Analytical Note

China Economic Insights

China's Property Market: Navigating a Path Toward Stability[1]

January 16, 2026

"Housing markets are subject to boom-and-bust cycles that carry systemic risks; stabilizing them is therefore crucial for broader macroeconomic stability and sustained growth."

- Susan M. Wachter
Systemic Risk and Market Institutions, 2009

I. Introduction

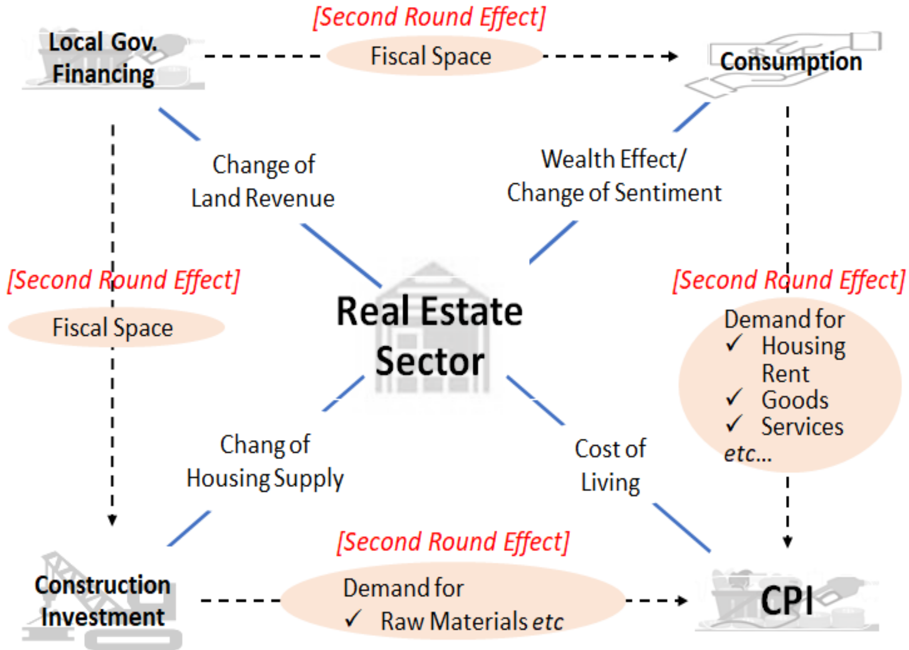
1. **The real estate sector is a critical component of the economy given its strong interlinkages with other segments of economic activity.** In China, developments in the property market[2] have significant implications for inflation, investment, local government financing, and household consumption through both direct and indirect channels (Figure 1). As of the first half of 2025, the real estate sector accounts for approximately 12 percent of nominal GDP[3] and constitutes a major share of household wealth. According to AMRO (2024), property market cycles in China are highly correlated with both credit and real economic cycles, indicating that prolonged weakness in the property sector may weigh on both financial and real activity. For instance, a sustained downturn in real estate could generate negative spillover effects on broader economic dynamics, including through adverse wealth effects that dampen consumption and exacerbate deflationary pressures.

2. **China's real estate market exhibits distinct, tier-differentiated dynamics.** Although property prices have continued to decline across all city tiers, the pace of depreciation has moderated in Tier 1 cities, whereas Tier 2 and 3 areas remain subject to more pronounced and persistent price adjustments. In light of these disparities, this analytical note aims to analyze the underlying causes of the real estate downturn and assess the likely timing of recovery across different tiers, before deriving relevant policy implications. The

[1] Prepared by Jungsung Kim (Jungsung.kim@amro-asia.org) of the Country Surveillance Group, and cleared by Jae Young Lee, Group Head, Country Surveillance; authorized by Dong He, Chief Economist. The author would like to thank Dek Joe SUM helpful suggestions and comments. The views expressed in this note are the author' and do not necessarily represent those of the AMRO or AMRO management. Unless otherwise indicated, the analysis is based on information available up to Q2 2025.
[2] Property market in this analytical note means residential property market.
[3] Furthermore, when industries indirectly related to the real estate sector are included, this share surpasses 25 percent.

analysis first identifies the structural and cyclical determinants of the ongoing weakness and situates the market within a broader property cycle framework.

Figure 1. Structure of Real Estate Sector's linkage with Other Segments of Economy



Sources: AMRO staff illustrations.

II. Recent Trends in China's Property Market

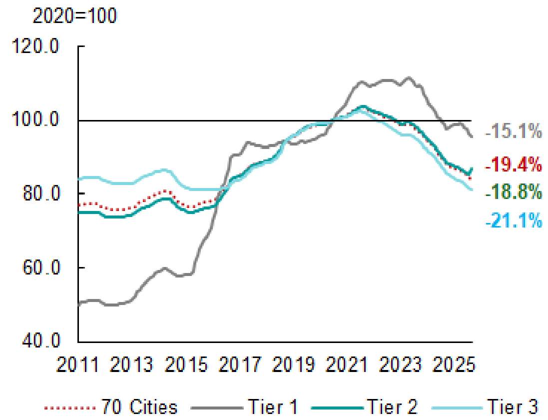
3. **The prolonged downturn in China's real estate market has been driven primarily by subdued homebuyer sentiment and persistent supply-demand imbalances.** As of September 2025, existing property prices have declined by approximately 15 percent, 19 percent, and 21 percent from their respective peaks in Tier 1, Tier 2, and Tier 3 cities (Figure 2). According to a survey by the People's Bank of China (PBOC), the proportion of respondents expecting housing prices to rise in the following quarter fell sharply from 31.2 percent in Q4 2021 to 12.5 percent in Q4 2024. Moreover, unsold housing inventory remains substantially elevated in Tier 3 cities, highlighting a pronounced mismatch between supply and demand in lower-tier regions (Figure 3).

4. **China's property market has yet to enter the stage of recovery as of Q2 2025.** This analytical note employs the Christiano-Fitzgerald (CF) filtering method (2003) [4]—widely used in asset price cycle analysis—to estimate China's real estate cycle.[5] Applying the CF filter to both real estate prices and sales volumes and plotting them on the X-Y plane allows for an intuitive visualization of the market's current position in the cycle. The dataset consists of the year-on-year change of existing residential real estate prices and housing sales across

[4] CF filtering offers an advantage over the HP filter by improving the issue of excessive endpoint estimation and allowing researchers to flexibly set the frequency based on a priori beliefs (Christiano-Fitzgerald, 2003). The use of CF filtering in estimating real estate cycles is increasingly being adopted in various countries, including Korea. Related research includes a recent study by Kwon and Choi (2019), who utilized CF filtering to estimate the overall real estate cycle in Korea as well as regional cycles within the country.
[5] According to Janssen et al. (1994), the real estate market cycles through recovery, boom, slowdown, and recession in a counterclockwise direction, influenced by changes in prices and sales volumes. During a boom, both sales and prices rise, while in a slowdown, sales decrease but prices remain robust. In a recession, both prices and sales decline, and during recovery, while prices continue to fall, sales increase.

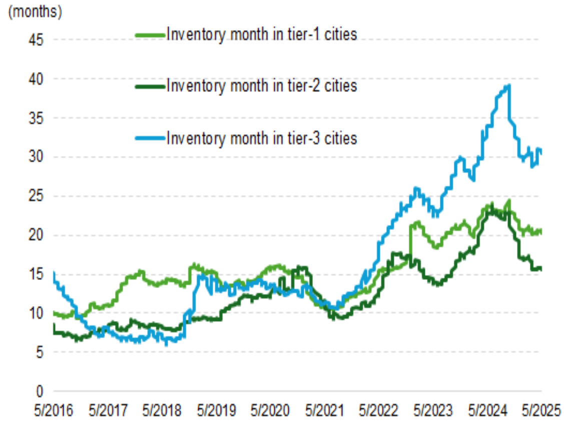
70 Chinese cities from 2011 to Q2 2025. As of Q2 2025, the market is positioned in the late "recession" stage (Figure 4). Findings reveal that, since 2013, the Chinese real estate market has undergone two distinct cycles, with the second cycle commencing in 2019. This analysis primarily stems from the continued weakness in both property prices and sales volumes in the real estate market (Figure 5). The current downturn is propelled by accumulated oversupply, worsening sentiment amid concerns over developers' insolvencies, and COVID-related lockdowns.

Figure 2. Property Price by Tier



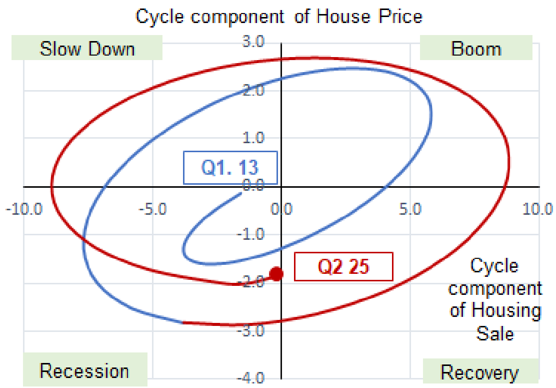
Source: NBS via CEIC; AMRO staff calculations
Note: The latest data is as of September 2025.

Figure 3. Inventory to Sales by Tier



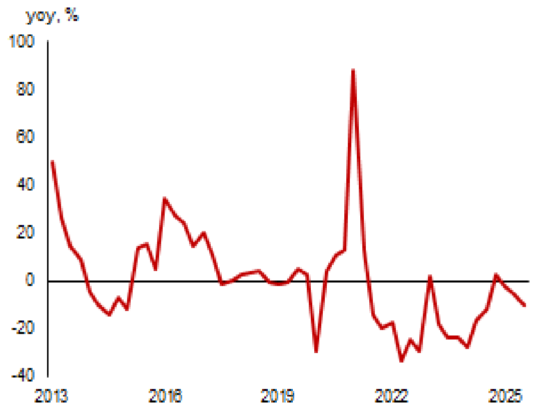
Source: China Real Estate Information System (CREIS), AMRO staff calculations.

Figure 4. Property Cycle



Source: AMRO staff estimations.

Figure 5. Property Sales



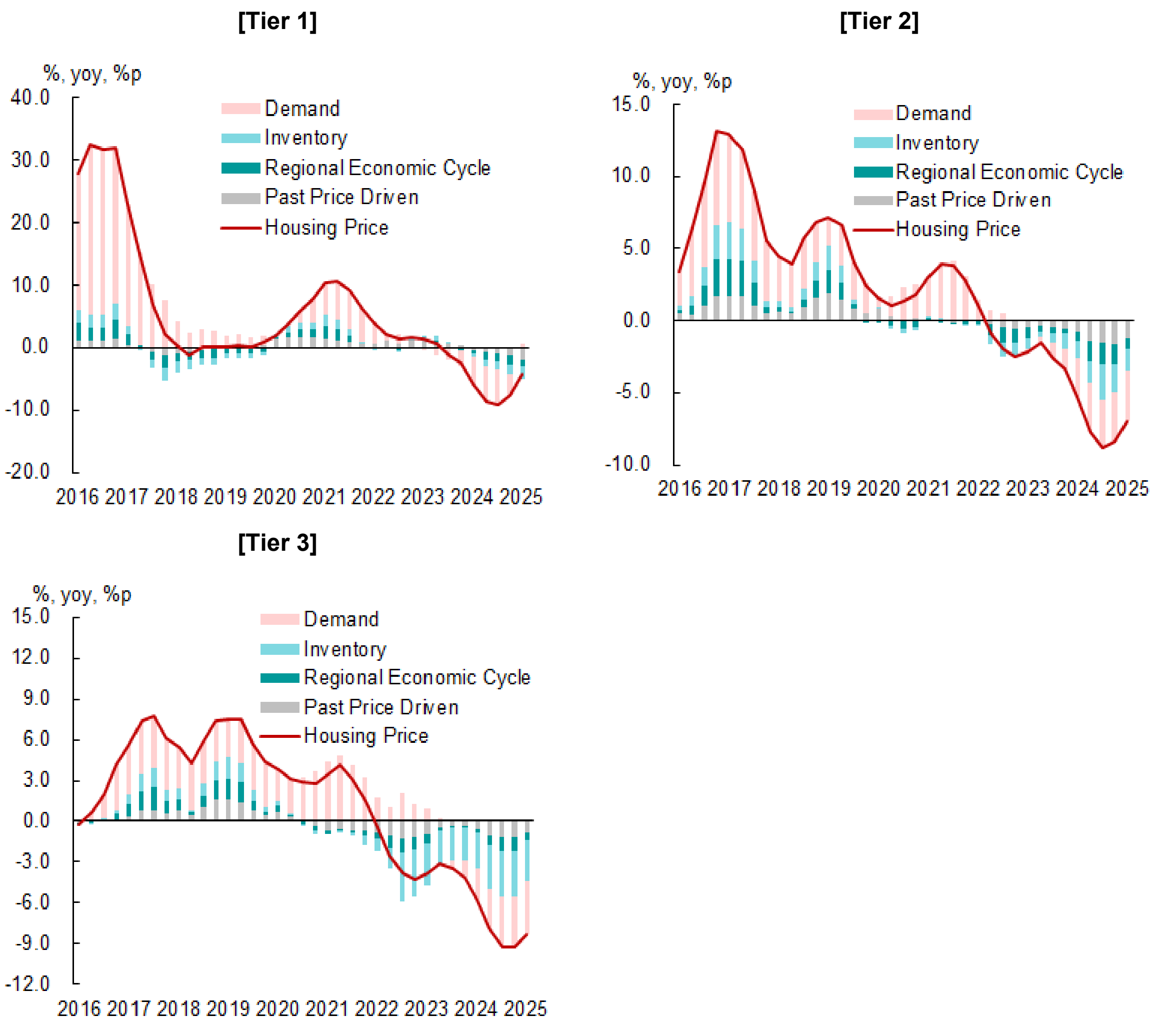
Source: NBS via Haver; AMRO staff calculations
Note: The latest data is as of Q3 2025.

III. Decomposition of Property Prices by Tiers

5. **Both demand and supply factors play central roles in shaping China's residential price dynamics.** Persistent price declines have been driven mainly by weak demand and the accumulation of unsold inventory. To quantify their respective roles of demand-side (homebuyers) and supply-side (inventory) factors, a historical decomposition of property prices is conducted using a Bayesian Vector Autoregression (BVAR) model with sign

restrictions, as proposed by Bobeica and Jarociński (2017)[6]. The model specification begins with a standard VAR framework (equation 1), incorporating four variables: residential property prices (year-on-year changes), the cyclical component of regional GDP (capturing real economic activity), housing inventory (supply factor, year-on-year changes), and property sales volume (demand factor, year-on-year changes). Sign restrictions are imposed as follows: supply shocks exert a negative effect on housing prices, whereas both demand shocks and real economic activity have positive influences.[7] The models are applied separately across different city tiers in China to enhance the relevance of policy implications. The results indicate that, despite temporal variation across time and regions, both demand and supply factors consistently shape China's property price movements (Figure 6).

Figure 6. Historical Decomposition of China's Property Prices



Source: AMRO staff estimations.
Note: Regional economic cycles are estimated by applying HP filtering based on weighted average of each region by tiers.

[6] In Bobeica and Jarociński (2017), the authors use a Bayesian Vector Autoregression (BVAR) model with sign restrictions to identify structural shocks—specifically, demand and supply shocks in the Euro area—and assess their effects on inflation. Instead of using traditional identification methods (like Cholesky decompositions), they impose sign restrictions on the impulse response functions to identify aggregate demand and supply shocks. For example, a demand shock is assumed to increase output and inflation (positive signs).

[7] Bayesian inference is employed for model estimation, with prior distributions for parameters specified using the Minnesota prior introduced by Litterman (1986), a standard in BVAR applications. Structural shocks in the model are categorized into real economic shocks, supply shocks, demand shocks, and trend components in historical property prices. The estimation covers the period from Q1 2016 to Q2 2025.

<The structure of BVAR model with sign restriction>

$$\boldsymbol{X_t} = \boldsymbol{B_0} + \sum_{k=1}^{p} \boldsymbol{B_k X_{t-k}} + \boldsymbol{u_t} \text{ .... (equation.1)}$$

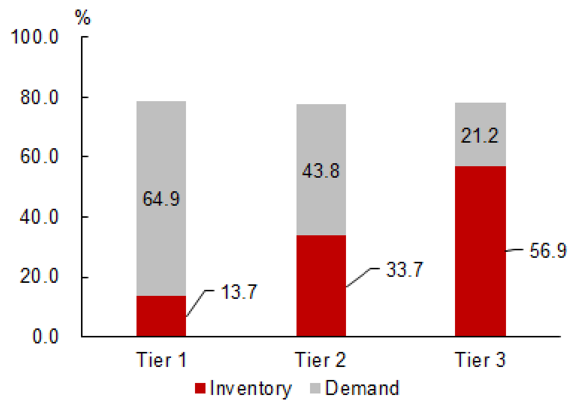
$$where, X_t = \{Economic\ cycle, Inventory, Sales, and\ property\ price\},$$
$$B_0\ and\ B_k\ denote\ the\ vector\ of\ intercept\ terms\ and\ coefficient\ matrix$$

	Economic cycle	Inventory	Sales	Property Price
Economic cycle	+	.	.	.
Inventory	.	+	.	.
Sales	+	.	+	.
Property Price	+	—	+	+

Note: 1) '.' denotes no restriction. (+) and (—) mean positive and negative impact.

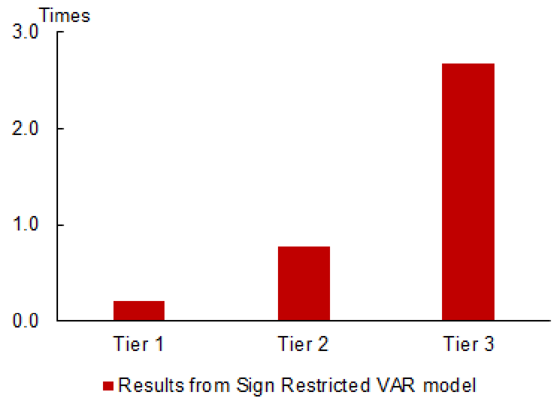
6. **A notable finding is that the impact of supply shocks—proxied by inventory—is more pronounced in lower-tier cities.** An analysis of the cumulative effects of supply and demand factors during the recent downturn in housing prices reveals that Tier 3 cities are the most influenced by supply-side pressures (housing inventory), followed by Tier 2 cities.[8] In contrast, Tier 1 cities are more heavily affected by demand weakness rather than excess supply (Figure 7). In Tier 3 cities, supply shocks account for approximately 57 percent of the recent decline in residential property prices, indicating that inventory-related pressures exert a disproportionately negative impact compared with Tier 1-2 areas. When comparing the relative magnitudes of supply and demand shocks during the recent downturn, the estimated impact of supply shocks in Tier 3 cities is nearly three times larger than that of demand shocks (Figure 8).

Figure 7. Share of Supply and Demand Factors to Price Dynamics in Recent Downturn



Source: AMRO staff estimations
Note: The onset of the recent price downturn occurred at different times across city tiers: in Tier 1 cities, the decline began in the third quarter of 2023; in Tier 2 cities, it started in the second quarter of 2022; and in Tier 3 cities, the downward trend emerged as early as the first quarter of 2022.

Figure 8. Ratio for Supply Factor Impact to Demand Factor in Recent Downturn



Source: AMRO staff estimations

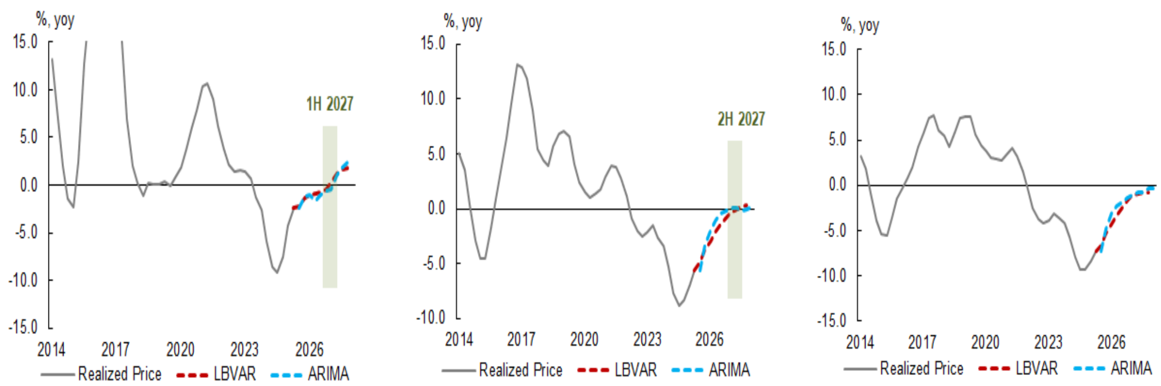
[8] While the choleski scheme only allow generating constraints over the contemporaneous responses, the restriction methodology with sign restricted BVAR permits to implement restrictions at any period.

IV. Price Forecast by Tiers

7. **China's property market is projected to continue exhibiting divergent trajectories across tiers.** To forecast housing prices over the next two years, two widely recognized models—Autoregressive Integrated Moving Average (ARIMA)[9] and Large Bayesian Vector Autoregression (LBVAR)—are employed, utilizing data from the first quarter of 2014 to the second quarter of 2025.[10] The LBVAR model is calibrated following the methodology outlined in AMRO (2025). Model estimates suggest that residential property prices in Tier 1 cities are expected to recover more rapidly, supported by resilient demand fundamentals and stronger income growth, whereas a meaningful rebound in Tier 3 cities appears unlikely within the forecast horizon (Figure 9). The sluggish recovery in lower-tier markets reflects elevated housing inventories, weak sales momentum, and ongoing structural adjustments. To estimate the LBVAR model, a comprehensive dataset comprising 20 variables was constructed, encompassing the domestic block (such as consumption, investment, and industrial production, etc), the labor block (including unemployment rate and employment ratio, etc), the financial block (such as M3 and credit, etc), and the external block (including exports, imports, and global trade, etc).

Figure 9. Property Price Forecast by Tiers

[Tire 1] **[Tire 2]** **[Tire 3]**

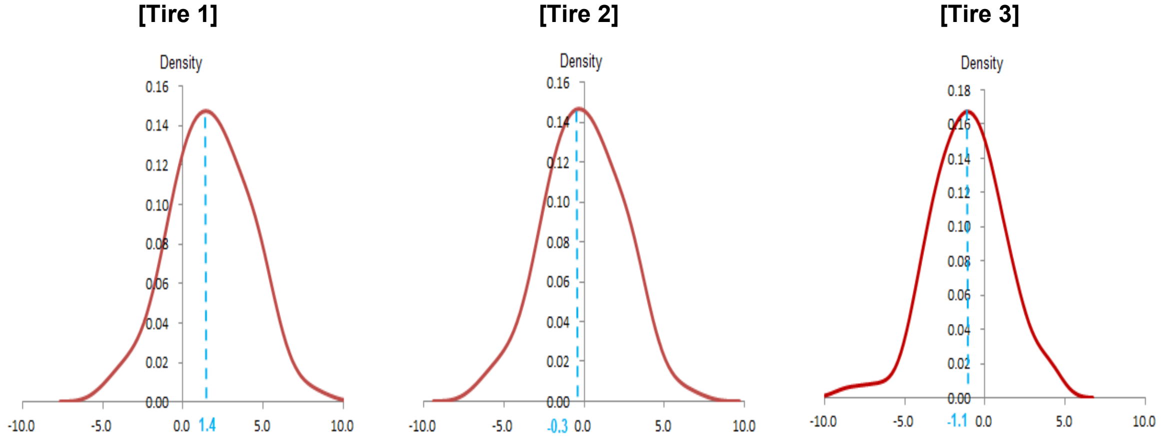


Source: AMRO staff estimations
Note: 1) Dotted lines represent forecast.

8. **Indeed, continued declines in real estate prices appear more likely in lower-tier cities.** Based on the distribution of real estate price forecasts for the second quarter of 2027 using the LBVAR model, Tier 1 cities are projected to record a 1.4 percent increase, while Tier 2 and Tier 3 cities are expected to decline 0.3 percent and 1.1 percent, respectively (Figure 10). Notably, a comparison of the forecast distributions reveals that Tier 3 cities exhibit a more left-skewed distribution than Tier 1 cities, indicating a higher degree of price-at-risk.

[9] For more details, refer to appendix
[10] For the ARIMA model estimation, autoregressive (AR) and moving average (MA) terms were assigned up to a maximum of four. Among the plausible combinations ranging from ARIMA(1,1) to ARMA(4,4), then adopts the highest fitted models based on the Akaike Information Criterion (AIC) for the forecasts.

Figure 10. Forecast Distribution by Tiers as of Q2 2027



Source: AMRO staff estimations
Note: 1) Red lines represent kernel density of forecasts. 2) Blue numbers represent medians of forecast distributions. 3) The burn-in size is set to 1,000, and the simulation size is 5,000.

9. **It is also important to note that such projections are subject to change depending on market developments.** If authorities implement more proactive measures to reduce housing inventory and stimulate demand, the timing of market recovery could be brought forward relative to current expectations. Moreover, model-based forecasts may vary depending on the chosen framework and estimation period. Therefore, the outlook presented in this note is based on currently available information and should be interpreted with caution, as it remains sensitive to future policy actions, shifts in market sentiment, and broader economic developments.

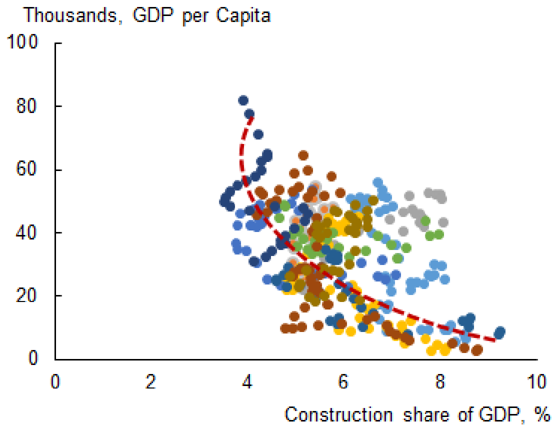
V. Policy Implications

10. **Over the past few years, a broad range of measures has been implemented by the authorities to stabilize the real estate market.** These initiatives have led to signs of nascent recovery in property sales and have eased financing pressures faced by developers.

- On the demand side, authorities have alleviated the financial burden on home buyers by guiding reductions in mortgage rates and repeatedly relaxing down-payment requirements.
- To ease financing stress for developers and ensure the completion of pre-sold housing units, multiple rounds of funding have been provided to support designated "whitelist" projects.
- In addition, to address the issue of unsold housing inventory, authorities have encouraged local governments to purchase unsold units for conversion into affordable housing, thereby enhancing housing supply efficiency.

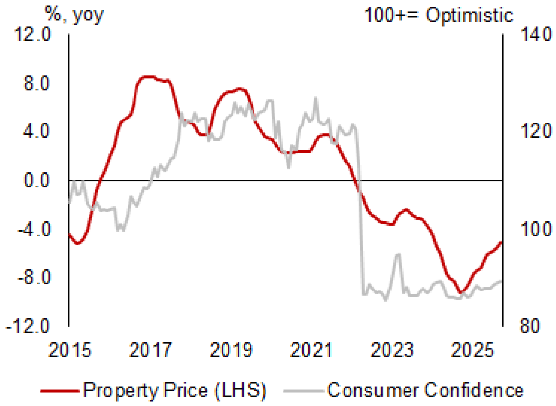
11. **Going forward, region-specific and tier-differentiated policies will be increasingly important to stabilize the real estate market.** The ongoing policy shift from debt-driven expansion to high-quality growth is consistent with China's transition toward a more sustainable development path. As the economy matures, the declining relative contribution of construction and property sectors mirrors structural trends observed in advanced economies (Figure 11). However, careful calibration of policy mix will be required to mitigate potential side effects during this transition and will remain critical. In recent years, sharp declines in housing prices have been accompanied by a significant deterioration in consumer sentiment (Figure 12).[11]

Figure 11. GDP per Cpaita and Construction Share in GDP



Source: OECD; AMRO staff calculations
Note: 1) The latest data is 2023.2) An analysis was conducted on 13 OECD member countries for which data were available.4) Red dotted line represents trend.

Figure 12. Property Price and Consumer Confidence



Source: NBS via CEIC; AMRO staff calculations.

- In Tier 1–2 cities, where recovery is expected to occur sooner, policy should focus on allowing market forces to restore equilibrium. Financial and tax easing measures should be implemented in a gradual and targeted manner. In addition, initiatives such as "Trade-in Program,"[12] which facilitate upgrading from old to new housing units, could help stimulate effective demand while supporting urban renewal. The objective is to allow these markets to adjust organically while safeguarding financial stability.

- In lower-tier cities, where the recovery is likely to remain protracted due to persistent inventory overhanging, more targeted and proactive government intervention will be necessary. This could include purchase subsidies, preferential mortgage rates, and tax incentives for first-time buyers, alongside fiscal support for converting unsold housing into affordable housing.

- Across all city tiers, restoring homebuyer confidence remains a prerequisite for a sustained recovery. Authorities could consider further ensuring the timely

[11] Such views are frequently reflected in numerous investment bank reports and research institute analyses. Most recently, Beyond the Horizon (2025) characterized China by declining industrial goods prices and subdued consumer demand.
[12] The Chinese authorities announced the "Trade in Program" in 2024, and it is being implemented in many cities. This policy is evaluated to have contributed to easing the housing market inventory and improving the living environment of homebuyers.

completion of pre-sold homes, strengthening consumer protection mechanisms, and maintaining funding continuity for “whitelist” projects. Establishing a transparent compensation framework for delays or disruptions would further reinforce policy credibility. Such measures will allow government intervention to serve as a catalyst for restoring trust and fostering a more sustainable, market-driven stabilization.

Appendix. Procedure to Forecast using ARIMA Model

Following Box and Jenkins (1976), the series y_t follows ARIMA (p, d, q) model if:

$$D(\boldsymbol{y_t}, \boldsymbol{d}) = \boldsymbol{\beta x_t} + \boldsymbol{v_t}$$

$$\boldsymbol{v_t} = \boldsymbol{p_1 v_{t-1}} + \boldsymbol{p_2 v_{t-2}} + \cdots + \boldsymbol{p_p v_{t-p}} + \boldsymbol{\theta_1 e_{t-1}} + \boldsymbol{\theta_2 e_{t-2}} + \cdots + \boldsymbol{\theta_q e_{t-q}}$$

The ARIMA model prioritizes determining the order and the form of variable transformation to achieve stationarity by differentiating the variables. Therefore, the following procedure is undertaken to estimate the ARIMA model:

1. Selecting any transformations or the level of differencing of the dependent variable.
2. Parameters are estimated.
3. Forecasting

In the first stage, various orders of p and q are compared to determine which values best fit the model. This note employs the Akaike Information Criterion (AIC) as the standard for evaluation. Additionally, it should be noted that the Bayesian Information Criterion (BIC) or the Hannan-Quinn criterion (HQ) can also be utilized as supplementary measures. In this note, the orders of AR and MA are assigned up to a maximum of 4, after which the top 20 models fitting the Akaike Information Criterion (AIC) standard are extracted.

In the second stage, the values of the parameters are estimated using methods such as maximum likelihood estimation or least squares estimation. This note applies to the maximum likelihood estimation method.

Use the fitted model to make forecasts. The ARIMA model can generate forecasts for the specified number of future periods, and these forecasts can be plotted to visualize performance. The model's efficacy is evaluated by comparing these forecasts against actual values in the test dataset, using metrics such as the Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE). This note forecasts real estate price cycle up to eight quarters from the second quarter of 2025, utilizing twenty ARIMA models.

For simplicity, consider forecasting a stationary and invertible ARMA(p,q) process:

$$(1 - \boldsymbol{\phi_1 L} - \boldsymbol{\phi_1 L^2} - \cdots - \boldsymbol{\phi_p L^p})(\boldsymbol{y_t} - \mu) = (1 + \boldsymbol{\theta_1 L} + \boldsymbol{\theta_2 L^2} + \cdots + \boldsymbol{\theta_q L^q})\, \boldsymbol{e_t}$$

Then,

$$(\widehat{Y_{t+1|t}} - \boldsymbol{\mu}) = \boldsymbol{\phi_1}(\boldsymbol{Y_1} - \boldsymbol{\mu}) + \boldsymbol{\phi_2}(\boldsymbol{y_{t-1}} - \mu) + \cdots + \boldsymbol{\phi_p}(\boldsymbol{y_{t-p+1}} - \mu) + \boldsymbol{\theta_1 \hat{e}_t} + \boldsymbol{\theta_2 \widehat{e_{t-1}}} + \cdots$$

The s period ahead forecasts would be

$$(\widehat{Y_{t+s|t}} - \boldsymbol{\mu}) = \boldsymbol{\phi_1}(\boldsymbol{\hat{Y}_{t+s-1|t}} - \boldsymbol{\mu}) + \boldsymbol{\phi_2}(\boldsymbol{\hat{Y}_{t+s-2|t}} - \boldsymbol{\mu}) + \cdots + \boldsymbol{\phi_p}(\boldsymbol{\hat{Y}_{t+s-p|t}} - \boldsymbol{\mu}) + \boldsymbol{\theta_s \hat{e}_t} + \boldsymbol{\theta_{s+1} \hat{e}_{t-1}} + \cdots + \boldsymbol{\theta_q \hat{e}_{t+s-q}}$$

For s = 1, 2, 3, ……….., q

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