 3}, \sigma^2_{\varepsilon 4}\right]$.

vii　Refers to the 10 elements of $\left[\sigma^2_{u11}, \sigma^2_{u12}, \sigma^2_{u13}, \sigma^2_{u14}, \sigma^2_{u22}, \sigma^2_{u23}, \sigma^2_{u24}, \sigma^2_{u33}, \sigma^2_{u34}, \sigma^2_{u44}\right]$.

viii　The discussion here is specified for the four-variable VAR model, which is this study's most frequently estimated case. When generalized to an n-variable model, the number of unknown parameters becomes n2, while the information obtained from the reduced-form VAR estimation corresponds to the variance–covariance matrix of the residuals, which contains $\frac{n(n+1)}{2}$ distinct elements due to its symmetry. Therefore, at least $\frac{n(n-1)}{2}\left(=n^2-\frac{n(n+1)}{2}\right)$ additional restrictions are required for identification.

ix　Chapter 7 Appendix of the Economic Planning Agency's Economic Research Institute (in Japanese) (2000) provides a clear introduction to alternative identifying restrictions for structural VAR models, such as block-recursive and long-run/short-run restrictions.

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Appendix Table: List of Data

<table>
<tr><th colspan="4">Variable name</th><th>Variable notation</th><th>Unit</th><th>Data sources</th></tr>
<tr><td rowspan="14">Time series data: period 1983Q1–2024Q4</td><td colspan="3">Real GDP
(Expenditure approach) *1</td><td>y</td><td>bn. yen</td><td>Cabinet office, Annual report on national accounts</td></tr>
<tr><td rowspan="3">Price index</td><td colspan="2">All items</td><td>p_1</td><td rowspan="3">2020 = 100</td><td rowspan="3">Statistics Bureau, Ministry of Internal Affairs and Communications, consumer price index (CPI)</td></tr>
<tr><td colspan="2">All items, less fresh food (Core CPI)</td><td>p_2</td></tr>
<tr><td colspan="2">All items, less fresh food and energy (Core core CPI)</td><td>p_3</td></tr>
<tr><td rowspan="3">Average contractual interest rate on bank loan</td><td rowspan="3">Outstanding loans and bills discounted/long-term loans</td><td>City banks</td><td>r_1</td><td rowspan="3">%</td><td rowspan="3">Bank of Japan,
Time series data</td></tr>
<tr><td>Regional banks</td><td>r_2</td></tr>
<tr><td>Second-tier regional banks</td><td>r_3</td></tr>
<tr><td rowspan="4">Land price *2</td><td rowspan="2">The official land price
(Chika kōji)</td><td>Simple average</td><td>p_w1a</td><td rowspan="4">yen / m^2</td><td rowspan="4">Ministry of Land, Infrastructure, Transport and Tourism, Land prices and real estate appraisal</td></tr>
<tr><td>Weighted average</td><td>p_w1w</td></tr>
<tr><td rowspan="2">The land price survey
(Chika chōsa)</td><td>Simple average</td><td>p_w2a</td></tr>
<tr><td>Weighted average</td><td>p_w2w</td></tr>
<tr><td rowspan="2">Exchange rate</td><td colspan="2">JPY–USD exchange rate</td><td>ex_1</td><td>denominated in local currency</td><td rowspan="2">Bank of Japan,
Time series data</td></tr>
<tr><td colspan="2">Real effective exchange rate</td><td>ex_2</td><td>2020 = 100</td></tr>
</table>

* Note 1: The 2000 chained-price GDP (1983Q1–2010Q1) was linked to the 2015 chained-price GDP (1994Q1–2024Q4) by applying an adjustment factor of 1.06.

* Note 2: The official land price (Chika kōji) is based on values as of January 1, while the land price survey (Chika chōsa) is based on values as of July 1. To ensure consistency with flow data, a one-period lag is applied. The average values are calculated by the author.