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Abstract

Leveraging Korea's unique *jeonse* system—a lump-sum lease arrangement that enables inference of intrinsic housing values—and urban district-level monthly-frequency data, this paper proposes a novel method to decompose housing price fluctuations into supply, residential demand, and speculative demand shocks. We find speculative demand accounts for nearly 50% of cumulative housing price growth in Korea and over 60% in the Seoul metropolitan area. Importantly, housing booms driven by residential demand increase regional consumption, employment, and output ("good booms"), while those driven by speculation reduce them ("bad booms"). Using comprehensive quarterly individual panel data, we show that only speculative demand shocks trigger excessive household leverage, creating a debt overhang that explains these differential aggregate effects. While monetary easing significantly amplifies speculative demand, an equivalent tightening fails to produce a comparable contraction. Conversely, macroprudential tools—such as lower loan-to-value limits—curb speculative surges more effectively, yet they also risk dampening residential demand.

JEL Classification: E50; G10; R30; R21

Keywords: House prices; Good booms and bad booms; High-frequency identification; Sign-restriction approach; Jeonse; Debt overhang; Policy mix

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1 Introduction

Housing markets play a central role in shaping macroeconomic fluctuations. Yet, despite extensive research, the literature has not reached a consensus on the primary drivers of housing booms and busts (e.g., Landvoigt, 2017; Kaplan, Mitman and Violante, 2020; Cox and Ludvigson, 2021). This lack of consensus likely stems from the dual nature of housing as both a consumption good and an investment asset yielding capital gains (Ioannides and Rosenthal, 1994; Goodman, 1988; Arrondel and Lefebvre, 2001; Dusansky and Koç, 2007), a feature that opens the door to speculative behavior interacting with credit market conditions (Landvoigt, Piazzesi and Schneider, 2015; Garriga, Manuelli and Peralta-Alva, 2019; Mian and Sufi, 2022). To the extent that housing speculation is, by definition, not accompanied by corresponding expansions in productive capacity, their presence provides a natural explanation for why some booms end in recessions while others do not (Burnside, Eichenbaum and Rebelo, 2016; Gertler, Kiyotaki and Prestipino, 2020; Gorton and Ordonez, 2020).[1]

This raises a fundamental question: What distinguishes a "good" housing boom from a "bad" one? Must we wait until the burst of the boom? In other words, can speculative episodes that are likely to culminate in economic slowdowns be distinguished in *ex-ante* from sustainable booms grounded in fundamentals? Answering this question remains empirically challenging since the dual role of housing complicates pricing dynamics.

A growing body of literature emphasizes the importance of speculative demand, driven by expectations of future capital gains, in explaining housing price fluctuations.[2] Related to the discussion of good versus bad housing booms, recent evidence shows that

[1]See Duca, Muellbauer and Murphy (2021) for a comprehensive review of the housing market and its interaction with a credit market and the macroeconomy.

[2]The literature remains divided on whether housing price fluctuations are primarily driven by expectations or by credit conditions. While Case and Shiller (2003) and Kaplan et al. (2020) highlight the role of beliefs, Mian and Sufi (2009) and Cox and Ludvigson (2021) emphasize credit standards and borrowing constraints. Adding further nuance, Greenwald and Guren (2025) suggest that the relative importance of beliefs and credit conditions may depend on market segmentation. Given the focus of our analysis, we do not separately identify belief-driven and credit-driven speculative demand.

booms fueled by speculative demand amplify macroeconomic fluctuations, generating stronger expansions during upswings and deeper contractions during downturns (e.g., Gao, Sockin and Xiong, 2020; DeFusco, Nathanson and Zwick, 2022).

This paper develops a novel high-frequency approach to decompose housing price fluctuations into contributions from supply, residential demand, and speculative demand shocks. The analysis exploits a distinctive institutional feature of the Korean housing market—the *jeonse* or (*chonsei*) system—which enables a more direct assessment of housing's fundamental value than traditional rent or income-based metrics.[3] In a jeonse contract, tenants pay a large deposit instead of monthly rent and recover the full amount at lease expiration. This structure implies that jeonse prices reflect the value of housing services in the spot market, excluding expectations of capital gains (Ambrose and Kim, 2003; Cho, 2006).

A natural question is why we do not simply rely on the standard price-to-rent ratio to measure speculative behavior in housing markets. In a frictionless asset–pricing framework, the fundamental value of a house is the present value of future rents, suggesting that deviations of prices from rents could reveal speculative components. In practice, however, price-to-rent ratios face two conceptual and empirical limitations.

First, the financial commitments required for home purchase differ sharply from those for renting. Borrowing constraints and liquidity needs generate systematic demographic differences between owners and renters, so rental prices and sales prices are formed in partially segmented markets. Moreover, rental units often differ from owner-occupied units in size, quality, and location. As a result, observed rents and observed transaction prices frequently refer to different properties, making price-to-rent ratios sensitive to compositional differences rather than speculative demand per se. Second, even when comparable rental units exist, the fundamental value of housing $V_t = \sum_{k\geq 1} E_t R_{t+k} / \prod_{j=0}^{k-1}(1+$

[3] Although the jeonse system is unique to Korea today, similar arrangements, such as *antichresis* contracts, have existed historically in civil law jurisdictions. Under these contracts, tenants provide a lump-sum deposit refunded at the end of the lease term. See Navarro and Turnbull (2010) for further discussion.

i_{t+j}) depends on the entire expected path of future rents (i.e., *flows*) and discount rates, neither of which is directly observable. Imputing V_t requires strong auxiliary assumptions on rent and interest rate dynamics, which introduces model dependence and estimation fragility.

By contrast, the jeonse system provides a directly observed *stock* price for the very same dwellings traded in the sales market. The same apartment is frequently listed both for jeonse and for sale, and many transactions embed a jeonse component. Because such arrangements arise when counterparties differ in expectations or liquidity needs, the jeonse and sales markets are tightly linked. A simple no–arbitrage condition between the jeonse deposit and financial returns implies that jeonse prices equal the present value of rental services and thus capture the intrinsic consumption value of housing. Consequently, the divergence between sales and jeonse prices offers a much cleaner and more direct measure of speculative demand than conventional price-to-rent ratios.

To identify the structural drivers of housing price fluctuations, we augment a standard supply-demand framework with the sales-to-jeonse price ratio. Using a high-frequency panel model covering 176 urban districts, we extend the methodology of Shapiro (2024). Alongside conventional indicators—sales prices and transaction volumes—we incorporate the sales-to-jeonse ratio to separate residential from speculative demand shocks. We estimate the model district by district, letting coefficients vary to capture heterogeneity in local amenities, incomes, housing supply elasticities, and etc.

Under this framework, we classify a district-level housing price change as demand-driven (supply-driven) if residuals in the sales price and transaction volume equations have the same (opposite) sign. Among demand-driven episodes, we define speculative demand shocks as instances where sales price growth exceeds jeonse price growth, and residential demand shocks as those where the opposite holds. These three shocks are constructed to be mutually orthogonal at the district level, allowing structural interpretation. Aggregating across districts using housing inventory weights, we compute the national contributions of each factor to housing price dynamics.

Compared to prior studies, our identification strategy offers a key advantage in its minimal structural assumptions and intuitive appeal. In contrast to approaches relying on short-run restrictions, we do not require a pre-specified variable ordering. Furthermore, building on Jump and Kohler (2022) and Shapiro (2024), our method relaxes assumptions even relative to traditional sign-restriction approaches, as it does not require additional criteria for selecting admissible impact responses. For example, a closely related work by Ben-David, Towbin and Weber (2025) identifies expectation components of the U.S. housing market by applying a sign restriction approach to the impulse response functions to various structural shocks. In contrast, our simple residual-based approach facilitates *near* real-time identification of speculative demand without any further assumptions, offering practical applications.

We have four main findings. First, speculative demand shocks are the dominant driver of housing price fluctuations in Korea from January 2007 to December 2024, accounting for 50.8% of the cumulative change, followed by supply (35.2%) and residential demand (13.9%) shocks. In the Seoul metropolitan area, where the sales-to-jeonse price ratio is higher than the rest (i.e., higher expectations of future capital gains), speculative demand shocks account for an even greater share, at 62.2%.

Second, and most importantly, the macroeconomic consequences of the residential and speculative demand shocks differ markedly. Using district-level panel local projections akin to a difference-in-differences approach, we find that a positive residential demand shock raises regional consumption, output, and employment, whereas a speculative demand shock lowers them. A (negative) supply shock resulting in price appreciation leads to a mild contraction, though the effect is only marginally significant. These results suggest that residential demand-driven booms are benign ("good booms"), while speculative booms entail negative consequences ("bad booms"). This insight contributes to the discussion by highlighting that housing booms may generate adverse economic effects even prior to their bust. Moreover, the high-frequency nature of our identification implies its potential as an early warning indicator for policymakers to detect and respond to bad housing booms.

Third, we further investigate the mechanism underlying these differential effects using comprehensive micro-level panel data from the Bank of Korea's Household Debt Database. We find that while supply and residential demand shocks have minimal impact on household debt, speculative demand shocks generate significant and persistent increases in household leverage, particularly in mortgage debt. This excessive debt accumulation following speculative housing booms creates a debt overhang effect that constrains future consumption, explaining why such booms ultimately damage economic activity despite the positive wealth effect through price appreciation.

Lastly, we assess the effectiveness of policy tools in containing speculative booms. Expansionary monetary policy amplifies speculative demand with limited effect on residential demand, while equivalent monetary tightening does little to dampen speculation, revealing a strong asymmetry in policy efficacy. By contrast, macroprudential tightening—such as reducing loan-to-value (LTV) limits—effectively curbs housing price growth across all shock types, albeit with some delay. Notably, loosening macroprudential constraints does not generate a commensurate expansionary effect. These findings highlight the importance of a well-calibrated mix of monetary and macroprudential policies in managing housing market risks.

The remainder of the paper is organized as follows. Section 2 describes the institutional details of the jeonse system and derives the equilibrium relationship between sales and jeonse prices required to identify speculative housing demand. Section 3 outlines our methodology for decomposing housing price dynamics into supply, residential demand, and speculative demand. Section 4 presents the results of our decomposition analysis. Section 5 quantifies the macroeconomic effects of structural housing shocks and discusses the distinction between good and bad housing booms. Section 6 examines the household debt channel underlying these differential effects using individual-level data. Section 7 investigates the role of monetary and macroprudential policies in containing speculative dynamics. Section 8 concludes.

2 Jeonse System in Korea

2.1. Institutional Background of jeonse System

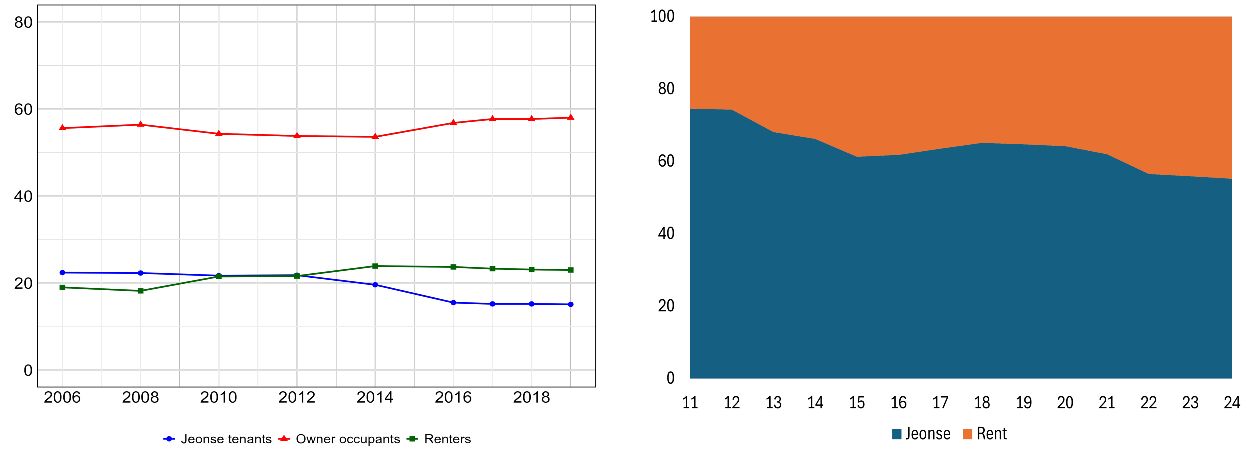
While additional institutional details of the Korean housing market are provided in the Appendix A, this section briefly introduces its most distinctive feature: the jeonse system. Under a typical jeonse contract, tenants provide a large lump-sum deposit—usually between 40% and 80% of the property's sales value—to the homeowner. During the lease term, which generally spans two years, tenants are exempt from making monthly rental payments. At contract expiration, the homeowner is legally obligated to return the full deposit. In the event of default, the property may be liquidated through auction to reimburse the tenant. Functionally, the jeonse contract operates as a form of implicit financial exchange: the tenant forgoes rental payments, while the homeowner effectively utilizes the deposit as a low-cost funding source.

This system remains a significant component of Korea's rental housing market. Panel (a) of Figure 1 illustrates the composition of housing tenure types from 2006 to 2019. Over this period, the share of households residing under jeonse contracts remained relatively stable between 15% and 20%, comparable to the proportion of monthly rental arrangements. This persistent presence highlights the institutional importance of jeonse in Korea's housing market. Panel (b) of Figure 1 shows the share of jeonse transactions among total leases from 2011 to 2024. Although this share has declined somewhat over time, jeonse contracts still account for a substantial portion of the market. For a theoretical explanation of its coexistence with conventional rental contracts, see Park and Pyun (2020).

Figure 1: Share of jeonse in Korea

(a) Share of housing occupancy types

(b) Share of jeonse in total lease transactions

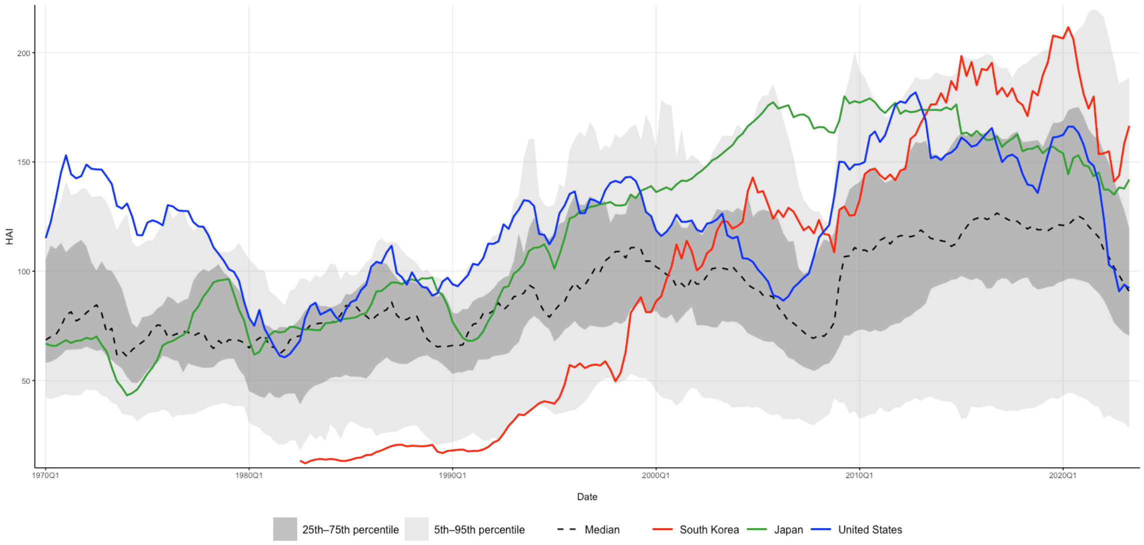


Panel (a) shows the share of households classified as owner-occupants, jeonse tenants, and monthly renters over time. The renter category includes mixed contracts that combine reduced monthly payments with a partial lump-sum deposit. Data are from the Korean Housing Survey. Panel (b) shows the share of jeonse and monthly rent in total lease transactions over time. Data are from the Ministry of Land, Infrastructure, and Transport.

A substantial body of literature attributes the emergence and persistence of the jeonse system to Korea's underdeveloped financial system during the period of rapid industrialization. In the 1960s and 1970s, financial policies favored corporate lending through artificially low interest rates, while credit for housing and consumer loans remained expensive and scarce. Government housing policies prioritized the construction of new housing units over the expansion of rental supply, further tightening rental market conditions.

The absence of an accessible, long-term mortgage market helps explain the continued relevance of jeonse in an international context. Biljanovska, Fu and Igan (2023) developed a cross-country measure of housing affordability for 40 OECD countries spanning five decades. Their housing affordability index (HAI) evaluates a household's capacity to meet regular mortgage payments without compromising basic consumption needs. The HAI accounts for average house prices, mortgage interest rates, loan-to-value (LTV) ratios, and mortgage maturities, offering a more comprehensive assessment of affordability than earlier measures.

Figure 2: Housing affordability measure: Korea vs. OECD countries



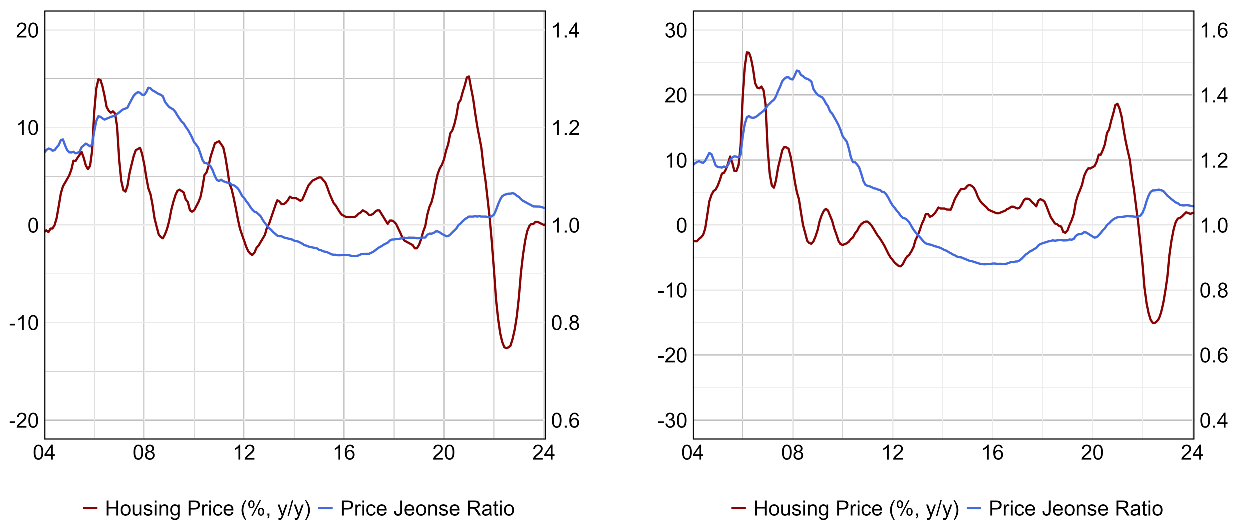
Note: This figure plots the housing affordability index (HAI) from 1970Q1 to 2023Q2, as constructed by Biljanovska et al. (2023).

As shown in Figure 2, Korea exhibited the lowest level of housing affordability among OECD countries until the mid-1990s, implying a widespread inability to finance home purchases through long-term mortgages. This institutional constraint helps explain the unique and persistent role of jeonse contracts as an alternative housing arrangement. For landlords, jeonse offered a cost-effective financing mechanism; for tenants, it provided a lower-cost alternative to homeownership. These mutual incentives sustained the jeonse system's prominence in Korea's housing market (e.g., Ambrose and Kim, 2003; Cho, 2006; Kim, 2013).

Following the Asian Financial Crisis, however, Korea's housing affordability improved markedly, surpassing the level of most OECD countries. The concurrent rise in housing prices suggests that financial access expanded even more significantly, creating the potential for speculative dynamics in the housing market. Figure 3 plots the evolution of housing prices alongside the sales-to-jeonse price ratio. Notably, the ratio exhibits lower-frequency movements than housing prices, suggesting that it encapsulates additional information—particularly regarding expectations of capital gains—that is not captured by price changes alone. In subsequent sections, we exploit this feature to identify speculative housing demand.

Figure 3: The evolution of housing prices and the sales-to-jeonse price ratio

(a) Nationwide (b) Seoul Metropolitan Areas



Note:Year-over-year housing price growth (red solid line) and the sales-to-jeonse price ratio (blue solid line) from 2004M11 to 2024M12. The sales-to-jeonse ratio is computed as the ratio of the housing sales price index to the jeonse price index, which explains values below one.

2.2. Identifying Speculative Demand Using Jeonse Prices

This section develops a simple dynamic model intended to discipline the identifying assumptions of the empirical analysis. Households choose consumption, savings, residential location, and a tenure mode among monthly rent, jeonse (lump-sum lease), and ownership. The physical supply of housing units in each location is fixed in the short run. All units are owned by households, who may either occupy their unit or supply it to the rental or jeonse market. The institutional fact that large-scale corporate landlords are virtually absent in the Korean housing market is consistent with this assumption. A no-arbitrage condition between rental and jeonse usage anchors jeonse prices to the present value of rental services, thereby identifying the fundamental consumption value of housing. Sales prices may deviate from fundamentals and reflect a speculative component, which we recover using the relative behavior of sales and jeonse prices.

Environment Time is discrete, $t = 0, 1, 2, \ldots$. A household derives utility from consumption c_t and the housing services associated with its chosen location (or quality) $h_t \in \mathcal{H}$:

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, h_t), \qquad u_c > 0,\ u_{cc} < 0,\ u_h > 0.$$

The individual state at the beginning of period t is (a_t, h_{t-1}, d_{t-1}), where a_t denotes financial assets, h_{t-1} is the previous location, and $d_{t-1} \in \{R, J, O\}$ indexes the previous tenure choice (rent, jeonse, ownership). In period t, the household chooses

$$(c_t, a_{t+1}, h_t, d_t), \qquad d_t \in \{R, J, O\}.$$

Each location h has the following prices:

- $R_t(h)$: monthly rent,
- $J_t(h)$: jeonse deposit,
- $P_t(h)$: sales price.

The one-period risk-free interest rate is i_t.

Ownership and usage options A household owning a unit in location h may use it in one of three mutually exclusive ways:

1. **Self-occupancy**: pecuniary payoff 0.
2. **Renting out**: pecuniary payoff $R_t(h)$.

3. **Offering a jeonse contract**: the household receives $C_t(h)$, invests it at rate i_t, earns $i_t J_t(h)$, and returns $J_t(h)$ at $t+1$.

Thus, the financial return from ownership is

$$\pi_t(h,d) = \begin{cases} 0, & d = O, \\ R_t(h), & d = R, \\ i_t J_t(h), & d = C. \end{cases} \tag{1}$$

No-arbitrage between rent and jeonse In equilibrium, owners must be indifferent between renting out and offering a jeonse contract:

$$\pi_t(h,R) = \pi_t(h,C) \quad \Longrightarrow \quad R_t(h) = i_t J_t(h).$$

Thus,

$$J_t(h) = \frac{R_t(h)}{i_t} \qquad \forall h, t, \tag{2}$$

a relation that follows directly from the portfolio choice of housing owners and requires no dedicated landlord sector.

Household problem Let $V_t(a_t, h_{t-1}, d_{t-1})$ denote the beginning-of-period value function. The household solves

$$V_t(a_t, h_{t-1}, d_{t-1}) = \max_{c_t, a_{t+1}, h_t, d_t} \{u(c_t, h_t) + \beta E_t V_{t+1}(a_{t+1}, h_t, d_t)\}$$

subject to

$$\begin{aligned} c_t + a_{t+1} + \mathbf{1}_{\{d_t=R\}} R_t(h_t) + \mathbf{1}_{\{d_t=J\}} J_t(h_t) + \mathbf{1}_{\{d_t=O\}} P_t(h_t) \\ = y_t + (1+i_t)a_t + \mathbf{1}_{\{d_{t-1}=C\}} J_{t-1}(h_{t-1}) + \mathbf{1}_{\{d_{t-1}=J\}} P_t(h_{t-1}). \end{aligned} \tag{3}$$

The right-hand side of equation (3) captures income, financial returns, the refund of past jeonse deposits, and proceeds from selling previously owned units. The constraint allows for arbitrary relocation ($h_t \neq h_{t-1}$) and tenure switching ($d_t \neq d_{t-1}$).

To bring the model closer to district-level transaction data, we distinguish the allocation of the fixed housing stock across occupants from the transactions that occur in the sales market. This distinction allows the physical stock to remain fixed while the marketed supply of units varies over time through households' relocation and tenure-switching decisions.

Occupancy market clearing Each location h has an exogenously fixed physical stock

$$\overline{H}^s(h).$$

This stock is fully allocated across renters, jeonse tenants, and owner-occupants:

$$H_t^R(h) + H_t^J(h) + H_t^O(h) = \overline{H}^s(h). \tag{4}$$

Transaction market clearing Only a subset of this stock is listed for sale in any given period. We define the *flow supply* in location h as the mass of households who owned a unit in h in period $t-1$ but do not continue owning that same unit in period t:

$$h_t^s(h) = \int \mathbf{1}_{\{h_{t-1}(i)=h,\, d_{t-1}(i)=O,\, \left(h_t(i)\neq h \text{ or } d_t(i)\neq O\right)\}}\, di.$$

Thus $h_t^s(h)$ includes: (i) owners who relocate to another location (and hence list their former unit for sale), and (ii) owners who remain in h but switch to rent or jeonse. The physical stock $\overline{H}^s(h)$ remains fixed, but $h_t^s(h)$ varies endogenously with household decisions.

Similarly, the *flow demand* in location h consists of households that become owners of a unit in h in period t, having not been owners of that same unit in period $t-1$:

$$h_t^d(h) = \int \mathbf{1}_{\{h_t(i)=h,\ d_t(i)=O,\ \left(h_{t-1}(i)\neq h \text{ or } d_{t-1}(i)\neq O\right)\}}\, di.$$

Thus, $h_t^d(h)$ includes both incoming migrants who purchase in h and residents of h who switch from rent or jeonse to ownership; it excludes households who simply remain owner-occupants of the same unit. Sales prices clear the flow market:

$$h_t^s(h) = h_t^d(h). \tag{5}$$

Taken together, household relocating from h to h' generates two simultaneous effects: the listing of its original unit increases flow supply $h_t^s(h)$ in the origin market, while its search for a new home increases flow demand $h_t^d(h')$ in the destination market. Aggregated across households, these relocation and tenure-switching decisions produce the short-run fluctuations in transaction volumes that we interpret empirically as flow supply and demand shocks corresponding to transaction data. Crucially, such shocks operate through the transaction market without altering the fixed physical stock $\overline{H}^s(h)$, maintaining consistency with the model's short-run supply assumptions.

Fundamental value of housing The fundamental consumption value of housing services in location h is the discounted present value of future rents:

$$V_t(h) = \sum_{k=1}^{\infty} \frac{E_t R_{t+k}(h_{t+k})}{\prod_{j=0}^{k-1}(1+i_{t+j})}.$$

Using the rental–jeonse no-arbitrage condition $R_t(h) = i_t J_t(h)$ immediately implies

$$J_t(h) \propto V_t(h), \tag{6}$$

so jeonse prices provide a direct market-based measure of the intrinsic consumption value of housing.

Identifying speculative demand using jeonse prices A purchased home in location h satisfies the standard asset-pricing recursion:

$$P_t(h) = \frac{R_{t+1}(h_{t+1}) + E_t P_{t+1}(h_{t+1})}{1 + i_t}.$$

This recursion admits the decomposition

$$P_t(h) = V_t(h) + B_t(h), \tag{7}$$

where $B_t(h)$ captures temporary deviations of sales prices from fundamentals driven by expectations about future price appreciation. Differentiating yields

$$\frac{\dot{B}_t(h)}{B_t(h)} = \frac{\dot{P}_t(h)}{P_t(h)} - \frac{\dot{J}_t(h)}{J_t(h)}, \tag{8}$$

so the growth differential between sales and jeonse prices directly measures the growth of the speculative component.

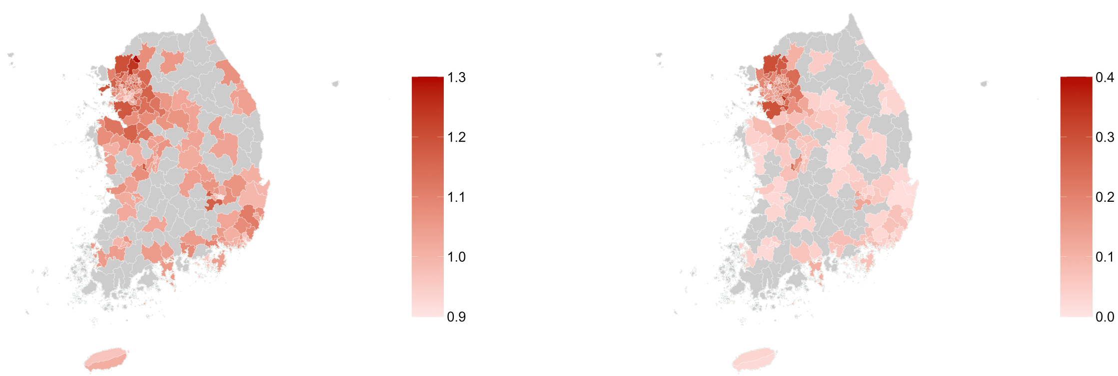
This framework implies that the sales-to-jeonse ratio provides a transparent indicator of speculative demand. When households expect capital gains, sales prices rise more rapidly than fundamentals and the ratio increases. When such expectations recede, the ratio declines. Although prices cannot diverge permanently from intrinsic values, short-run deviations are plausible and informative—particularly in monthly data, where fundamentals evolve slowly while expectations can change rapidly. Accordingly, the sales-to-jeonse ratio serves as our primary high-frequency measure of speculative dynamics.[4]

[4]Our approach is related to empirical strategies that exploit institutional features to separate intrinsic values from residual claims. For example, Giglio, Maggiori and Stroebel (2016) use the price difference between long-maturity leaseholds and freeholds in the United Kingdom to recover the transversality condition, while Bäcker-Peral, Hazell and Mian (forthcoming) construct a real-time measure of long-term

To assess whether this conceptual framework aligns with observed housing market behavior, Figure 4 reports the cross-sectional distribution of the sales-to-jeonse ratio across 176 urban districts. Both the level and volatility of the ratio are markedly higher in the Seoul metropolitan area, consistent with the intuition that speculative forces are stronger in high-priced markets with tight supply constraints. This pattern also persists across subregions within the Seoul metropolitan area (Appendix Figure B1), providing empirical support for the use of the sales-to-jeonse ratio as a measure of speculative demand.

Figure 4: Summary of the district-level sales-to-jeonse ratio

(a) Mean (b) Standard Deviation



Note: The left panel shows the average and the right panel shows the standard deviation of the sales-to-jeonse price ratio across 176 urban districts from 2003M11 to 2024M12. Districts shown in gray correspond to rural areas for which high-frequency data are unavailable.

3 Empirical Methodology

A key distinction in our empirical setting is that the "supply shocks" we identify do not reflect changes in the physical stock of housing units, which is effectively fixed in the short run. Instead, the supply variation observed in transaction-level data arises from shifts in the *flow* supply of existing homes entering the resale market. The stock of housing evolves only slowly through new construction or redevelopment, none of which appears

housing yields using very long leasehold contracts.

in our high-frequency transactions database. What fluctuates at business-cycle and seasonal frequencies is the fraction of existing units that homeowners choose to list for sale, which increases the flow supply of units available for purchase, placing downward pressure on prices and generating the inverse comovement between prices and transaction volumes that typifies supply-driven episodes. Because these movements operate entirely through the resale channel, they coexist naturally with our model's assumption of a fixed housing stock and do not interfere with our identification of speculative demand using the differential behavior of sales and jeonse prices.

Thus, within a standard supply–demand framework, the housing market in district i can be represented by an upward-sloping housing supply curve (9) and a downward-sloping housing demand curve (10). We first exploit the distinct responses of prices and transaction volumes to identify conventional supply and demand shocks.

$$q_i = \sigma^i p_i + \alpha^i \tag{9}$$

$$p_i = -\delta^i q_i + \beta^i, \tag{10}$$

where q_i represents quantity (or transaction volume of house), p_i represents sales price of house in district i, $\sigma^i (> 0)$ is the slope of the housing supply curve, $\delta^i (> 0)$ is the slope of the housing demand curve, and α^i and β^i are the intercepts, all of which are allowed to vary across districts. Commonly, supply shock ($\epsilon^s_{i,t}$) is delineated as a shift of the supply curve, denoted by the shift of α^i in equation (11). Similarly, a demand shock ($\epsilon^d_{i,t}$) is illustrated as a shift of the demand curve, expressed as the shift of β^i in equation (12).

$$\epsilon^s_{i,t} = \Delta\alpha^i = (q_{i,t} - \sigma^i p_{i,t}) - (q_{i,t-1} - \sigma^i p_{i,t-1}) \tag{11}$$

$$\epsilon^d_{i,t} = \Delta\beta^i = (p_{i,t} + \sigma^i q_{i,t}) - (p_{i,t-1} + \sigma^i q_{i,t-1}) \tag{12}$$

As discussed in the previous section, the standard supply-demand framework is insufficient for analyzing the housing market due to its asset market characteristics. To further refine our identification of housing market shocks, we exploit the jeonse price as an additional identifying variable. Let j_i denote the jeonse price in district i and r_i represent the ratio of the sales price to the jeonse price in the same region. Following the discussion in Section 2, the following equation establishes the relationship between the jeonse price—serving as a proxy for the intrinsic consumption value of housing—and the sales price:

$$r_i = \gamma^i, \quad r_i = \frac{p_i}{j_i}$$

Further, we decompose demand shocks into "residential demand" and "speculative demand" shocks, defining them as follows:

$$\text{Residential demand shock: } \operatorname{sign}(\epsilon^d_{i,t}) \neq \operatorname{sign}(\epsilon^r_{i,t}), \quad \epsilon^r_{i,t} = \Delta\gamma^i = \gamma_{i,t} - \gamma_{i,t-1} \tag{13}$$

$$\text{Speculative demand shock: } \operatorname{sign}(\epsilon^d_{i,t}) = \operatorname{sign}(\epsilon^r_{i,t}), \quad \epsilon^r_{i,t} = \Delta\gamma^i = \gamma_{i,t} - \gamma_{i,t-1} \tag{14}$$

Equations (13) and (14) formalize our classification of demand shocks. A demand shock is identified as speculative if the resulting fluctuation in the sales price exceeds that of the intrinsic value of housing proxied by the jeonse price. Conversely, if the fluctuation in the sales price is smaller than the corresponding change in the jeonse price, the shock is classified as a residential demand shock. While this identification strategy is relatively simple, it offers an intuitive framework that effectively captures the institutional features of the Korean housing market. Importantly, we do not impose separate supply curves for the sales and jeonse markets, thereby substantially reducing the number of identifying restrictions. This simplification is empirically justified by the fact that these two markets are not segmented.

Under this identifying structure, consider a case in which a positive speculative demand shock raises both the housing sales price and the sales-to-jeonse price ratio. As discussed in Section 2, this pattern reflects a situation in which the sales price increases more rapidly than the intrinsic value, consistent with expectations of future price appreciation exceeding fundamentals. Such dynamics are broadly consistent with the theoretical properties of speculative demand in asset markets.[5]

In sum, equations (9) through (14) can be translated and estimated through the following structural VAR model:

$$A^i z_{i,t} = \Sigma_{j=1}^{N} A^i_j z_{i,t-j} + \epsilon_{i,t}, \tag{15}$$

where $z_{i,t} = \begin{bmatrix} q_{i,t} & p_{i,t} & r_{i,t} \end{bmatrix}'$ represents a vector comprising the following three variables, housing transaction volume, housing sales price, and sales-jeonse price ratio, in district i period t and $A^i = \begin{bmatrix} 1 & -\sigma^i & 0 \\ \delta^i & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}'$ represents a coefficient matrix based in (9), (10), and (3), and $\epsilon_{i,t} = \begin{bmatrix} \epsilon^s_{i,t} & \epsilon^d_{i,t} & \epsilon^r_{i,t} \end{bmatrix}'$ represents a set of housing supply shocks, housing demand shocks, and shocks causing changes in the sales-jeonse price ratio. Lastly, a structural VAR in (15) can be rewritten as the following reduced-form VAR (16):

$$Z_{i,t} = (A^i)^{-1} \Sigma_{j=1}^{N} A^i_j Z_{i,t-j} + v_{i,t} \tag{16}$$

In (16), the reduced-form error term $v_{i,t} = \begin{bmatrix} v^s_{i,t} & v^d_{i,t} & v^r_{i,t} \end{bmatrix}'$ can be expressed as $\epsilon_{i,t} = A^i v_{i,t}$. By examining the sign of $v_{i,t}$, it is possible to determine whether the shock is a supply shock, a residential demand shock, or a speculative demand shock. First, as shown

[5]Before proceeding, it is useful to compare our identification strategy with alternative approaches. One method involves estimating residential and speculative demand shocks jointly within a structural model, which requires stronger assumptions about functional forms and parameter values. Another alternative is to impose a threshold on the absolute difference between sales and jeonse price changes: demand shocks are classified as residential if the difference is small and speculative if it exceeds a given cutoff. However, the choice of threshold is inherently arbitrary and can significantly influence the estimated contribution of each shock type.

in and Jump and Kohler (2022) and Shapiro (2024), the sign of $\epsilon^s_{i,t}$ and $\epsilon^d_{i,t}$ can be inferred using the sign of $v_{i,t}$ as illustrated in the following equations[6]:

$$\text{Positive (+) supply shock: } v^p_{i,t} > 0,\ v^q_{i,t} < 0 \ \rightarrow\ \epsilon^s_{i,t} > 0$$

$$\text{Negative (-) supply shock: } v^p_{i,t} < 0,\ v^q_{i,t} > 0 \ \rightarrow\ \epsilon^s_{i,t} < 0$$

$$\text{Positive (+) demand shock: } v^p_{i,t} > 0,\ v^q_{i,t} > 0 \ \rightarrow\ \epsilon^d_{i,t} > 0$$

$$\text{Negative (-) demand shock: } v^p_{i,t} < 0,\ v^q_{i,t} < 0 \ \rightarrow\ \epsilon^d_{i,t} < 0$$

Moreover, by exploiting the correspondence between the sign of $v^r_{i,t}$ and $\epsilon^r_{i,t}$, it is possible to distinguish between residential demand shocks and speculative demand shocks as defined in Section 3. Specifically, this identification is achieved as follows:

$$\text{Positive (+) residential demand shock: } v^p_{i,t} > 0,\ v^q_{i,t} > 0,\ v^r_{i,t} < 0$$

$$\text{Negative (-) residential demand shock: } v^p_{i,t} < 0,\ v^q_{i,t} < 0,\ v^r_{i,t} > 0$$

$$\text{Positive (+) speculative demand shock: } v^p_{i,t} > 0,\ v^q_{i,t} > 0,\ v^r_{i,t} > 0$$

$$\text{Negative (-) speculative demand shock: } v^p_{i,t} < 0,\ v^q_{i,t} < 0,\ v^r_{i,t} < 0$$

Our methodology offers notable advantages over existing approaches used to identify housing market shocks in the literature. First, compared to commonly employed short-run restrictions, which assume unidirectional effects between variables within a given period, sign restrictions impose weaker and more intuitive assumptions based on a simple supply-demand framework (see, e.g., Uhlig, 2005). Second, as emphasized by Shapiro (2024), our methodology imposes even weaker assumptions than the standard sign restriction approach widely used in the literature, making it particularly well-suited for

[6] Unlike Shapiro (2024), we normalize the sign of shocks such that a positive shock corresponds to an increase in housing sales prices.

analyzing housing price dynamics, where imposing stringent identifying assumptions is often challenging.[7] Lastly, we estimate the model separately for each district, allowing coefficients to vary freely across locations so as to capture heterogeneity in housing market conditions—such as differences in local amenities, resident income levels, and supply elasticities.

4 Identifying Housing Speculation

4.1. Data and Estimation

We utilize data on housing sales prices, transaction volumes, and the sales-to-jeonse price ratio for 176 urban districts, spanning from January 2006 to December 2024.[8] The housing sales price index is sourced from the "National Housing Price Trend Survey" by the Korea Real Estate Board, while regional transaction volume data is obtained from the "Real Estate Transaction Situation" report published by the same agency. The sales-to-jeonse price ratio is computed by dividing the housing sales price index by the housing jeonse price index for each district, which represents the smallest administrative unit covered in the "National Housing Price Trend Survey." These data are seasonally adjusted.

The following trivariate VAR model is estimated for each district:

$$y_{i,t} = \alpha + \Sigma_{j=1}^{N} \Phi_j^i y_{i,t-j} + v_{i,t}, \quad y_{i,t} = [q_{i,t} \;\; p_{i,t} \;\; r_{i,t}]', \tag{17}$$

[7] The standard approach typically infers impact responses from the identified model, achieving only set identification. That is, any identified set may be consistent with multiple models. Consequently, selecting specific impulse response functions within the identified set necessitates additional information, which undermines the flexibility and simplicity of sign restrictions (Fry and Pagan, 2011). In contrast, our methodology does not require any additional assumptions, as it relies exclusively on the sign of residuals derived from the constraints outlined above rather than on specific impact responses.

[8] The analysis primarily covers the period from January 2006 for most regions, as housing transaction volume data generally becomes available from that date. However, due to administrative district reorganizations, certain regions entered the dataset at later stages. Among the total 226 districts in Korea (corresponding to 3,144 counties in the United States), 176 urban districts provide consistently available data for the three key variables. Appendix E details the districts included in this study, specifying the start and end dates of the data for each district, along with their average weights over the sample period.

where $q_{i,t}$ represents the log of transaction volumes, $p_{i,t}$ denotes the log of the housing sales price index, and $r_{i,t}$ is the sales-to-jeonse price ratio in district i at time t. We adopt a benchmark specification with 12 lags to account for persistent movements in the data, which may be driven by low-frequency factors such as demographic and technological changes.

After estimating the VAR model at the district level, we identify three types of housing market shocks by examining the signs of the estimated residuals, as discussed in Section 3. Specifically, using the signs of the estimated $v_{i,t}$ in equation (17), housing price fluctuations in district i during period t are categorized as follows:

$$I_{i\in sup(+),t} = \begin{cases} 1 \quad if \quad \hat{v}^p_{i,t} > 0,\ \hat{v}^q_{i,t} < 0 \\ 0 \qquad otherwise \end{cases} \tag{18}$$

$$I_{i\in sup(-),t} = \begin{cases} 1 \quad if \quad \hat{v}^p_{i,t} < 0,\ \hat{v}^q_{i,t} > 0 \\ 0 \qquad otherwise \end{cases} \tag{19}$$

$$I_{i\in dem_{Res}(+),t} = \begin{cases} 1 \quad if \quad \hat{v}^p_{i,t} > 0,\ \hat{v}^q_{i,t} > 0,\ \hat{v}^r_{i,t} < 0 \\ 0 \qquad otherwise \end{cases} \tag{20}$$

$$I_{i\in dem_{Res}(-),t} = \begin{cases} 1 \quad if \quad \hat{v}^p_{i,t} < 0,\ \hat{v}^q_{i,t} < 0,\ \hat{v}^r_{i,t} > 0 \\ 0 \qquad otherwise \end{cases} \tag{21}$$

$$I_{i\in dem_{Spc}(+),t} = \begin{cases} 1 \quad if \quad \hat{v}^p_{i,t} > 0,\ \hat{v}^q_{i,t} > 0,\ \hat{v}^r_{i,t} > 0 \\ 0 \qquad otherwise \end{cases} \tag{22}$$

$$I_{i\in dem_{Spc}(-),t} = \begin{cases} 1 \quad if \quad \hat{v}^p_{i,t} < 0,\ \hat{v}^q_{i,t} < 0,\ \hat{v}^r_{i,t} < 0 \\ 0 \qquad otherwise \end{cases} \tag{23}$$

Once the shocks driving housing price fluctuations in district i during period t are identified, we compute the share of districts experiencing each type of shock in period t:

$$\theta_{s,t} = \Sigma_i I_{i \in s,t} w_{i,t}, \tag{24}$$

where $s \in \{sup(+), sup(-), dem_{Res}(+), dem_{Res}(-), dem_{Spc}(+), dem_{Spc}(-)\}$ and $w_{i,t}$ represents the weight of district i in the calculation of the house sales price index.[9] For example, $\theta_{sup(+),t} = 1$ indicates that all districts experienced a positive supply shock in period t, while $\theta_{dem_{Spc}(+),t} = 0.5$ suggests that 50% of districts were affected by a positive speculative demand shock. Figure B2 in the Appendix B depicts the fluctuations in these shares over the sample period. As expected, positive and negative shocks exhibit negative correlations for each type of housing market shock.

4.2. Decomposing National Housing Price Dynamics

Building on the categorization of housing sales price changes established in Section 4.1., we decompose national housing price dynamics into three components: driven by supply, residential demand, and speculative demand shocks. Given the classification in equations (18) through (23), variations in housing prices in district i during period t are now categorized into three indicator functions:

$$I_{i \in sup,t} = \begin{cases} 1 \quad \textit{if} \quad I_{i \in sup(+),t} = 1 \textit{ or } I_{i \in sup(-),t} = 1 \\ 0 \qquad\qquad \textit{otherwise} \end{cases}$$

$$I_{i \in dem_{Res},t} = \begin{cases} 1 \quad \textit{if} \quad I_{i \in dem_{Res}(+),t} = 1 \textit{ or } I_{i \in dem_{Res}(-),t} = 1 \\ 0 \qquad\qquad \textit{otherwise} \end{cases}$$

[9] Since the National Housing Price Trend Survey does not provide district-level weights, we use the ratio of each district's housing inventory to the total housing inventory as a weight. As the housing inventory data is available only on an annual basis, monthly weights are interpolated using a linear method.

$$I_{i \in dem_{Spc},t} = \begin{cases} 1 & \text{if} \quad I_{i \in dem_{Spc}(+),t} = 1 \text{ or } I_{i \in dem_{Spc}(-),t} = 1 \\ 0 & \text{otherwise} \end{cases}$$

Based on this categorization, the following equation decomposes national housing sales price dynamics into the three identified components:

$$\pi_t = \Sigma_{i=1}^{N} I_{i \in sup,t} w_{i,t} \pi_{i,t} + \Sigma_{i=1}^{N} I_{i \in dem_{Res},t} w_{i,t} \pi_{i,t} + \Sigma_{i=1}^{N} I_{i \in dem_{Spc},t} w_{i,t} \pi_{i,t},$$

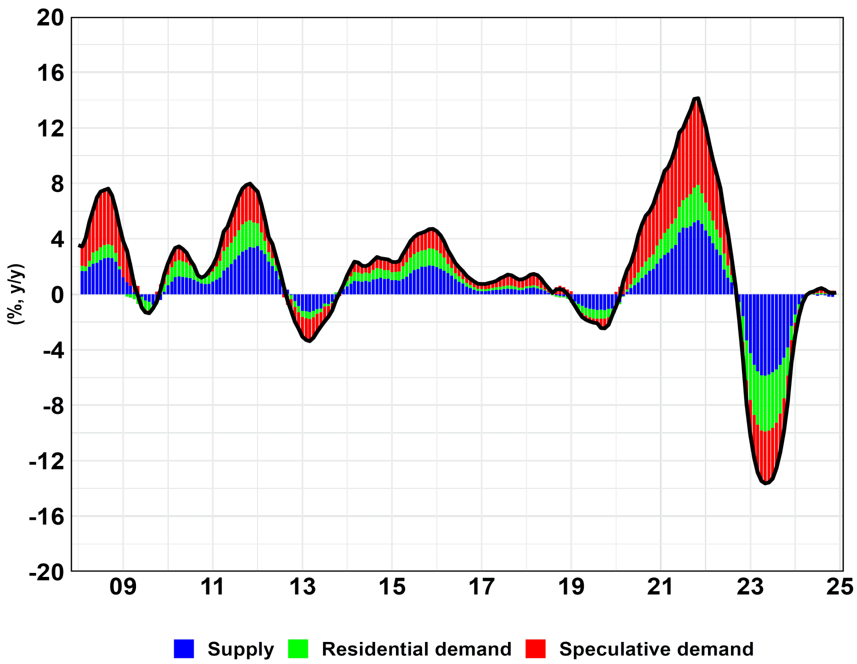
where π_t represents the national housing sales price growth rate, $\pi_{i,t}$ denotes the housing sales price growth rate in district i, and $w_{i,t}$ is the corresponding weight of district i in period t. For the subsequent discussion, we refer to these components as the "supply factor," "residential demand factor," and "speculative demand factor" driving aggregate housing prices.

The sum of the three factors may not perfectly match observed housing price dynamics due to variations in district-level weights, administrative district reorganizations, and seasonal adjustments applied at the district level. Figure B3 in the Appendix B compares the actual housing sales price growth rate with the sum of the three structural components. Given the exceptionally high correlation of 0.999 between the two series, any discrepancy is negligible.

Figure 5 presents our first main empirical finding: the decomposition of year-over-year housing price changes in Korea from January 2007 to December 2024 into three structural components—supply, residential demand, and speculative demand shocks. The black solid line denotes national housing price growth, while the blue, green, and red shaded areas represent the contributions of supply, residential demand, and speculative demand shocks, respectively. Year-over-year changes are computed as the running sum of monthly price changes over a 12-month window:

$$\pi_{t,t-12} = \sum_{k=0}^{11} \pi_{t-k,t-k-1}, \qquad \pi^i_{t,t-12} = \sum_{k=0}^{11} \pi^i_{t-k,t-k-1}, \quad i \in \{sup, dem_{Res}, dem_{Spc}\}.$$

Figure 5: Supply, residential demand, and speculative demand-driven housing price growth (year-over-year)

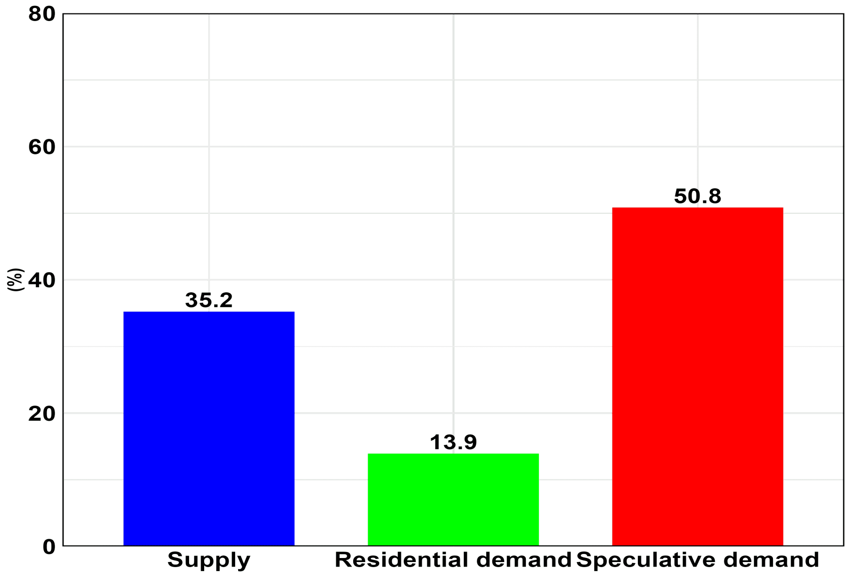


Note: The black line represents the year-over-year growth rate of national housing prices. The shaded areas reflect the contributions of supply (blue), residential demand (green), and speculative demand (red) shocks.

The decomposition yields three key insights. First, speculative demand emerges as the dominant driver of housing price dynamics over the sample period, accounting for 50.8% of cumulative housing price growth. In comparison, supply and residential demand contributed 35.2% and 13.9%, respectively (see Figure 6).[10] These results are consistent with prior studies emphasizing the importance of speculative forces in Korean housing markets using aggregate data (e.g., Xiao and Park, 2010; Kim and Lim, 2016; Lee, Ann and Park, 2022; Lee and Park, 2024).

[10]The contribution of each component is computed as the ratio of cumulative growth from each housing market shock to the cumulative growth in national housing prices.

Figure 6: Average contribution of each housing market shock to Korean housing price dynamics



Note: Each component's contribution is computed as the ratio of its cumulative growth to that of total housing prices over the period from January 2007 to December 2024.

Second, the three shocks exhibit strong aggregate-level co-movement. The correlation between supply and residential demand factors is particularly high ($\rho = 0.81$), followed by correlations between supply and speculative demand ($\rho = 0.72$), and between residential and speculative demand ($\rho = 0.68$).[11] These correlations suggest a close interplay between transaction volume and price dynamics, implying that conventional identification strategies based on short-run restrictions and aggregate data may suffer from omitted variable bias or simultaneity concerns.

Figures B4 and B5 in the Appendix B present analogous decompositions for the Seoul metropolitan area. The pattern of price fluctuations closely mirrors the national trend, though speculative demand plays an even more prominent role in driving housing prices in this district. In contrast, Figures B6 and B7 present analogous decompositions for non-metropolitan areas. The role of speculative demand weakens significantly in these re-

[11] Although the housing market shocks are orthogonal at the district level by construction, national-level aggregates reflect correlated movements due to cross-sectional summation.

gions—accounting for less than 40%—highlighting a notable divergence in housing market dynamics between metropolitan and non-metropolitan areas.

5 Macroeconomic Effects of Structural Housing Shocks

Given the dominant role of speculative housing demand shocks in driving national housing prices (Figures 5 and 6), we now ask: Do speculative and residential demand shocks exert different effects on the real economy? This question holds significant policy relevance, particularly because our empirical strategy enables the *near* real-time identification of speculative versus residential demand shocks—a task traditionally infeasible *ex ante*.

A key advantage of our framework lies in the orthogonality of structural housing shocks at the district level. This design facilitates causal identification of their macroeconomic effects using disaggregated data, thereby mitigating the endogeneity concerns inherent in aggregate-level studies (e.g., Beltratti and Morana, 2010; Cesa-Bianchi, 2013). Crucially, our identification relies solely on contemporaneous district-level housing market data and does not incorporate forward-looking or macroeconomic information beyond the information set of an econometrician.

5.1. Panel Local Projections

To estimate the dynamic macroeconomic responses to housing market shocks, we employ panel local projections.[12] Motivated by the finite-sample improvements associated with long-difference estimators, as discussed in Piger and Stockwell (2025), we employ a

[12]Unlike VAR-based methods that derive impulse responses by iteratively multiplying coefficient matrices, the local projection approach estimates each horizon-specific response via separate regressions. This method has desirable properties: it is robust to model misspecification, less sensitive to the compounding of estimation errors, and readily accommodates nonlinear and asymmetric responses (Jordà, 2005).

cumulative response framework:

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_i^h + \alpha_t^h + \beta^h \text{shock}_{i,t} + \gamma^h X_{i,t-1} + \varepsilon_{i,t+h}, \tag{25}$$

where $Y_{i,t}$ denotes the log level of the outcome of interest (employment, establishments, or gross regional domestic product) in district i at time t; $\text{shock}_{i,t}$ is one of the three identified shocks; and $X_{i,t-1}$ is a vector of controls including the lagged growth rate of $Y_{i,t}$, lagged values of the identified shocks, and lagged population measures (log population and population growth). We include district α_i^h and year α_t^h fixed effects, akin to a difference-in-differences framework, to control for unobserved heterogeneity and national macroeconomic shocks and policy responses. To address spatial correlation across regions (e.g., Brady, 2014; Lee et al., 2022), we use Driscoll-Kraay standard errors (Driscoll and Kraay, 1998).

5.2. Good Housing Booms, Bad Housing Booms

We begin by estimating Equation (25) using 154 district-level output data from 2010 to 2021. Panel (a) of Figure 7 presents the estimated impulse responses where the sign of the shock is normalized to increase housing prices. Supply shocks have limited and statistically insignificant effects on output—an outcome that is consistent with supply-driven price increases operating primarily through declines in transaction volumes. In contrast, housing demand shocks generate sharply divergent outcomes: residential demand shocks raise output persistently, whereas speculative demand shocks reduce it. These results are robust when using value-added output (Figure C8 in the Appendix C).[13]

These findings provide a mechanism for why some housing booms coincide with macroeconomic expansions, whereas others precede downturns. In our sample, the bulk

[13]To evaluate whether differential persistence in the two demand shocks could explain the heterogeneous outcomes, we examine their serial correlation across districts. The average district-level AR(1) coefficient is close to zero and very similar across the two shocks (0.031 and 0.038), suggesting that differences in persistence are unlikely to drive our results.

of housing price fluctuations appears to be driven by speculative demand (Figure 6). Accordingly, our results align with Choi, Kim and Yun (2025), who document contractionary effects of nationwide housing booms using the granular instrumental-variable approach of Gabaix and Koijen (2024). They are also consistent with Lee and Park (2024), who show that residential housing demand shocks are expansionary, whereas speculative housing demand shocks are contractionary in aggregate data using sign restrictions. Because both studies exploit the informational content of Jeonse prices—which exclude expected capital gains—this convergence of evidence supports our identification strategy.

Panels (b) and (c) extend the analysis using employment and the number of establishments data for 155 districts from 2007 to 2023. The results reinforce those from the output analysis, except that the negative supply shock has a significantly negative effect on the number of establishments. Taken together, the heterogeneous responses of district-level activity to the identified shocks are pronounced and consistent with an interpretation based on real versus speculative demand. These results bolster the credibility of our identification strategy and highlight its policy relevance as an early-warning indicator.

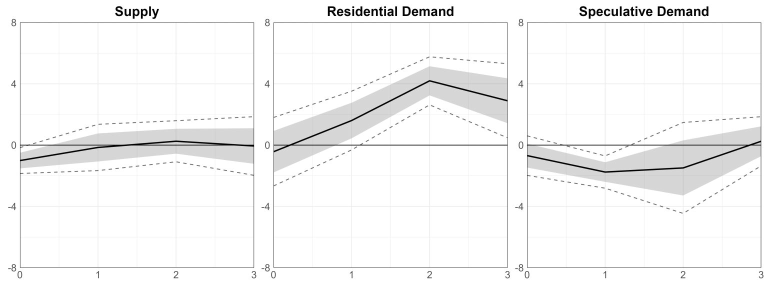
5.3. Robustness Checks

We conduct several robustness checks to validate our main findings in the previous section through alternative data, model specifications, and estimation techniques. For example, we employ a more aggregated geographical level (17 provinces as opposed to 176 districts), enabling higher-frequency analysis (monthly and quarterly) and examination of additional variables, including expenditure components of regional GDP and sectoral decomposition.

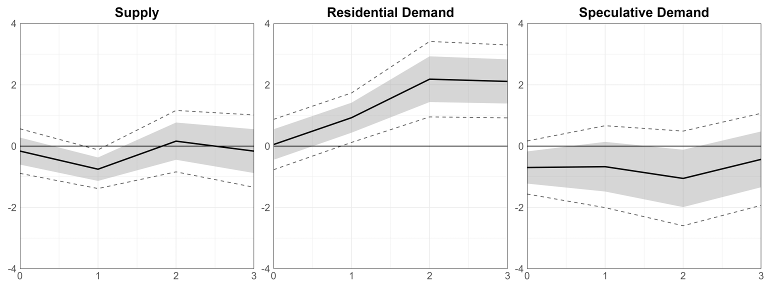
Alternative geographic aggregation To address potential concerns that district-level units may be too narrowly defined to capture commuting zones or local demand conditions, we conduct an additional robustness check using broader geographic aggregation.

Figure 7: Effects of supply, residential demand, and speculative demand shocks on regional economic activity

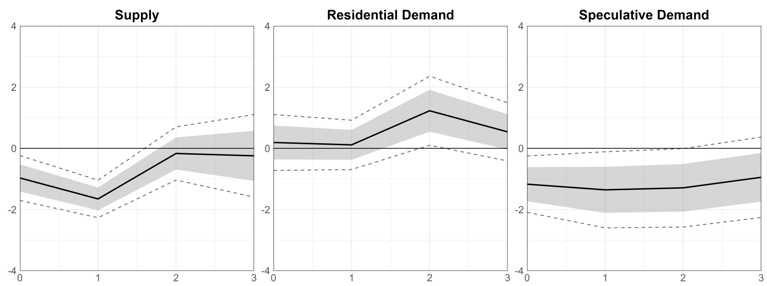
(a) Output



(b) Employment



(c) Number of establishments



Note: The panels depict the cumulative impulse responses for panel local projections. The sign of the shock is normalized to increase housing prices. The shaded areas indicate the 68% confidence interval, while the dotted line represents the 90% confidence interval. The dependent variables are total output (top panel), employment (middle panel), and the number of establishments (bottom panel). The models are estimated using the data from 154 districts from 2010 to 2021 for output and 155 districts from 2007 to 2023 for employment and the number of establishments. Standard errors are calculated following Driscoll and Kraay (1998).

We re-estimate our baseline specifications using province- and city-level data for gross regional domestic product (GRDP), employment, and the number of establishments rather than the district-level data employed in our main analysis. Figure C9 in the Appendix C demonstrates that our key findings that residential demand shocks generate positive effects on regional economic activity, while speculative demand shocks produce negative impacts remain robust to this alternative geographic aggregation.

Monthly labor market data To examine the robustness of our findings using higher-frequency data matched to the original frequency of shocks, we estimate cumulative impulse responses for monthly labor market indicators. We employ the employment-to-population ratio for ages 15–64 and the labor force participation rate, both of which are available at province- and city-level and serve as key proxies for regional economic activity. Consistent with our baseline results, Figure C10 shows that residential demand shocks exert positive effects on labor market outcomes, while speculative demand shocks generate negative impacts.

Alternative fixed-effects specification We test the robustness of our findings to an alternative model specification by re-estimating the impulse responses using the following specification:

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_i^h + \alpha_{province,t}^h + \beta^h \text{shock}_{i,t} + \gamma^h X_{i,t-1} + \varepsilon_{i,t+h}. \tag{26}$$

Compared to Equation (25), this specification includes the interaction of time and province fixed effects alongside district-level fixed effects. This approach controls for province-specific time trends and macroeconomic shocks, thereby accounting for distinct economic fluctuations at the province level that may confound our identification. Figure C11 presents the results. The findings remain largely unchanged compared to our baseline estimates, confirming that our conclusions are robust to controlling for time-varying province-level economic conditions.

Nickell bias in local projections To address concerns about Nickell bias from including lagged dependent variables and fixed effects, we re-estimate Equation (25) using a one-step difference GMM estimator (e.g., Arellano and Bond, 1991; Judson and Owen, 1999). Figure C12 strengthens our core results that residential demand and speculative demand shocks have sharply different effects on economic activity.

5.4. Investigating the Mechanism

While the baseline output responses document clear differences across supply, residential demand, and speculative demand shocks, these aggregate patterns do not necessarily reveal the channels through which local economic activity adjusts. Each housing market shock may affect household balance sheets, borrowing constraints, or expectations in distinct ways, and these differences can propagate through specific components of regional expenditure or through the sectoral composition of output. For this reason, we examine how each shock affects the expenditure-side components of GRDP and subsequently conduct a sectoral decomposition to illuminate the underlying mechanisms.

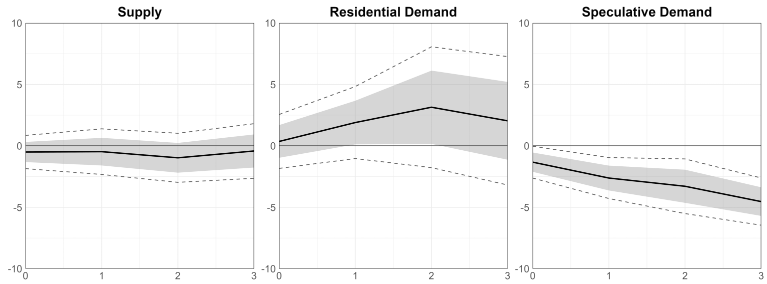
Consumption and investment To illuminate the underlying mechanisms driving these divergent outcomes of structural housing shocks, we estimate impulse responses for each expenditure-side component of GRDP at the province- and city-level. Figure 8 presents the results.

Panel (a) shows that residential demand shocks modestly raise private consumption, although the effects are not statistically significant, whereas speculative demand shocks significantly and persistently depress it. Panel (b), by contrast, indicates that speculative demand shocks do not have negative effects on investment. This pattern is consistent with the collateral channel: housing price appreciation relaxes financing constraints for firms and entrepreneurs and thus supports investment, regardless of the underlying source of the housing wealth effect (Bahaj, Foulis and Pinter, 2020; Chaney, Sraer and Thesmar, 2012).

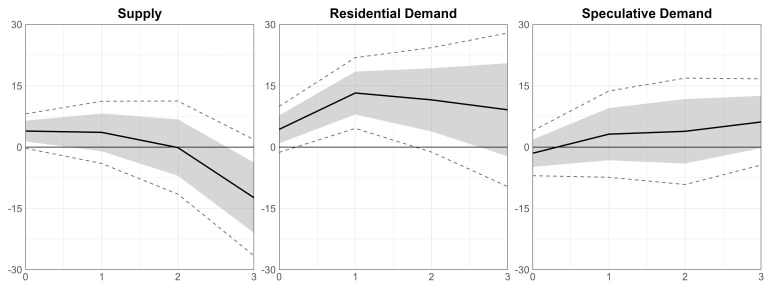
Importantly, the more adverse effect of speculative demand shocks on consumption

Figure 8: Inspecting mechanism using each expenditure component

(a) Private consumption



(b) Gross fixed capital formation



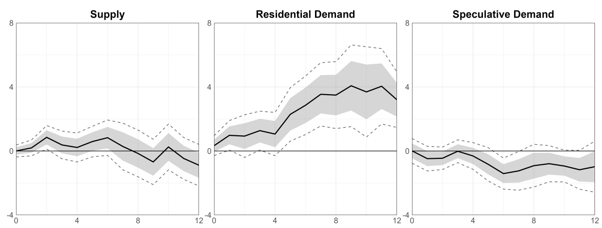
Note: The panels depict cumulative impulse responses from panel local projections using city- or province-level GRDP expenditure components. Panels (a) and (b) present responses of private consumption and gross fixed capital formation, respectively. The x-axis denotes quarters. The sign of the shock is normalized to increase housing prices. The shaded area represents the 68% confidence interval, and the dashed line indicates the 90% confidence interval. The cumulative impulse responses are estimated using data from 17 provinces spanning 2006 to 2023, with data sourced from the Regional Income Statistics. Standard errors are computed following Driscoll and Kraay (1998).

than on investment can be rationalized by a debt-overhang mechanism. When speculative demand fuels a housing boom without corresponding improvements in household balance sheets, households may take on substantial mortgage debt to finance purchases. Servicing this debt subsequently crowds out consumption, even as investment remains supported through collateralized borrowing. We investigate this possibility more directly using micro-level data in the following section.

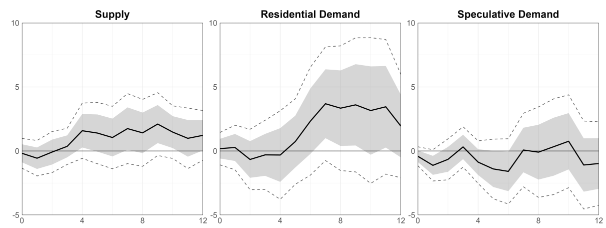
Sectoral analysis We then estimate impulse responses using quarterly GRDP data disaggregated by economic sectors. Figure 9 presents the results. The baseline findings remain robust to this alternative data frequency: supply shocks exert minimal effects on total GRDP, residential demand shocks generate positive impacts, and speculative demand shocks produce negative effects.

Figure 9: Inspecting mechanism using quarterly sectoral GRDP

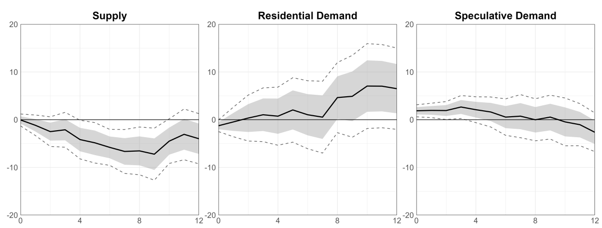
(a) Total output



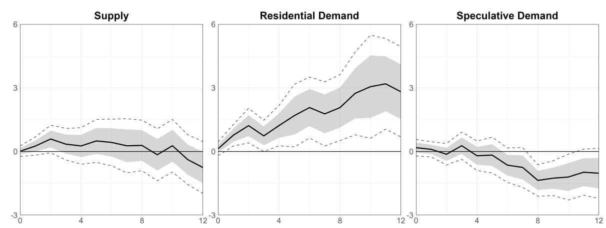
(b) Mining, quarrying, and manufacturing



(c) Construction



(d) Services



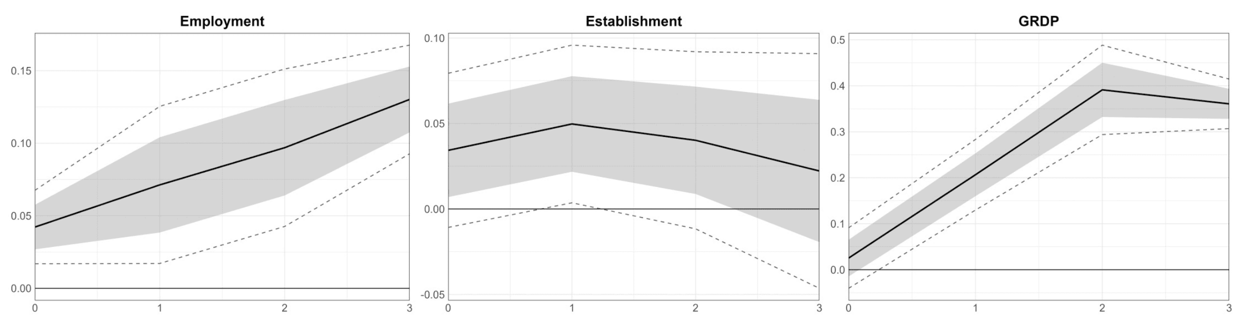
Note: The panels depict cumulative impulse responses from panel local projections using quarterly GRDP data. Panels (a), (b), (c), and (d) present responses of total GRDP, mining, quarrying, and manufacturing sector output, construction sector output, and service sector output, respectively. The sign of the shock is normalized to increase housing prices. The shaded area represents the 68% confidence interval, and the dashed line indicates the 90% confidence interval. The cumulative impulse responses are estimated using data from 17 provinces spanning 2015Q1 to 2024Q4, with data sourced from the Quarterly Gross Regional Domestic Product statistics. Standard errors are computed following Driscoll and Kraay (1998).

The sectoral decomposition provides additional insights into the transmission mechanisms. First, none of the housing market shocks meaningfully affect the mining, quarrying, and manufacturing sector, except for a modest—though statistically insignificant—positive response to residential demand shocks. Second, both demand shocks raise construction activity, although the estimates are only marginally significant. Given the direct link between housing prices and construction, the absence of a negative response to speculative demand shocks is unsurprising. Third, the divergence between residential and speculative demand shocks is most pronounced in the services sector. This pattern is consistent with the strong connection between services and regional consumption: services output tends to respond more sensitively to local demand conditions. Given our earlier finding that residential and speculative demand shocks have opposite effects on private consumption, the sectoral results offer corroborating evidence for this consumption channel operating through the services sector.

To illustrate the importance of distinguishing among structural drivers of housing price fluctuations, we estimate the reduced-form relationship between house price growth and regional economic activity. Specifically, we examine the dynamic responses of employment, the number of establishments, and GRDP to local house price appreciation by replacing each housing market shock with house price growth in equation (25). As shown in Figure 10, all three outcome variables exhibit a positive and statistically significant response, consistent with the conventional view that rising housing prices stimulate local economic activity.

While this finding aligns with the widely held narrative that housing booms generate beneficial macroeconomic spillovers, our structural decomposition reveals that such naive correlations obscure important heterogeneity in the underlying shocks. These results emphasize the central implication of our analysis: not all housing booms are equal. Without accounting for their sources, conventional estimates risk conflating expansionary "good" booms with contractionary "bad" booms—an omission with significant implications for both policy evaluation and macroeconomic forecasting.

Figure 10: Effects of housing price growth on regional economic activity



Note: The panels depict the cumulative impulse responses to employment (left), the number of establishments (center), and output (right) to the annual house price growth. The shaded areas indicate the 68% confidence interval, while the dotted line represents the 90% confidence interval. Standard errors are calculated following Driscoll and Kraay (1998).

6 Structural Housing Shocks and Household Debt

The distinct responses of economic activity to residential demand versus speculative demand shocks are both theoretically interesting and empirically important in their own right. However, a critical question makes these findings even more compelling: what makes these differential effects?

One possible explanation lies in the *debt overhang effect*. An extensive literature documents that housing booms lead to excessive increases in household debt, which subsequently constrains consumption and attenuates the positive wealth effects typically associated with rising housing prices (Dynan, Mian and Pence, 2012; Mian and Sufi, 2011; Mian, Rao and Sufi, 2013). Building on this literature, we hypothesize that speculative demand shocks generate larger increases in household debt compared to residential demand shocks, and that these differential leverage dynamics explain the divergent macroeconomic effects we observe.

To test this hypothesis, we analyze the impulse responses of household debt to each type of shock using proprietary micro-level data about household debt collected by the Bank of Korea. The granular nature of our data enables us to trace precisely how different housing demand shocks translate into distinct patterns of household leverage and subsequent economic outcomes.

6.1. Data

We employ the Household Debt Database from the Bank of Korea, which is designed following the Federal Reserve Bank of New York Consumer Credit Panel (Lee and Van der Klaauw, 2010). This longitudinal panel tracks individual credit information from a major credit bureau at a quarterly frequency. The sample encompasses approximately 2.4% of the total population engaged in credit activities in Korea—roughly one million individuals—using stratified random sampling based on birth date. The dataset maintains representative proportions across age groups, regions, and credit rating categories.

As highlighted in previous studies (Kim, Park and Kim, 2018; Song and Song, 2025), this dataset offers several advantages. First, it provides comprehensive information on both individual characteristics (age, district-level location, income) and detailed financial transaction data (loan amounts and types), enabling micro-level analyses infeasible with aggregate data. Second, because the dataset derives from actual financial transaction records, it is largely immune to measurement error, sample attrition, and recall bias that commonly plague survey data (Zinman, 2009).[14]

6.2. Empirical Methodology

We estimate impulse responses of household debt to housing shocks using panel local projection methods. We extend the two-way fixed effect framework by incorporating multi-way fixed effects to address endogeneity concerns.

Our specification is:

$$Y_{i,j,t+h} - Y_{i,j,t-1} = \alpha_t^h + \alpha_{i,j}^h + \beta^h \text{shock}_{j,t} + \gamma^h X_{i,j,t} + \varepsilon_{i,j,t+h}, \tag{27}$$

where $Y_{i,j,t}$ denotes the log loan amount for individual i in district j at time t; $\text{shock}_{j,t}$ represents one of our three identified shocks; and $X_{i,j,t}$ includes lagged dependent variable in growth terms and income growth.

We employ two loan measures. First, total debt covers 745,640 individuals from 2010Q1 to 2024Q4. Second, mortgage debt encompasses 290,318 individuals from 2012Q1 to 2024Q4.[15] Individual-district fixed effects ($\alpha_{i,j}^h$) control for time-invariant individual and location characteristics, while time fixed effects (α_t^h) absorb aggregate macroeconomic shocks. Following Abadie, Athey, Imbens and Wooldridge (2023), we cluster standard

[14] For additional details on the dataset, see Kim et al. (2018).

[15] Mortgage data begins in 2012 due to changes in loan classification standards that made detailed loan-type data available.

errors at the treatment level, which is district-by-time.

6.3. Results

Figure 11 presents the estimated impulse responses. Panel (a) shows that supply and residential demand shocks have statistically insignificant effects on total loan growth. In contrast, speculative demand shocks generate significantly positive and persistent increases in household debt. This stark difference supports our hypothesis: speculative demand-driven housing booms, unlike residential demand-driven booms, generate excessive household leverage that subsequently constrains consumption through debt overhang effects.

Panel (b) reinforces these findings using mortgage debt. While patterns largely mirror those for total loans, notable differences emerge. Supply shocks lead to moderate but statistically significant increases in mortgage debt. More importantly, the response to speculative demand shocks becomes both stronger and more persistent compared to total loans—an intuitive result given mortgages' direct connection to housing transactions.

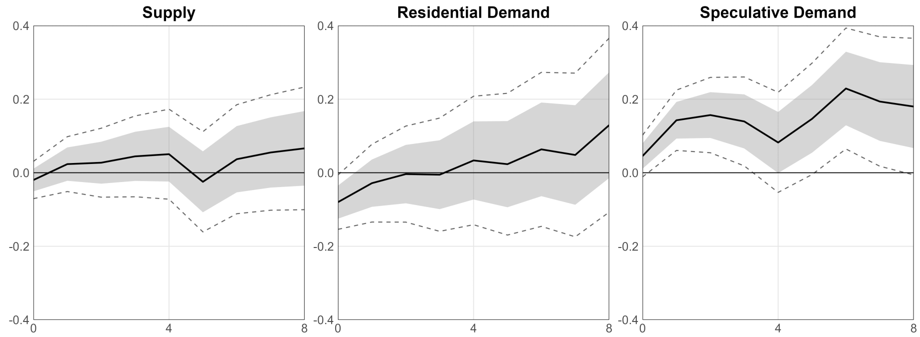
These results identify the mechanism underlying our main findings. Speculative demand shocks generate substantial increases in household debt, creating a debt overhang that dominates positive wealth effects from rising house prices. This debt accumulation channel explains why speculative housing booms, ultimately exert negative pressure on real economic activity.

7 Housing Price Dynamics and Policy Mix

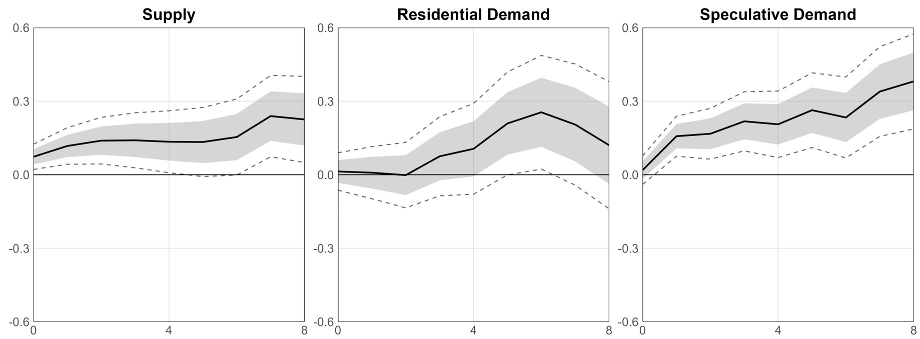
In this section, we examine the influence of monetary and macroprudential policies on housing price dynamics, emphasizing how to contain speculative demand using a policy mix. Specifically, we estimate the impulse responses of each housing shock component identified in Section 4 at the national level to exogenously identified monetary

Figure 11: Effects of Housing Shocks on Household Debt

(a) Total Loans



(b) Mortgage



Note: The panels depict cumulative impulse responses from panel local projections. The sign of the shock is normalized to increase housing prices. Shaded areas indicate 68% confidence intervals; dotted lines represent 90% confidence intervals. Panel (a) is estimated using total loans data for 745,640 individuals, 2010Q1–2024Q4, while Panel (b) is estimated using mortgages for 290,318 individuals, 2012Q1–2024Q4. Standard errors clustered at district-time level following Abadie et al. (2023).

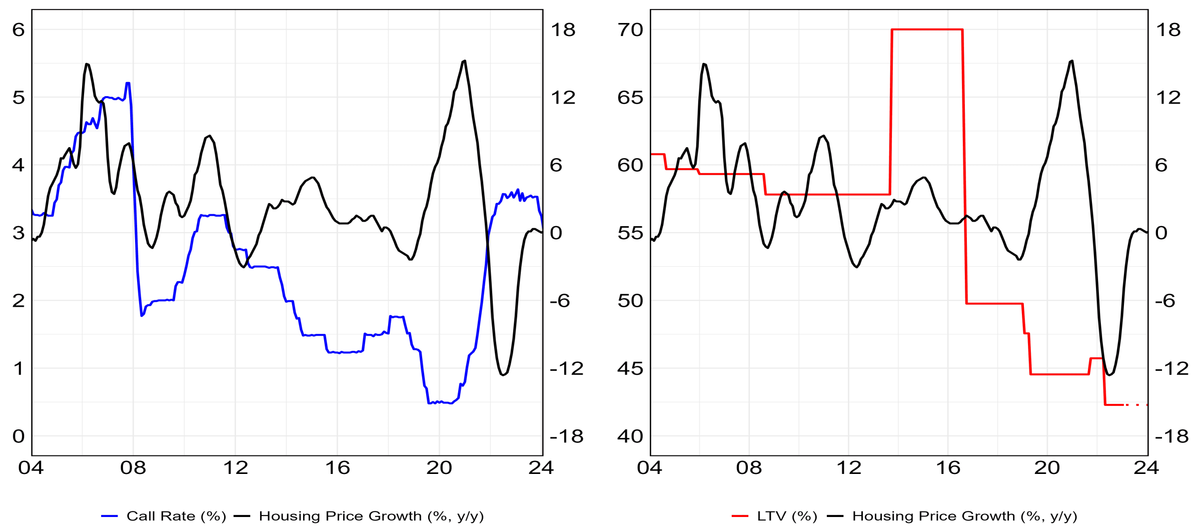
and macroprudential policy shocks. This approach also serves as an external validity test for the identified factors by assessing whether their responses to structural shocks align with theoretical predictions and previous empirical findings.

To this end, we first estimate a vector autoregression (VAR) model incorporating both monetary and macroprudential policies to identify structural policy shocks. Appendix D provides details on this process. We then estimate the dynamic effects of these exogenous structural shocks using local projections. Additionally, we investigate potential asymmetries in the responses by differentiating between reactions to positive and negative shocks, leveraging the flexibility of the local projection method.

While both monetary and macroprudential policies are well-documented as key determinants of housing prices (e.g., Ehrenbergerova, Bajzik and Havranek, 2023; Iacoviello, 2005; Kim and Mehrotra, 2022; Vandenbussche, Vogel and Detragiache, 2015), our study makes two key contributions to the literature.

First, we explicitly account for potential policy responses to macroeconomic variables and the interaction between monetary and macroprudential policy instruments to identify exogenous policy shocks. Given the endogeneity concerns surrounding macroprudential policies and their interplay with monetary policy, this identification strategy is critical for accurately estimating policy effects (Kim and Mehrotra, 2018). Second, to the best of our knowledge, this study is the first attempt to analyze the differential effects of structural policy shocks on residential versus speculative housing demand, offering novel insights into the transmission mechanisms of policy interventions in housing markets. Figure 12 shows the evolution of policy rates and loan-to-value (LTV) limits in accordance with housing price growth.

Figure 12: Evolution of policy rates and LTV limits



Note: The figure illustrates the evolution of call rates (left) and loan-to-value (LTV) limits (right) in relation to year-on-year housing price growth. The black solid line indicates housing price growth, the blue solid line denotes the call rate, and the red solid line represents LTV limits. The red dotted line marks periods with missing LTV data.

7.1. Monetary Policy and Housing Price Dynamics

We first analyze the responses of each identified factor to exogenous monetary policy shocks. The impulse response (β_j^h) is computed by regressing each of the housing price supply (π_{t+h}^{sup}), residential demand ($\pi_{t+h}^{dem_{Res}}$), and speculative demand factors ($\pi_{t+h}^{dem_{Spc}}$) preceding h period, on the structural monetary policy shock ($e_{MP,t}$) identified from a VAR model in the previous section and control variables, as illustrated below:

$$\pi_{t+h}^{j} = \alpha_j^h + \beta_j^h e_{MP,t} + \theta_j^h(L)Z_{t-1} + e_t$$

$$IRF_{t+h}^{MP} = \frac{\partial \pi_{t+h}^{j}}{\partial e_{MP,t}},$$

where π_{t+h}^{j} represents cumulative growth in the factors of $j \in \{sup, dem_{Res}, dem_{Spc}\}$ between $t-1$ to $t+h$, $e_{MP,t}$ represents the structural monetary policy shock in period t. Control variables, Z_{t-1}, include 12 lags of each dependent variable and the monetary policy shock.

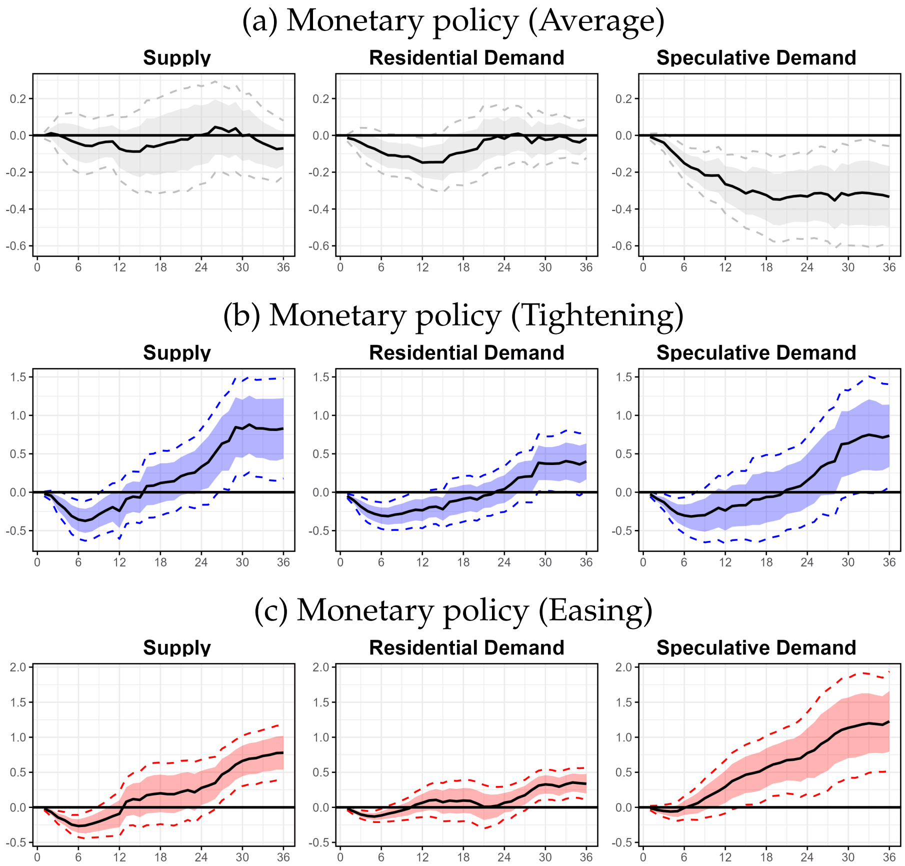
Considering potential asymmetry in the effect of monetary policy on the housing market (Aastveit and Anundsen, 2022), we also examine the asymmetric responses of the identified factors:

$$\pi_{t+h}^{j} = \alpha_j^h + \beta_j^{h,+} max[0, e_{MP,t}] + \beta_j^{h,-} min[0, e_{MP,t}] + \theta_j^h(L)Z_{t-1} + e_t$$

$$IRF_{t+h}^{MP} = \frac{\partial \pi_{t+h}^{j}}{\partial e_{MP,t}} = \begin{cases} \beta_j^{h,+} & \textit{if} \quad e_{MP,t} > 0 \\ \beta_j^{h,-} & \textit{if} \quad e_{MP,t} < 0 \end{cases}$$

Figure 13 reports the estimated impulse responses obtained from local projections. We begin by examining the average (i.e., linear) response of each structural component to a monetary policy shock. As shown in panel (a), a contractionary monetary policy shock

Figure 13: Effects of monetary policy shocks on housing price factors



Note: This figure shows the cumulative impulse responses of the nationwide supply, residential demand, and speculative demand factor to a 100bp increase of the externally identified monetary policy shock. The solid blue line indicates the 68% confidence interval, while the light blue dotted line represents the 90% confidence interval. Panel (a) shows the impulse response of each factor to monetary policy shocks without considering potential asymmetry. Panels (b) and (c) show the impulse response of each factor to tightening (easing) monetary policy shocks, respectively. The estimation sample spans from January 2007 to December 2024.

reduces both residential and speculative demand, consistent with theoretical predictions. However, the response is disproportionately concentrated in speculative demand. The magnitude of the speculative demand response is substantially larger and statistically more significant than that of the other components. An exogenous 100-basis-point increase in the policy rate leads to an immediate and statistically significant decline in housing price growth, driven almost entirely by a sharp contraction in speculative demand. This effect reaches approximately 0.3% after 15 months and remains persistent thereafter.

By contrast, the same shock generates only a modest and short-lived decline in housing price growth attributable to residential demand. These results suggest that speculative demand is highly sensitive to interest rate changes, validating our identification strategy and highlighting the role of speculative expectations in driving housing market volatility.

Panels (b) and (c) of Figure 13 present the impulse responses to contractionary and expansionary monetary shocks separately. A pronounced asymmetry emerges: monetary easing elicits a substantially larger response in speculative demand than monetary tightening of the same magnitude. Specifically, a 100-basis-point reduction in the policy rate generates more than 1.2% cumulative growth in speculative demand over three years, whereas an equivalent rate hike produces only a limited and statistically insignificant decline (Drechsler, Savov and Schnabl, 2022; Koeniger, Lennartz and Ramelet, 2022). In contrast, monetary tightening appears somewhat more effective than easing in dampening housing price growth driven by supply or residential demand shocks.

This asymmetry is consistent with prior evidence on downward rigidity in housing prices (e.g., Gao, Lin and Na, 2009; Li, 2015; Erlandsen and Juelsrud, 2023) and carries important implications for the design of monetary policy responses to housing market fluctuations. Moreover, given that speculative demand shocks have contractionary effects on real activity, these findings offer a potential explanation for the well-documented asymmetry in the transmission of monetary policy—namely, that monetary tightening tends to be more effective than easing in stabilizing economic outcomes (e.g., Tenreyro and Thwaites, 2016; Choi, Willems and Yoo, 2024). Taken together, the results suggest that monetary policy alone may be insufficient to mitigate financial instability stemming from housing speculation, reinforcing the case for complementary macroprudential interventions.

7.2. Macroprudential Policy and Housing Price Dynamics

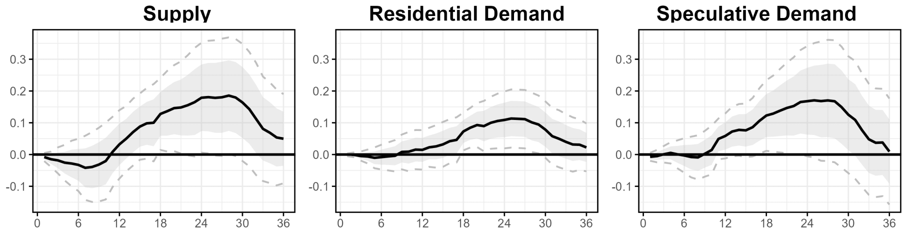
Next, we examine the responses of each identified factor to exogenous macroprudential policy shocks, with a particular focus on loan-to-value (LTV) limit shocks. We employ a similar specification to that used in the previous section for estimating impulse response functions, except that we replace the structural monetary policy shock ($e_{MP,t}$) with the structural macroprudential policy shock ($e_{PP,t}$). A positive macroprudential policy shock corresponds to an increase in LTV limits, indicating an easing of macroprudential regulation.

Figure 14 presents the estimated impulse responses to an LTV limit shock. As shown in Panel (a), a relaxation of LTV limits leads to an increase in all housing price factors. However, the impulse responses to LTV shocks exhibit several distinct characteristics compared to those of monetary policy shocks. While the effects of monetary policy shocks are predominantly concentrated on speculative demand, LTV shocks exert more evenly distributed effects across all three factors. Furthermore, LTV limits exhibit more delayed effects relative to monetary policy. Whereas the impulse responses to LTV shocks become statistically significant at the 68% confidence level only after approximately one year, the effects of monetary policy shocks—particularly on demand-related factors—are significant almost immediately.

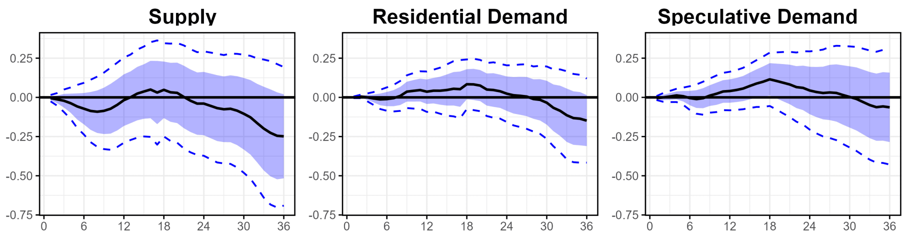
Additional differences between LTV and monetary policy shocks emerge when examining their asymmetric effects. Panels (b) and (c) of Figure 14 illustrate the responses of each factor to a positive LTV shock (LTV easing) and a negative LTV shock (LTV tightening), respectively. Unlike monetary policy shocks, an easing of LTV limits does not appear to significantly stimulate housing prices, whereas a tightening of LTV limits effectively curbs housing price growth, albeit with a lag. The estimated impulse responses indicate that a one percentage point exogenous tightening of LTV limits reduces housing price growth attributable to speculative demand by approximately 0.3% at its peak.

Figure 14: Effects of macroprudential policy shocks on housing market factors

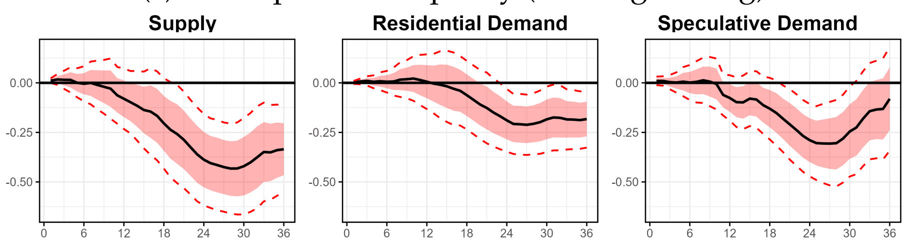
(a) Macroprudential policy (Average)



(b) Macroprudential policy (LTV Easing)



(c) Macroprudential policy (LTV Tightening)



Note: This figure shows the cumulative impulse responses of the nationwide supply, residential demand, and speculative demand factor to a 1%p increase in the externally identified LTV limit shock. The solid blue line indicates the 68% confidence interval, while the light blue dotted line represents the 90% confidence interval. Panel (a) shows the impulse response of each factor to LTV limits shocks without considering potential asymmetry. Panels (b) and (c) show the impulse response of each factor to easing (tightening) LTV limits shocks, respectively. The estimation sample is from January 2007 to December 2024.

Moreover, LTV tightening not only suppresses housing price growth linked to speculative demand but also dampens price growth driven by other factors. As shown in Panel (c), a one percentage point exogenous increase in LTV limits leads to declines in housing price growth driven by supply and residential demand factors of approximately 0.4% and 0.2%, respectively.

Figures 13 and 14 provide important policy implications for the coordination of monetary and macroprudential policies. First, the tightening of both monetary and macroprudential policies tends to be more effective than their easing, highlighting the asymmetric nature of housing price dynamics. Second, an exception to this pattern arises: monetary easing can substantially stimulate speculative demand, yet subsequent monetary tightening fails to effectively contain it. This asymmetry highlights the necessity of implementing macroprudential instruments alongside monetary policy, as they appear to be more effective in curbing housing price growth driven by speculative demand. Third, given the lagged effects of macroprudential measures, policymakers should exercise caution when altering the stance of macroprudential regulations.

8 Conclusion

This paper develops a novel real-time framework to identify speculative housing demand by exploiting the unique institutional feature of Korea's *jeonse* system. By combining high-frequency district-level data with a modified sign-restriction VAR framework, we decompose housing price fluctuations into supply, residential demand, and speculative demand shocks. Our identification strategy provides a tractable way to distinguish between "good" and "bad" housing booms, overcoming the empirical limitations of conventional pricing indicators such as the price-to-rent ratio.

Our empirical findings highlight the dominant role of speculative demand in explaining housing price fluctuations between 2007 and 2024. More importantly, the macroeconomic effects of different types of housing demand are highly asymmetric: residential demand shocks are expansionary, while speculative demand shocks are contractionary. These results suggest that speculative booms—despite appearing similar in price dynamics—entail adverse real effects and therefore require separate policy attention.

We identify household debt accumulation as the key mechanism underlying these differential effects. Using micro-level data from approximately one million households, we show that speculative demand shocks generate significant and persistent increases in household leverage, particularly in mortgage debt, while residential demand and supply shocks have minimal impact on household borrowing. This excessive debt accumulation creates a debt overhang that constrains future consumption, explaining why speculative housing booms ultimately damage economic activity despite initial wealth effects from rising prices.

Lastly, we evaluate the differential effectiveness of stabilization tools. While monetary easing significantly amplifies speculative demand, monetary tightening does not yield proportionate contractionary effects. In contrast, macroprudential tightening—especially through loan-to-value restrictions—proves more effective in curbing speculative housing activity, albeit with a lag. Taken together, these findings highlight the need for a coordinated monetary–macroprudential policy mix to contain speculative cycles and mitigate their macroeconomic fallout.

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Online Appendix (not for publication)

A Institutional features of Korea's housing market

Korea's housing market combines features common to advanced economies with a set of institutions that are distinctive in both design and macroeconomic consequences. The market is highly urbanized and spatially concentrated: economic activity and population are clustered in the Greater Seoul Metropolitan Area, and multi-family apartments—typically high-rise developments built and managed as integrated complexes—constitute the dominant housing form. Apartments function not only as consumption goods but also as widely held financial assets. This dual role heightens price sensitivity to interest rates, credit conditions, and policy announcements, and helps explain why housing cycles in Korea are closely intertwined with the broader financial cycle.

A defining institutional feature is the *jeonse* tenure system. Under jeonse, tenants pay a large, interest-free security deposit to the landlord for the duration of the lease (traditionally two years), in exchange for little or no monthly rent. Landlords use the deposit as a funding source—either to service debt, to purchase additional property, or to invest in other assets—so the rental market is directly linked to the credit system. Banks offer "jeonse loans" to households to help finance deposits, often secured by the leasehold right or the property itself. This configuration creates a triangular balance-sheet interaction among tenants, landlords, and banks that is unusual by international standards.

When interest rates fall, the opportunity cost of holding the deposit declines for landlords, the supply of jeonse contracts tends to expand, and deposit sizes can rise; when rates increase, jeonse becomes less attractive to landlords, pushing the market toward monthly rent or hybrid "ban (half)-jeonse" contracts that combine a smaller deposit with monthly payments. These shifts reallocate cash-flow risk between landlords and tenants and transmit financial conditions into housing affordability in ways that differ from pure monthly-rent systems.

Mortgage intermediation is dominated by banks and specialized public programs rather than by large-scale private-label securitization. Historically, a substantial share of mortgages have been variable-rate or subject to rate resets, with interest-only periods common at origination; this increases the pass-through from monetary policy to household debt service. To lengthen maturities and promote fixed-rate borrowing, the government has relied on public conduits and guarantees (e.g., via the Korea Housing Finance Corporation) that originate or back longer-term fixed-rate loans funded through covered bonds or mortgage-backed securities. The result is a segmented mortgage market in which pricing and product availability are shaped not only by bank balance-sheet conditions but also by eligibility criteria in public programs.

Macroprudential policy is a central, and unusually active, part of housing-market governance. Korean authorities deploy loan-to-value (LTV), debt-to-income (DTI), and, more recently, borrower-based debt service ratio (DSR) limits that cap the share of a borrower's aggregate income usable to service total principal and interest across all debts. These constraints are tightened or relaxed in response to housing market overheating, nationwide credit growth, or financial-stability concerns, and are often differentiated by geography (e.g., overheated or speculative zones), borrower type (first-time buyers vs. multiple-home owners), and property characteristics (pre-sale vs. existing units). Because banks operate nationally and compete across regions, borrower-based tools have been more influential than purely geographic credit allocations. Frequent recalibration of these tools makes the policy regime itself an important state variable for prices, transaction volumes, and expectations.

Taxation amplifies the policy lever. On the holding side, annual property taxes and an additional comprehensive real estate tax apply with progressive schedules that can include surcharges on multi-home owners. On the transaction side, acquisition taxes and capital gains taxes are adjusted to cool or stimulate activity, with higher rates frequently imposed on short holding periods or multiple-property portfolios. These parameters have been revised numerous times over the past two decades, generating anticipatory behavior (e.g., bunching of listings ahead of tax changes) and contributing to the perception that policy risk is part of the housing asset's return process. Because apartments are widely used as savings vehicles, tax shifts can reallocate portfolios between housing and financial assets, affecting both price momentum and household balance sheets.

On the supply side, the institutional structure centers on redevelopment and reconstruction of existing urban stock and on periodic waves of new-town development at the metropolitan fringe. Redevelopment is governed by safety inspections, floor-area-ratio constraints, environmental and infrastructure requirements, and—in many periods—pre-sale price ceilings designed to restrain the initial sale price to owner-occupiers. Korea's *pre-sale* (*bunyang*) system allows developers to sell units before completion, with buyers selected predominantly by subscription lotteries (*cheongyak*).

This approach can ease funding constraints for developers but also embeds policy parameters (allocation rules, eligibility, price caps) directly into the supply pipeline, affecting both the timing and composition of new units. Because large apartment complexes are delivered in discrete batches, completions arrive with long lags and in sizable blocks, producing pronounced cycles in vacancy and bargaining power. New-town programs—implemented in several "generations" since the late 1980s—augment supply and transport infrastructure, but the planning and build-out horizons are long relative to demand shocks, which limits their ability to smooth short-run price fluctuations.

Institutional features also shape the distribution of housing opportunities. Access to newly built, price-capped pre-sale units is rationed by points and lotteries that reward savings-plan participation, family status, and first-time ownership, while speculative-zone designations restrict leverage and resales. These rationing rules aim to prioritize end-users and dampen investor demand, but they can also create sizable option values embedded in pre-sale rights and induce secondary-market premia for allocation entitlements. In the rental market, the evolving mix between jeonse and rent alters the cash needs of renters over the life cycle: young households may face high upfront deposit requirements in jeonse regimes or high recurring cash-flow burdens under rent, with differing implications for consumption smoothing.

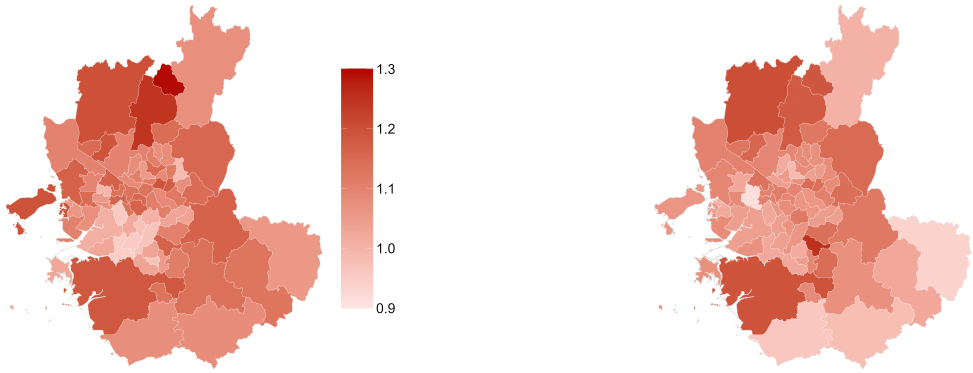
The macro-financial linkage is unusually tight. Household debt is large by international standards and is concentrated in housing loans and jeonse financing. Because collateral values co-move with the cycle and because lending standards are actively managed through macroprudential rules, feedback loops can arise: rising prices relax collateral constraints and, in boom phases, may coincide with regulatory forbearance in specific segments; downturns tighten both collateral and borrower-based constraints, amplifying deleveraging. Banks' nationwide branch networks and limited geographic segmentation mean that credit conditions are transmitted rapidly across regions, even when price movements are locally heterogeneous. In addition, the prevalence of adjustable-rate or resettable mortgages increases the speed at which policy-rate changes affect household cash flows, consumption, and default risk.

Demographic and spatial fundamentals interact with these institutions. Population aging and very low fertility imply slower household formation over the long run, but continued employment concentration in Seoul supports persistent demand for centrally located apartments and for units with high amenity access (schools, transit, and public services). Policy attempts to rebalance supply through redevelopment and transit-oriented growth have had to reconcile densification goals with neighborhood externalities and infrastructure constraints, reinforcing the central role of regulatory approvals and price caps in the timing of supply.

B Additional figures and tables

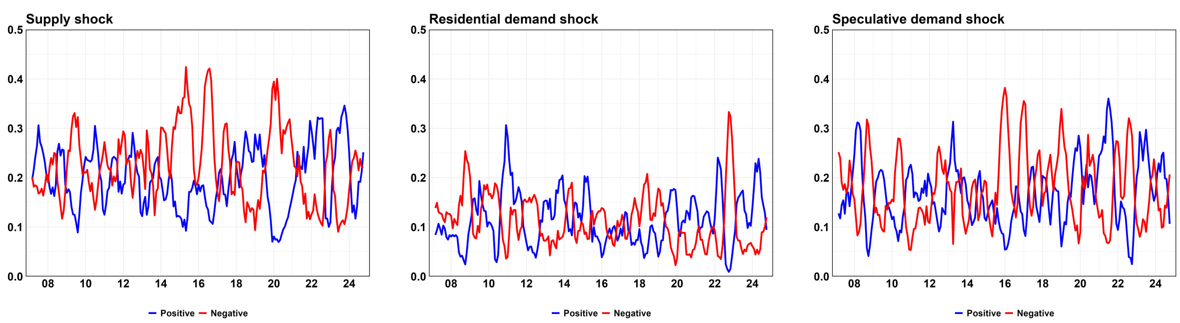
Figure B1: Heatmap for Sales-to-jeonse Ratio (Seoul Metropolitan Area)

(a) Mean (b) Standard Deviation



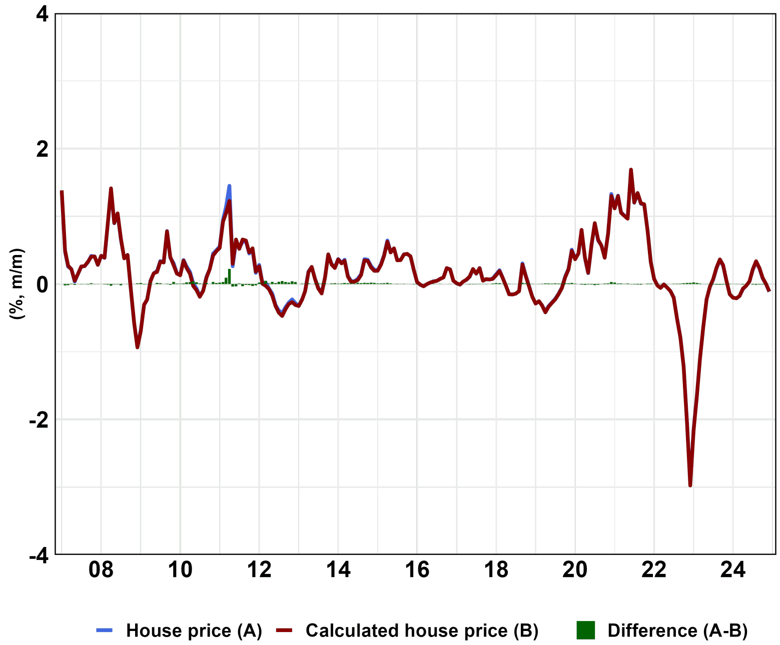
Note: The Sales-to-jeonse price ratio mean and s.d. across districts during 2003M11 to 2024M12 in Seoul Metropolitan Area.

Figure B2: Share of districts affected by each housing market shock



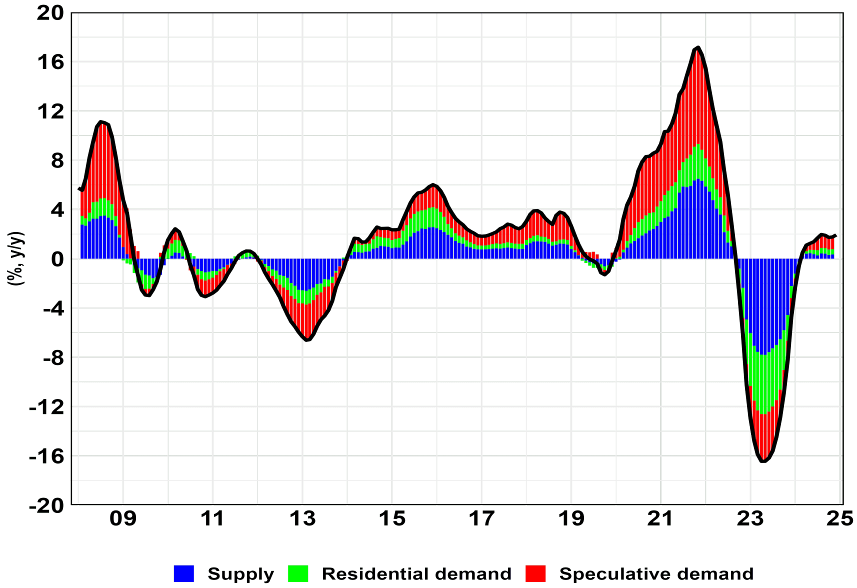
Note: The share of housing sales price changes at the district level, driven by supply, residential demand, and speculative demand shocks, respectively. The centered five-month moving average is used to smooth out the series. All series above sum to one for any given month.

Figure B3: Actual vs. computed housing price growth



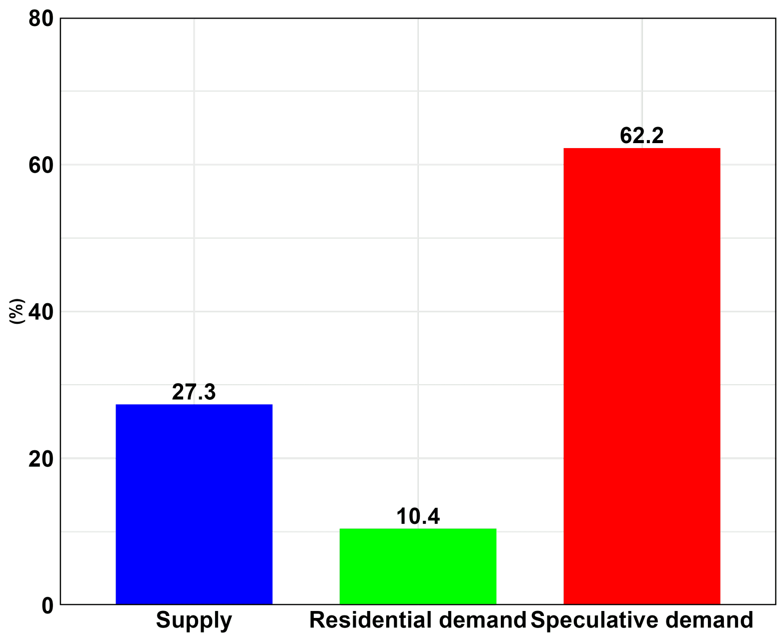
Note: House price refers to the month-over-month growth rate of the seasonally-adjusted national housing sales price obtained from the National Housing Price Trend Survey. The calculated house price is the sum of the supply, residential demand, and speculative demand factors.

Figure B4: Supply, residential demand, and speculative demand-driven housing price growth (Seoul metropolitan area)



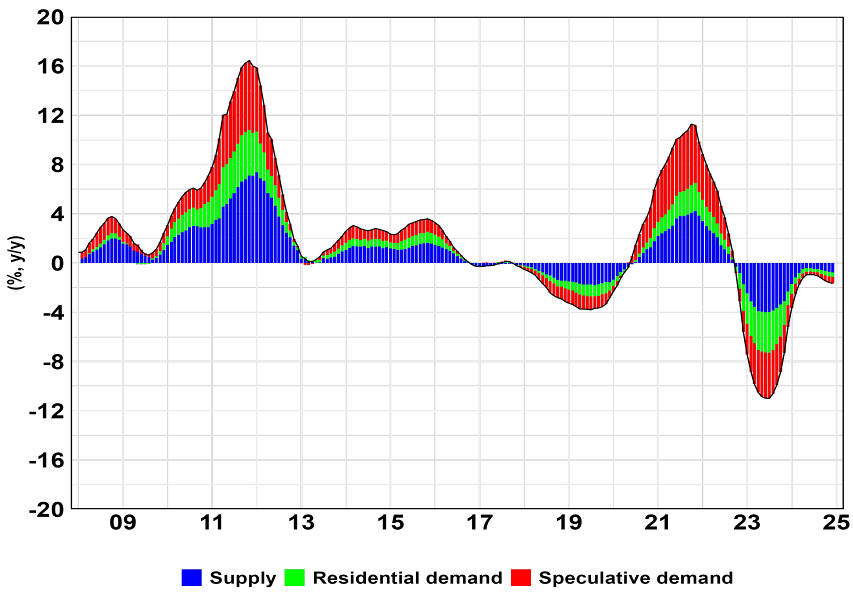
Note: The black solid line is the month-over-month growth rate of housing prices in Korea. The series is divided into supply (blue), residential demand (green), and speculative demand (red) factors.

Figure B5: Average contribution of each housing market shock to Korean housing price dynamics (Seoul metropolitan area)



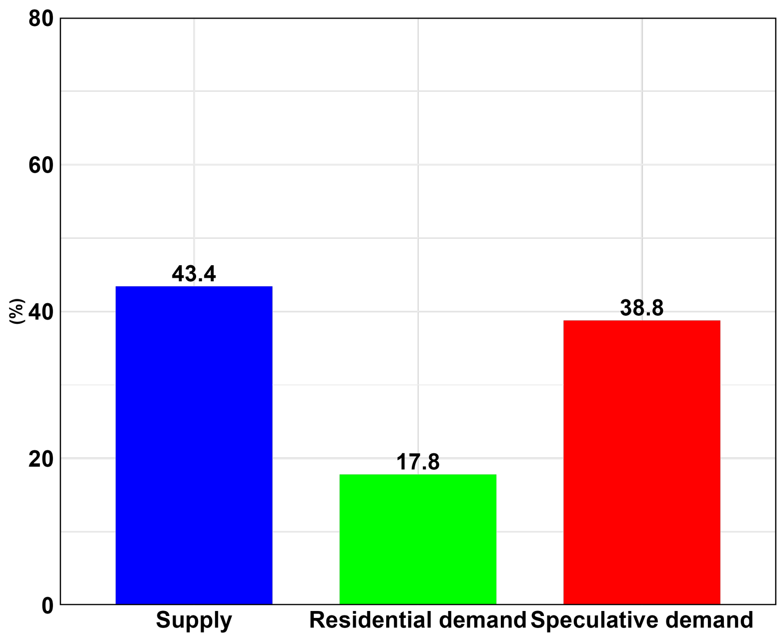
Note: Each component's contribution is computed as the ratio of its cumulative growth to that of total housing prices over the period from January 2007 to December 2024.

Figure B6: Supply, residential demand, and speculative demand-driven housing price growth (Non-metropolitan area)



Note: The black solid line is the month-over-month growth rate of housing prices in the Non-Seoul-Metropolitan Area. The series is divided into supply (blue), residential demand (green), and speculative demand (red) factors.

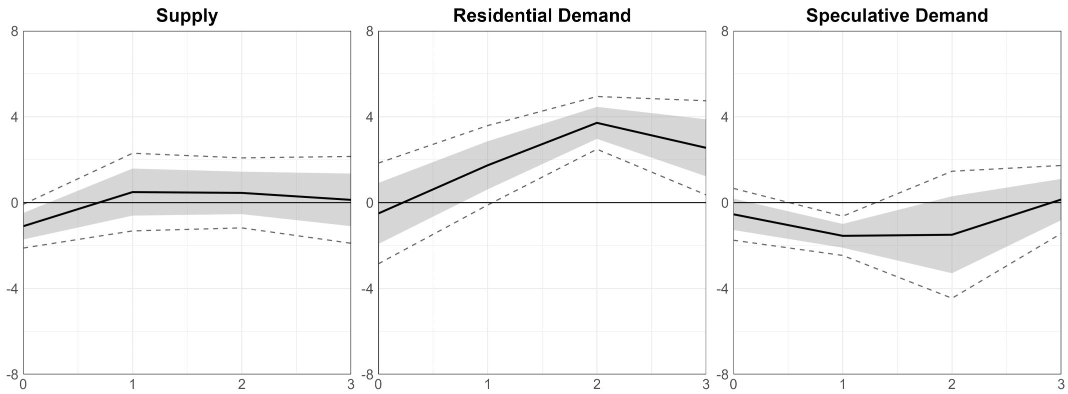
Figure B7: Average contribution of each housing market shock to Korean housing price dynamics (Non-metropolitan area)



Note: Each component's contribution is computed as the ratio of its cumulative growth to that of total housing prices over the period from January 2007 to December 2024.

C Robustness checks

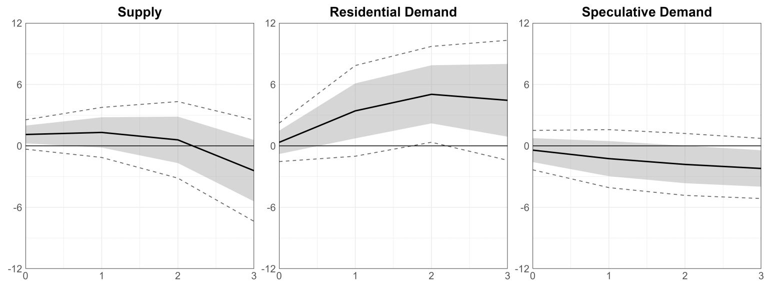
Figure C8: Robustness check: using value-added



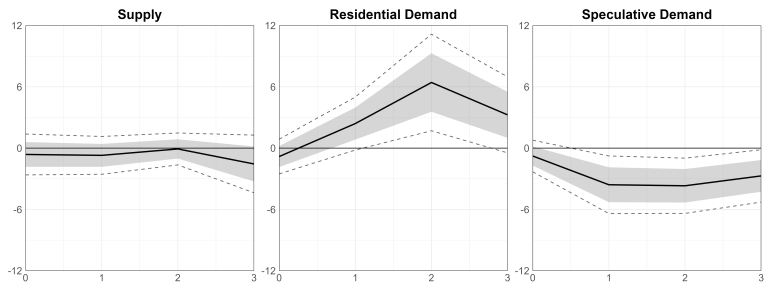
Note: The panels depict the cumulative impulse responses for panel local projections. The sign of the shock is normalized to increase housing prices. The shaded areas indicate the 68% confidence interval, while the dotted line represents the 90% confidence interval. The dependent variable is gross value-added. The models are estimated using the data from 155 districts from 2007 to 2023. Standard errors are calculated following Driscoll and Kraay (1998).

Figure C9: Robustness check: using province-level data

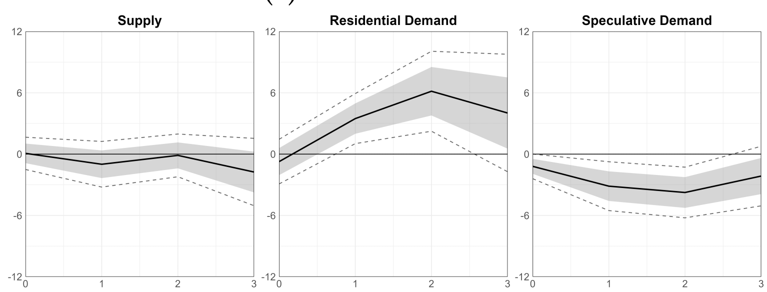
(a) Output



(b) Employment



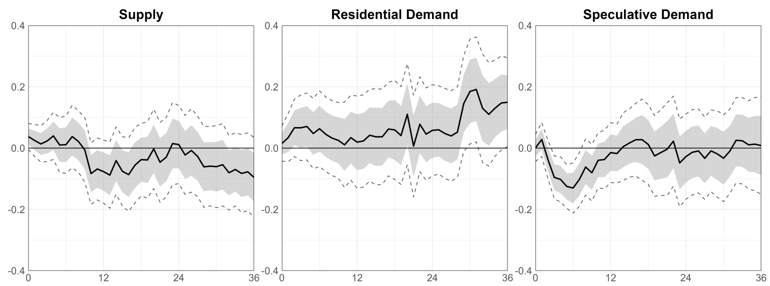
(c) Establishment



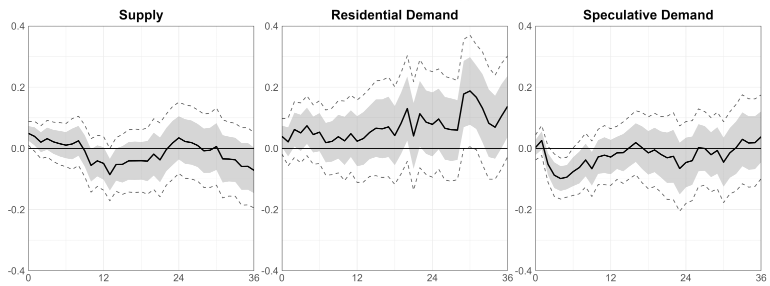
Note: The panels depict cumulative impulse responses from panel local projections using city- or province-level data. The sign of the shock is normalized to increase housing prices. Panel (a) shows responses of output (GRDP), while Panels (b) and (c) present responses of employment and the number of establishments. The sign of the shock is normalized to increase housing prices. The shaded area represents the 68% confidence interval, and the dashed line indicates the 90% confidence interval. The cumulative impulse responses in Panel (a) are estimated using data from 17 provinces spanning 2006 to 2023, with data sourced from the Regional Income statistics, whereas those in Panels (b) and (c) are estimated using data from 17 provinces spanning 2007 to 2023, with data sourced from the Actual Labor Condition at Establishment survey. Standard errors are computed following Driscoll and Kraay (1998).

Figure C10: Robustness check: using monthly labor data

(a) Employment to Population Ratio (15-64)



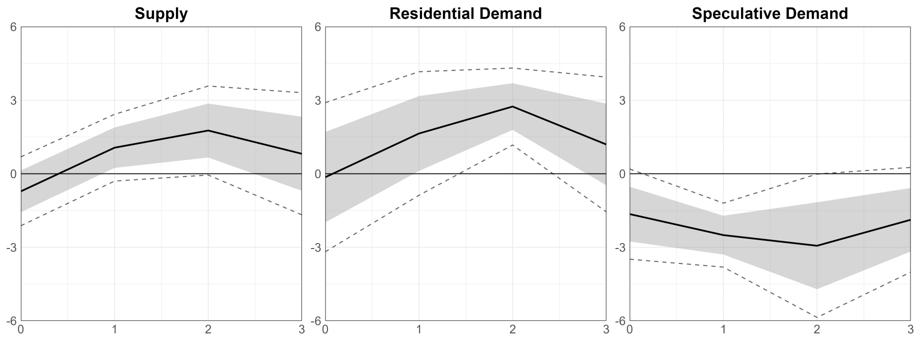
(b) Labor Force Participation Rate



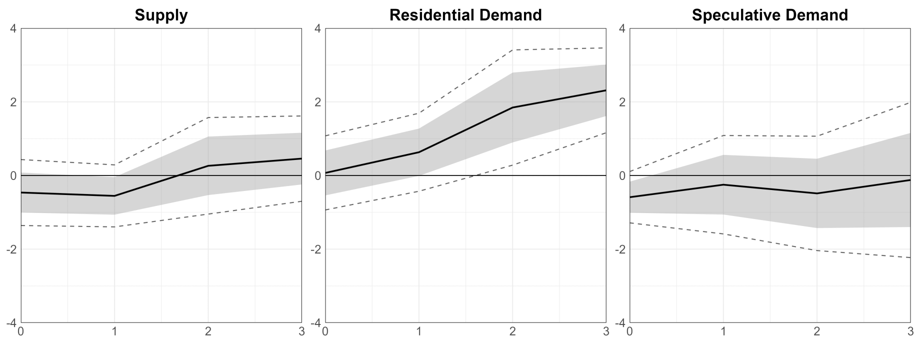
Note: The panels depict cumulative impulse responses from panel local projections using monthly labor data. Panel (a) presents responses of the employment-to-population ratio for ages 15–64, while Panel (b) shows responses of the labor force participation rate. The x-axis denotes months. The sign of the shock is normalized to increase housing prices. The shaded area represents the 68% confidence interval, and the dashed line indicates the 90% confidence interval. The models are estimated using data from 17 provinces spanning January 2006 to December 2024, with data sourced from the Economically Active Population Survey. Standard errors are computed following Driscoll and Kraay (1998).

Figure C11: Robustness check: controlling for time-varying local economic conditions

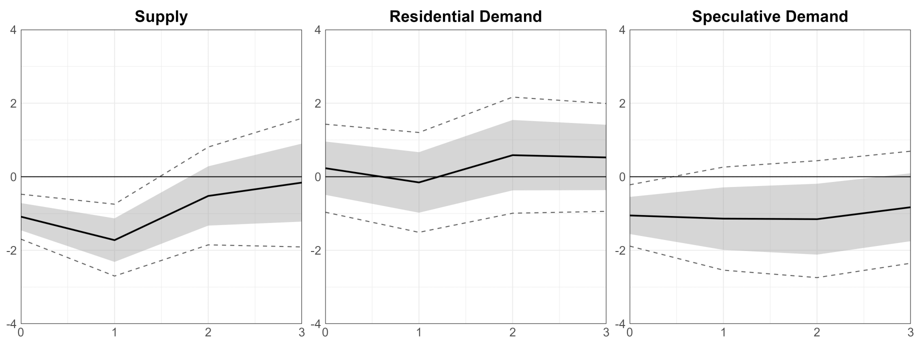
(a) Output



(b) Employment



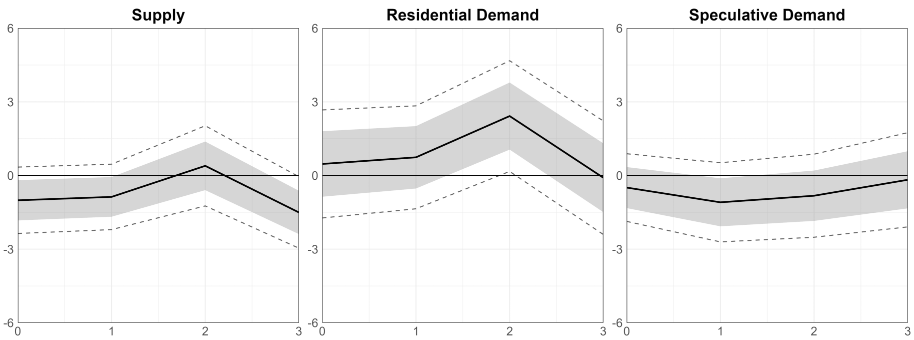
(c) Number of establishments



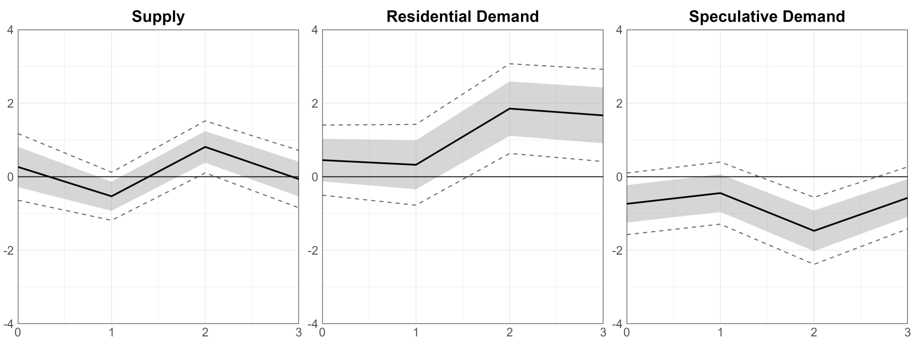
Note: The panels depict the cumulative impulse responses for panel local projections. The sign of the shock is normalized to increase housing prices. The shaded areas indicate the 68% confidence interval, while the dotted line represents the 90% confidence interval. The dependent variables are total output (top panel), employment (middle panel), and the number of establishments (bottom panel). The models are estimated using the data from 154 districts from 2010 to 2021 for output and 155 districts from 2007 to 2023 for employment and the number of establishments. Standard errors are calculated following Driscoll and Kraay (1998).

Figure C12: Robustness check: using a GMM estimator

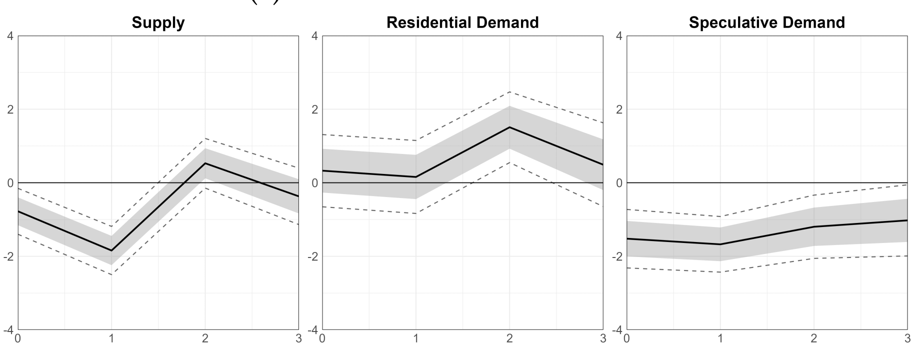
(a) Output



(b) Employment



(c) Number of establishments



Note: The panels depict the cumulative impulse responses for panel local projections. The sign of the shock is normalized to increase housing prices. The shaded areas indicate the 68% confidence interval, while the dotted line represents the 90% confidence interval. The dependent variables are total output (top panel), employment (middle panel), and the number of establishments (bottom panel). The models are estimated by the one-step difference GMM, using the data from 154 districts from 2010 to 2021 for output and 155 districts from 2007 to 2023 for employment and the number of establishments.

D Identification of Policy Shocks

The accurate identification of policy shocks is crucial for testing their effects on housing price dynamics. To address this issue, we jointly extract monetary and macroprudential policy shocks from the structural residuals of the VAR model. This identification strategy accounts for the characteristics of a small open economy and captures the dynamic interactions between monetary and macroprudential policies within the broader macroeconomic framework. Formally, consider an economy represented by the following structural equation:

$$G(L)y_t = a + C(L)x_t + e_t,$$

where $G(L)$ and $C(L)$ are matrix polynomials in the lag operator L, y_t is an $M \times 1$ data vector of endogenous variables at time t, x_t is an $K \times 1$ data vector of exogenous variables.

The term a represents a $M \times 1$ constant vector, while M and K are the numbers of endogenous and exogenous variables in the model, respectively. Lastly, e_t is a vector of structural disturbances. Under the assumption that structural disturbances are mutually uncorrelated, the variance-covariance matrix, denoted as $var(e_t)$, is represented by Λ, a diagonal matrix where the diagonal elements are the variances of structural disturbances.

We estimate the following reduced-form VAR:

$$y_t = \alpha + B(L)y_{t-1} + D(L)x_t + u_t,$$

where α is an $M \times 1$ constant vector, $B(L)$ and $D(L)$ are matrix polynomials in the lag operator L, u_t is an $M \times 1$ vector of reduced form residuals. The variance-covariance matrix of u_t is denoted as $var(u_t) = \Sigma$. The parameters of the structural form equation can be recovered from the estimated parameters of the reduced form equation by imposing an appropriate identification scheme.

The vector of endogenous variables, y_t, is defined as $[IP_t, CPI_t, RHL_t, PP_t, R_t]'$. Industrial production (IP_t) and the consumer price index (CPI_t) are included as measures of overall economic activity and as key targets of monetary policy. The stock of real household loans issued by depository corporations (RHL_t) is incorporated as a primary target of macroprudential policy.[16] An index of macroprudential policy (PP_t) and the policy rate (R_t) are included to facilitate the identification of macroprudential and monetary policy shocks, respectively.

The macroprudential policy index is constructed using the updated data from Alam, Alter, Eiseman, Gelos, Kang, Narita, Nier and Wang (2024). Specifically, among the various macroprudential policy instruments available in the dataset, we employ the average of the regulatory loan-to-value (LTV) limits across all existing categories in Korea. This measure offers two key advantages: first, it provides insight into the intensity of policy actions; second, it conveys information not only about the direction of policy adjustments but also the level of policy implementation (Alam et al., 2024).

The vector of exogenous variables, x_t, is specified as $[USIP_t, FFR_t]'$. U.S. industrial production ($USIP_t$) and the Federal Funds Rate (FFR_t) are included to account for potential spillover effects from U.S. economic activity and monetary policy on Korea, a small open economy. This inclusion is motivated by extensive empirical evidence highlighting the cross-border effects of U.S. monetary policy on credit growth and asset prices (e.g., Bruno and Shin, 2015; Albrizio, Choi, Furceri and Yoon, 2020; Miranda-Agrippino and Rey, 2020). All series are included in levels, and for all variables except PP_t, R_t, and FFR_t, a natural logarithm transformation is applied and multiplied by 100. The VAR model includes 12 lags to account for persistence in endogenous variables. We also include a dummy variable for the Global Financial Crisis (2008M7 to 2009M6) to account for macroeconomic turbulence during that period.

For identification, we impose zero restrictions on contemporaneous structural parameters, following Kim and Mehrotra (2018) and Kim and Mehrotra (2022). Specifically,

[16] Real loans are obtained by deflating nominal loans using the consumer price index.

we assume that macroeconomic variables (IP_t, CPI_t, RHL_t) are contemporaneously exogenous to both macroprudential policy (PP_t) and the policy rate (R_t). Additionally, we assume that macroprudential policy is contemporaneously exogenous to the policy rate.[17] Under these assumptions, macroprudential policy shocks (e_{PP}) and monetary policy shocks (e_{MP}) are identified as the structural residuals of PP_t and R_t in equation (D).

Our identification strategy is justified on two grounds. First, by jointly incorporating macroprudential policy measures and the policy rate within the VAR framework, we account for potential interactions between the two policy instruments. Second, by controlling for endogenous policy responses driven by macroeconomic conditions and isolating exogenous policy shocks, we mitigate potential downward bias in estimating the effects of macroprudential policies. Given that macroprudential measures, such as loan-to-value (LTV) limits, tend to be tightened during credit or housing booms, reliance on observed policy changes alone may be subject to attenuation bias (Kim and Mehrotra, 2022; Alam et al., 2024).

[17] The results remain robust when the ordering between macroprudential policy and monetary policy variables is reversed.

E District-level housing weight

Table E1: Details on the districts included in the study

Region	Subregion	Start date	End date	Avg. weight (%)
Seoul	Jongno-gu	2007-01-01	2024-12-01	0.139
Seoul	Jung-gu	2007-01-01	2024-12-01	0.234
Seoul	Yongsan-gu	2007-01-01	2024-12-01	0.363
Seoul	Seongdong-gu	2007-01-01	2024-12-01	0.619
Seoul	Gwangjin-gu	2007-01-01	2024-12-01	0.327
Seoul	Dongdaemun-gu	2007-01-01	2024-12-01	0.610
Seoul	Jungnang-gu	2007-01-01	2024-12-01	0.536
Seoul	Seongbuk-gu	2007-01-01	2024-12-01	0.754
Seoul	Gangbuk-gu	2007-01-01	2024-12-01	0.349
Seoul	Dobong-gu	2007-01-01	2024-12-01	0.696
Seoul	Nowon-gu	2007-01-01	2024-12-01	1.750
Seoul	Eunpyeong-gu	2007-01-01	2024-12-01	0.522
Seoul	Seodaemun-gu	2007-01-01	2024-12-01	0.482
Seoul	Mapo-gu	2007-01-01	2024-12-01	0.664
Seoul	Yangcheon-gu	2007-01-01	2024-12-01	0.909
Seoul	Gangseo-gu	2007-01-01	2024-12-01	1.127
Seoul	Guro-gu	2007-01-01	2024-12-01	0.787
Seoul	Geumcheon-gu	2007-01-01	2024-12-01	0.305
Seoul	Yeongdeungpo-gu	2007-01-01	2024-12-01	0.721
Seoul	Dongjak-gu	2007-01-01	2024-12-01	0.605
Seoul	Gwanak-gu	2007-01-01	2024-12-01	0.569
Seoul	Seocho-gu	2007-01-01	2024-12-01	0.939

Region	Sub-region (district)	Start Date	End Date	Avg. Weight (%)
Seoul	Gangnam-gu	2007-01-01	2024-12-01	1.348
Seoul	Songpa-gu	2007-01-01	2024-12-01	1.248
Seoul	Gangdong-gu	2007-01-01	2024-12-01	0.860
Busan	Jung-gu	2007-01-01	2024-12-01	0.056
Busan	Seo-gu	2007-01-01	2024-12-01	0.159
Busan	Dong-gu	2007-01-01	2024-12-01	0.111
Busan	Yeongdo-gu	2007-01-01	2024-12-01	0.281
Busan	Busanjin-gu	2007-01-01	2024-12-01	0.889
Busan	Nam-gu	2007-01-01	2024-12-01	0.601
Busan	Yeonje-gu	2007-01-01	2024-12-01	0.456
Busan	Suyeong-gu	2007-01-01	2024-12-01	0.355
Busan	Haeundae-gu	2007-01-01	2024-12-01	1.148
Busan	Gumjung-gu	2007-01-01	2024-12-01	0.446
Busan	Dongnae-gu	2007-01-01	2024-12-01	0.586
Busan	Gijang-gun	2007-01-01	2024-12-01	0.204
Busan	Buk-gu	2007-01-01	2024-12-01	0.872
Busan	Gangseo-gu	2013-01-01	2024-12-01	0.281
Busan	Sasang-gu	2007-01-01	2024-12-01	0.591
Busan	Saha-gu	2007-01-01	2024-12-01	0.820
Daegu	Jung-gu	2007-01-01	2024-12-01	0.159
Daegu	Dong-gu	2007-01-01	2024-12-01	0.758
Daegu	Seo-gu	2007-01-01	2024-12-01	0.189
Daegu	Nam-gu	2007-01-01	2024-12-01	0.158
Daegu	Buk-gu	2007-01-01	2024-12-01	1.124
Daegu	Suseong-gu	2007-01-01	2024-12-01	1.072
Daegu	Dalseo-gu	2007-01-01	2024-12-01	1.551

Region	Sub-region (district)	Start Date	End Date	Avg. Weight (%)
Daegu	Dalseong-gun	2007-01-01	2024-12-01	0.391
Gwangju	Dong-gu	2007-01-01	2024-12-01	0.186
Gwangju	Seo-gu	2007-01-01	2024-12-01	0.872
Gwangju	Nam-gu	2007-01-01	2024-12-01	0.567
Gwangju	Buk-gu	2007-01-01	2024-12-01	1.295
Gwangju	Gwangsan-gu	2007-01-01	2024-12-01	1.162
Incheon	Jung-gu	2007-01-01	2024-12-01	0.249
Incheon	Dong-gu	2007-01-01	2024-12-01	0.155
Incheon	Michuhol-gu	2019-07-01	2024-12-01	0.646
Incheon	Yeonsu-gu	2007-01-01	2024-12-01	0.951
Incheon	Namdong-gu	2007-01-01	2024-12-01	1.158
Incheon	Bupyeong-gu	2007-01-01	2024-12-01	1.150
Incheon	Gyeyang-gu	2007-01-01	2024-12-01	0.736
Incheon	Seo-gu	2007-01-01	2024-12-01	1.117
Daejeon	Dong-gu	2007-01-01	2024-12-01	0.489
Daejeon	Jung-gu	2007-01-01	2024-12-01	0.523
Daejeon	Seo-gu	2007-01-01	2024-12-01	1.220
Daejeon	Yuseong-gu	2007-01-01	2024-12-01	0.902
Daejeon	Daedeok-gu	2007-01-01	2024-12-01	0.422
Ulsan	Jung-gu	2007-01-01	2024-12-01	0.433
Ulsan	Nam-gu	2007-01-01	2024-12-01	0.818
Ulsan	Dong-gu	2007-01-01	2024-12-01	0.395
Ulsan	Buk-gu	2007-01-01	2024-12-01	0.549
Ulsan	Ulju-gun	2007-01-01	2024-12-01	0.392
Sejong	Sejong-si	2013-11-01	2024-12-01	0.933
Gyeonggi	Manan-gu	2007-01-01	2024-12-01	0.449

Region	Sub-region (district)	Start Date	End Date	Avg. Weight (%)
Gyeonggi	Dongan-gu	2007-01-01	2024-12-01	0.903
Gyeonggi	Sujeong-gu	2007-01-01	2024-12-01	0.223
Gyeonggi	Jungwon-gu	2007-01-01	2024-12-01	0.281
Gyeonggi	Bundang-gu	2007-01-01	2024-12-01	1.291
Gyeonggi	Cheoin-gu	2007-01-01	2024-12-01	0.326
Gyeonggi	Giheung-gu	2007-01-01	2024-12-01	1.136
Gyeonggi	Suji-gu	2007-01-01	2024-12-01	1.042
Gyeonggi	Jangan-gu	2007-01-01	2024-12-01	0.571
Gyeonggi	Gwonseon-gu	2007-01-01	2024-12-01	0.731
Gyeonggi	Paldal-gu	2007-01-01	2024-12-01	0.349
Gyeonggi	Yeongtong-gu	2007-01-01	2024-12-01	0.890
Gyeonggi	Sangnok-gu	2007-01-01	2024-12-01	0.459
Gyeonggi	Danwon-gu	2007-01-01	2024-12-01	0.627
Gyeonggi	Deogyang-gu	2007-01-01	2024-12-01	1.057
Gyeonggi	Ilsandong-gu	2007-01-01	2024-12-01	0.584
Gyeonggi	Ilsanseo-gu	2007-01-01	2024-12-01	0.842
Gyeonggi	Gwacheon-si	2007-01-01	2024-12-01	0.140
Gyeonggi	Gunpo-si	2007-01-01	2024-12-01	0.747
Gyeonggi	Uiwang-si	2007-01-01	2024-12-01	0.394
Gyeonggi	Anseong-si	2007-01-01	2024-12-01	0.396
Gyeonggi	Bucheon-si	2007-01-01	2024-12-01	1.522
Gyeonggi	Siheung-si	2007-01-01	2024-12-01	1.119
Gyeonggi	Gwangmyeong-si	2007-01-01	2024-12-01	0.737
Gyeonggi	Hwaseong-si	2007-01-01	2024-12-01	1.763
Gyeonggi	Osan-si	2007-01-01	2024-12-01	0.563
Gyeonggi	Pyeongtaek-si	2007-01-01	2024-12-01	1.140

Region	Sub-region (district)	Start Date	End Date	Avg. Weight (%)
Gyeonggi	Namyangju-si	2007-01-01	2024-12-01	1.641
Gyeonggi	Guri-si	2007-01-01	2024-12-01	0.428
Gyeonggi	Hanam-si	2007-01-01	2024-12-01	0.510
Gyeonggi	Gwangju-si	2007-01-01	2024-12-01	0.413
Gyeonggi	Icheon-si	2007-01-01	2024-12-01	0.373
Gyeonggi	Yeoju-si	2014-09-01	2024-12-01	0.138
Gyeonggi	Gimpo-si	2007-01-01	2024-12-01	0.949
Gyeonggi	Paju-si	2007-01-01	2024-12-01	0.977
Gyeonggi	Pocheon-si	2013-01-01	2024-12-01	0.185
Gyeonggi	Dongducheon-si	2007-01-01	2024-12-01	0.217
Gyeonggi	Yangju-si	2007-01-01	2024-12-01	0.564
Gyeonggi	Uijeongbu-si	2007-01-01	2024-12-01	1.083
Gangwon	Chuncheon-si	2007-01-01	2024-12-01	0.672
Gangwon	Wonju-si	2007-01-01	2024-12-01	0.925
Gangwon	Gangneung-si	2007-01-01	2024-12-01	0.476
Gangwon	Donghae-si	2013-01-01	2024-12-01	0.234
Gangwon	Taebaek-si	2013-01-01	2024-12-01	0.108
Gangwon	Sokcho-si	2013-01-01	2024-12-01	0.231
Gangwon	Samcheok-si	2013-01-01	2024-12-01	0.129
Chungcheongbuk	Sangdang-gu	2015-07-01	2024-12-01	0.420
Chungcheongbuk	Seowon-gu	2015-07-01	2024-12-01	0.501
Chungcheongbuk	Heungdeok-gu	2015-07-01	2024-12-01	0.610
Chungcheongbuk	Cheongwon-gu	2015-07-01	2024-12-01	0.447
Chungcheongbuk	Chungju-si	2007-01-01	2024-12-01	0.468
Chungcheongbuk	Jecheon-si	2013-01-01	2024-12-01	0.284
Chungcheongbuk	Eumseong-gun	2013-01-01	2024-12-01	0.117

Region	Sub-region (district)	Start Date	End Date	Avg. Weight (%)
Chungcheongnam	Dongnam-gu	2009-06-01	2024-12-01	0.627
Chungcheongnam	Seobuk-gu	2009-06-01	2024-12-01	1.037
Chungcheongnam	Gongju-si	2007-01-01	2024-12-01	0.166
Chungcheongnam	Boryeong-si	2013-01-01	2024-12-01	0.160
Chungcheongnam	Asan-si	2007-01-01	2024-12-01	0.825
Chungcheongnam	Seosan-si	2013-01-01	2024-12-01	0.365
Chungcheongnam	Nonsan-si	2007-01-01	2024-12-01	0.159
Chungcheongnam	Gyeryong-si	2007-01-01	2024-12-01	0.144
Chungcheongnam	Hongseong-gun	2013-01-01	2024-12-01	0.073
Chungcheongnam	Yesan-gun	2013-01-01	2024-12-01	0.072
Chungcheongnam	Dangjin-si	2013-01-01	2024-12-01	0.347
Jeollabuk	Wansan-gu	2007-01-01	2024-12-01	0.954
Jeollabuk	Deokjin-gu	2007-01-01	2024-12-01	0.749
Jeollabuk	Gunsan-si	2007-01-01	2024-12-01	0.736
Jeollabuk	Iksan-si	2007-01-01	2024-12-01	0.728
Jeollabuk	Jeongeup-si	2013-01-01	2024-12-01	0.179
Jeollabuk	Namwon-si	2013-01-01	2024-12-01	0.117
Jeollabuk	Gimje-si	2013-01-01	2024-12-01	0.107
Jeollanam	Mokpo-si	2007-01-01	2024-12-01	1.703
Jeollanam	Yeosu-si	2007-01-01	2024-12-01	0.674
Jeollanam	Suncheon-si	2007-01-01	2024-12-01	0.703
Jeollanam	Naju-si	2013-01-01	2024-12-01	0.224
Jeollanam	Gwangyang-si	2007-01-01	2024-12-01	0.415
Jeollanam	Muan-gun	2013-01-01	2024-12-01	0.074
Gyeongsangbuk	Nam-gu	2007-01-01	2024-12-01	0.495
Gyeongsangbuk	Buk-gu	2007-01-01	2024-12-01	0.715

Region	Sub-region (district)	Start Date	End Date	Avg. Weight (%)
Gyeongsangbuk	Gyeongju-si	2013-01-01	2024-12-01	0.443
Gyeongsangbuk	Gimcheon-si	2013-01-01	2024-12-01	0.261
Gyeongsangbuk	Andong-si	2013-01-01	2024-12-01	0.306
Gyeongsangbuk	Gumi-si	2007-01-01	2024-12-01	1.011
Gyeongsangbuk	Yeongju-si	2013-01-01	2024-12-01	0.158
Gyeongsangbuk	Yeongcheon-si	2013-01-01	2024-12-01	0.171
Gyeongsangbuk	Sangju-si	2013-01-01	2024-12-01	0.107
Gyeongsangbuk	Mungyeong-si	2013-01-01	2024-12-01	0.068
Gyeongsangbuk	Gyeongsan-si	2007-01-01	2024-12-01	0.636
Gyeongsangbuk	Chilgok-gun	2013-01-01	2024-12-01	0.173
Gyeongsangnam	Uichang-gu	2011-07-01	2024-12-01	0.422
Gyeongsangnam	Seongsan-gu	2011-07-01	2024-12-01	0.656
Gyeongsangnam	Masanhappo-gu	2011-07-01	2024-12-01	0.373
Gyeongsangnam	Masanhoewon-gu	2011-07-01	2024-12-01	0.422
Gyeongsangnam	Jinhae-gu	2011-07-01	2024-12-01	0.441
Gyeongsangnam	Jinju-si	2007-01-01	2024-12-01	0.701
Gyeongsangnam	Tongyeong-si	2013-01-01	2024-12-01	0.261
Gyeongsangnam	Sacheon-si	2013-01-01	2024-12-01	0.219
Gyeongsangnam	Gimhae-si	2007-01-01	2024-12-01	1.328
Gyeongsangnam	Miryang-si	2013-01-01	2024-12-01	0.155
Gyeongsangnam	Geoje-si	2007-01-01	2024-12-01	0.609
Gyeongsangnam	Yangsan-si	2007-01-01	2024-12-01	0.949
Jeju	Jeju-si	2007-01-01	2024-12-01	0.523
Jeju	Seogwipo-si	2013-01-01	2024-12-01	0.154