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Steering through Uncertainties: Insights from LBVAR model on Hong Kong, China's Economic Prospects

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Steering through Uncertainty: Insights from LBVAR model on Hong Kong, China's Economic Prospects

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Abstract

The purpose of this paper explores the impact of various risk factors on Hong Kong, China[3]'s economy, which is substantially reliance on the global economy and mainland China. To address these issues, the paper first identifies a range of risk factors: China's economic slowdown, prolonged property market adjustments, and escalating trade policy uncertainty. These factors are critical in shaping Hong Kong's economic landscape. Following the identification of risks, the paper employs a Large Bayesian Vector Autoregression (LBVAR) model, utilizing 21 macroeconomic variables to generate a medium-term economic outlook for the economy. This approach allows for a nuanced understanding of the economy's trajectory under normal conditions. The analysis then assesses the potential impacts of these identified risk factors by comparing hypothetical GDP paths–affected by one standard deviation shocks from risk factors–to the baseline projection. The results of the baseline projection anticipate a gradual decline in Hong Kong's GDP growth, reaching a lower bound of 2 percent by 2027. Further analysis reveals that an economic slowdown in mainland China has a more significant and prolonged impact on Hong Kong compared to other risk factors. This paper is distinctive as it represents the first quantitative analysis that maps each risk factor's impact on Hong Kong's economy, as reported in AMRO's annual consultation report.

JEL classification:	E17, E30, F62, R30
Keywords:	Scenario analysis, Large Bayesian VAR model, Projection, Spillover effects, Cycles, Property market, Trade policy uncertainty

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[3] Hereafter Hong Kong, China will be referred to as Hong Kong in the paper for brevity.

Abbreviations

AMRO	ASEAN+3 Macroeconomic Research Office
ASEAN	Association of South-East Asian Nations (Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam)
CF	Christiano-Fitzgerald
CMIM	Chiang Mai Initiative Multilateralisation (CMIM)
COVID-19	Coronavirus disease 2019
HK	Hong Kong, China (hereafter "Hong Kong" for brevity)
HKMA	Hong Kong Monetary Authority
IMF	International Monetary Fund
IP	Industrial Production
LBVAR	Large scale Bayesian Vector Autoregression
LFP	Labor Force Participation
LTV	Loan To Value
RPP	Residential Property Price
SAR	Special Administrative Region
SE	Scenario
SSVS	Spike and Slab Variable Selection
TPU	Trade Policy Uncertainty
TV	Target Variable
VAR	Vector Autoregression
VIX	Volatility Index

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I. Introduction

Hong Kong, China[4] occupies an important position as an international financial and trade center both regionally and globally. Its strategic location, world-class infrastructure, and historical role as a gateway between China and the global economy have established Hong Kong as a vital node in international trade and finance (Dantong et al. 2020). As one of the most open economies in the world, it thrives on the free flow of goods, services, capital, and talent. These characteristics have enabled it to develop a highly sophisticated service-based economy, where financial services, trade, and tourism form the backbone of its economic structure.

However, Hong Kong's substantial reliance on the global economy and China has also exposed it to vulnerabilities arising from global economic fluctuations, trade uncertainties, and geopolitical tensions. As an international hub, Hong Kong is acutely affected by changes in global economic dynamics, such as shifts in trade policy and geoeconomic uncertainty. Its unique position as a Special Administrative Region (SAR) of China further links its economic fortunes to the policies and performance of the mainland economy. Additionally, domestic factors such as the prolonged downturn of the property market could place pressure on Hong Kong’s ongoing economic recovery. Understanding these dynamics would be critical for policymakers and stakeholders in the years to come.

This study aims to explore the factors that are likely to shape the future of the Hong Kong economy and to provide empirical estimates of their potential impact using the LBVAR model. This study is distinct in two critical ways. First, it represents the first attempt to provide a quantitative analysis for each factor displayed in risk maps in AMRO’s country surveillance report. AMRO presents risk assessment through defined risk maps in the report for each member economics. For example, tentative risk map for Hong Kong for 2025 report is shown as below (Figure 1). For measuring economic impact, this paper selects three significant factors in the risk map for Hong Kong economy—slower economic growth in China, continued slowdown in the property market, and escalating trade policy uncertainty (TPU)— and applies scenario analysis, avoiding a focus on a single shock[5]. Second, it utilizes a LBVAR model that incorporates a broader set of variables, allowing for a more comprehensive analysis of the complex interactions and transmission channels between these factors. To achieve its objectives, the study addresses the following key questions:

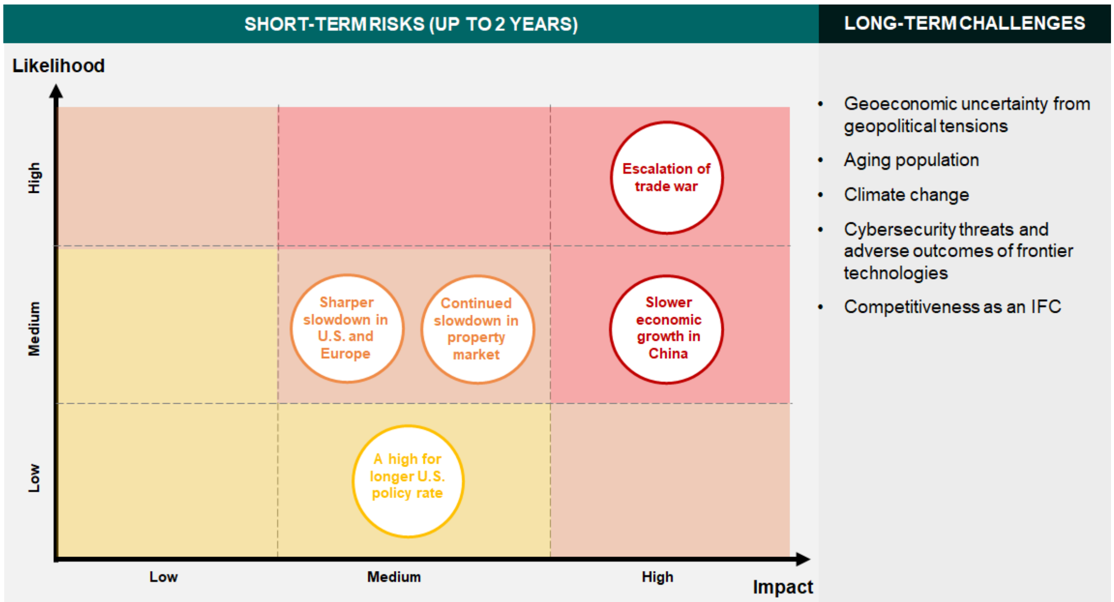
- Given a comprehensive dataset that encompasses real, financial, and external variables, what are the baseline medium-term projections for Hong Kong's economy?

- How large is the quantitative impact of the stated factors on Hong Kong's baseline growth trajectory?

- What policy measures can be considered to enhance the resilience of the Hong Kong economy?

[4] Hereafter Hong Kong, China will be referred to as Hong Kong in the paper for brevity.
[5] A representative paper that simulated scenario analysis for the Hong Kong economy is Abeysinghe, Tilak, and Kway Guan Tan (2020), which analyzed the impact of COVID-19. This paper provided valuable insights into how a COVID-19 shock could affect the economy.

Figure 1. **Tentative Risk Map for Hong Kong, China 2025**



Source: AMRO staff illustrations.

This paper finds that Hong Kong's GDP growth could gradually decline at a moderate pace if the risks are not adequately managed. Scenario analysis, assuming one standard deviation shock for each risk factor, reveals that Hong Kong's economic prospects are more intricately linked to developments in the Chinese economy than to domestic factors, including the property market. A comparison analysis between the baseline projection and hypothetical scenarios incorporating shocks from various risk factors indicates that the risk of a slowdown in Mainland China has the most significant and persistent impact on Hong Kong's economy. Trade policy uncertainty (TPU) emerges as the second most influential factor, while a downturn in the property market shows the least impact.

The paper is organized as follows. Section II provides an overview of the three key risk factors that could drive Hong Kong economy. Section III presents literature review on the LBVAR model. Section IV and V explains the model and conducts a projection for Hong Kong GDP over a three-year horizon. Finally, section VI offers policy implications derived from the paper.

II. Key Risk Factors for Hong Kong's Economic Trajectory

This section outlines three critical factors that could impact Hong Kong's economy in the coming years: potential deceleration of China's economy, prolonged weakness in the property sector, and intensified trade policy uncertainty (TPU)[6].

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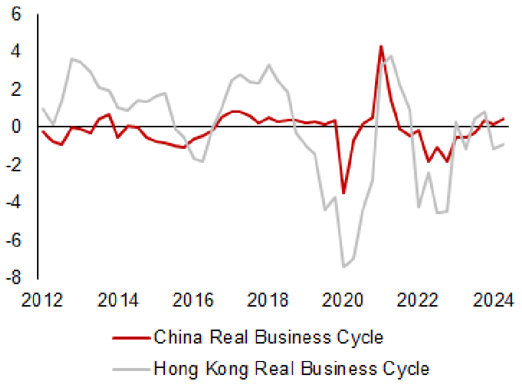
[6] The selection of these three risk factors—slower economic growth in China, trade policy uncertainty (TPU), and continued property market weakness—as the focus of analysis is based on their high expected impact and relevance to Hong Kong. Both the slowdown in China's economy and TPU are assessed to have a "high" influence on Hong Kong's growth trajectory due to the economy's strong external linkages and trade exposure. Real estate market weakness, while not a common feature across all ASEAN+3 economies, is particularly relevant for Hong Kong and Mainland China—making it a more targeted risk rather than a broad regional trend. In contrast, the risk of a "high-for-longer" U.S. policy rate is a factor that affects all economies in the region. While its impact may vary across countries, it has been extensively analyzed in prior studies and is therefore excluded from this paper's core risk analysis.

A. Potential Deceleration of China's Economy

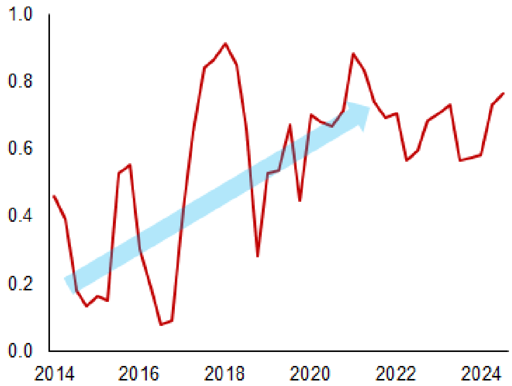
Due to Hong Kong's high degree of economic integration with Mainland China, a slowdown in the mainland economy could exert a substantial impact on Hong Kong's economic performance. Figure 2 highlights the real business cycles[7] of China and Hong Kong, showing a clear pattern of co-movement between the two economies over the observed period. The cycles exhibit synchronized peaks and troughs, with notable alignment during periods of economic expansion and contraction, such as the sharp downturn in 2020 caused by COVID-19 and the subsequent recovery. Depicting the 8-quarter rolling correlation of the two cycles, it reveals a generally high and increasing correlation over time as shown in Figure 3. This underscores how a potential deceleration of the mainland could drag Hong Kong's economic dynamics.

Figure 2. Business Cycle for Hong Kong and China
(Point)



Source: AMRO staff estimations.
Note: Data as of the third quarter of 2024. Real business cycles are estimated using principal analysis.

Figure 3. Business Cycle Correlation between Hong Kong and China
(Point)



Source: AMRO staff calculations.
Note: Correlation is 8 quarters moving average.

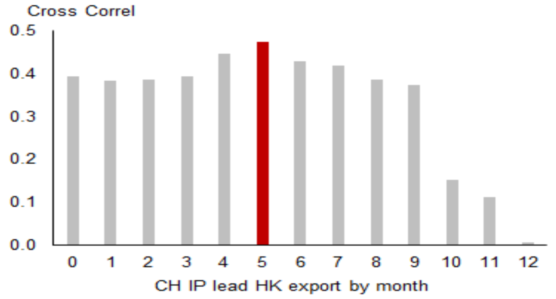
This close relationship between Hong Kong and China's business cycle can be explained by the strong influence of China's manufacturing output on Hong Kong's trade performance. The year-on-year changes in Hong Kong's exports closely track fluctuations in China's industrial production (Figure 4). The estimated cross-correlation and Granger-causality test result provide further evidence of this relationship (Figure 5). The highest correlation occurs at a 4-to-6-month lag, indicating that changes in China's industrial production precede movements in Hong Kong's exports by several months. The Granger-causality test also supports this finding[8].

[7] Both the business cycle for Hong Kong and China are estimated based on principal analysis. 21 data utilized for Hong Kong and 15 data used for China. Estimation period is from first quarter 2012 to fourth quarter 2024. Studies such as HKMA (2006) also highlight the growing synchronization of real business cycles between China and Hong Kong.
[8] The null hypothesis that "China's industrial production does not cause Hong Kong's exports" rejected at a 10 percent significance level, while the reverse is not true.

Figure 4. Hong Kong Export and China IP
(Percent; Year on year)

Source: National authorities via Haver Analytics; AMRO staff calculations.
Note: Data is up to December of 2024.

Figure 5. Cross Correlation between Hong Kong Export and China IP, Result for Granger-Causality test



Null Hypothesis	F-stat.	Pro.
China IP ≠> HK export	3.035	0.084*
HK export ≠> China IP	0.056	0.813

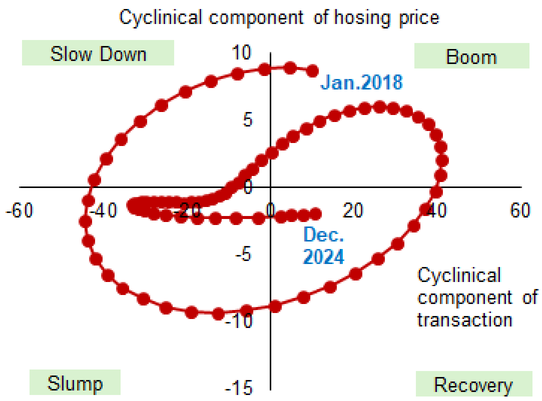
Source: AMRO staff calculations.
Note: ***, ** and * denote that null hypothesis is rejected at 1 percent, 5 percent, and 10 percent significant level respectively. The data for the test is from January 2014 to December 2024.

B. Continued Adjustment in Property Market

The risk of prolonged weakness in the property market due to a sustained high-interest environment could impose pressure on Hong Kong's economy. CF filtering analysis[9] was employed to estimate the property cycle and indicates that Hong Kong's residential property market has gradually transitioned from the "slump" phase to the "recovery" stage with the authority's support[10] (Figure 6). However, overall market sentiment still remains subdued (Figure 7). Hong Kong's residential property market has remained sluggish for several years. Property prices have plummeted by 27 percent from their recent peak in 2021 to the end of 2024 (Figure 8). Prolonged weakness in the property market negatively affects the economy through reduced real estate-related investment and negative wealth effects. Indeed, the sustained downturn in the property sector has led to a continued decline in construction investment in Hong Kong (Figure 9).

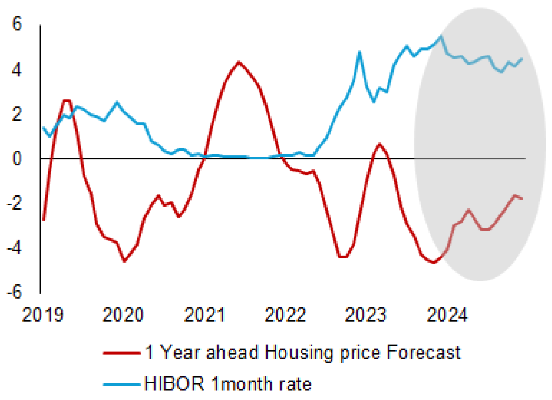
[9] Applying the Christiano-Fitzgerald (CF) filter to both real estate prices and sales volumes and plotting them on the XY plane allows for an intuitive visualization of the market's current position in the cycle. According to Janssen et al. (1994), the real estate market cycles through recovery, boom, slowdown, and slump 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. 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). AMRO (2024) provides more detail as well as analysis result for Chinese property market.
[10] In February 2024, the HKMA raised the loan-to-value (LTV) limits for residential properties valued below HKD 30 million and above HKD 35 million to 70 percent and 60 percent, respectively. By October, the LTV cap was standardized at 70 percent regardless of property value. Additionally, the government abolished stamp duties on residential property transactions from February 2024. The base rate was reduced from 5.25 percent in October 2024 to 4.75 percent in December 2024,

Figure 6. Residential Property Cycle



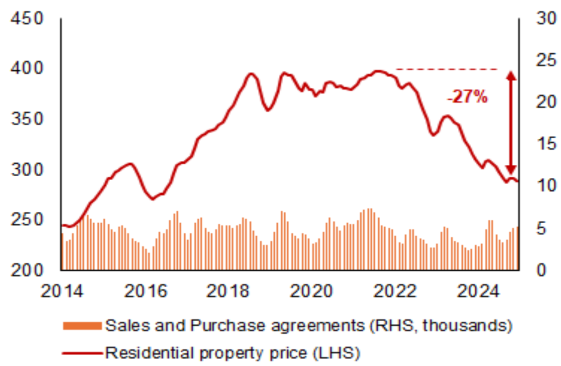
Source: National authorities via Haver Analytics; AMRO staff estimates.
Note: Christiano-Fitzgerald filter is applied to estimate cycle. Data from January 2004 to December 2024 is used for estimation.

Figure 7. Property Price Survey and Interest Rate in Hong Kong
(Year on year, Percent)



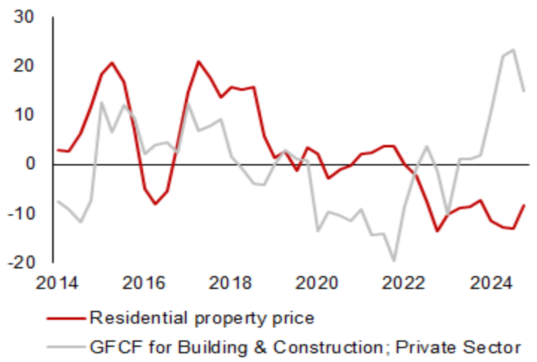
Source: National authorities via Haver Analytics; Royal Institution of Chartered Surveyors (RICS); AMRO staff calculations.
Note: Data is up to the end of 2024.

Figure 8. Residential Property Price and Sales Volume in Hong Kong
(Index, 1999=100, Thousands)



Source: National authorities via Haver Analytics; AMRO staff calculations.
Note: Data is up to the end of 2024.

Figure 9. Residential Property Price and GFCF for Construction
(Year on year, Percent)



Source: National authorities via Haver Analytics; AMRO staff calculations.
Note: Data is up to the end of 2024. GFCF refers to gross fixed capital formation. Data for GFCF was used 4 quarters ago.

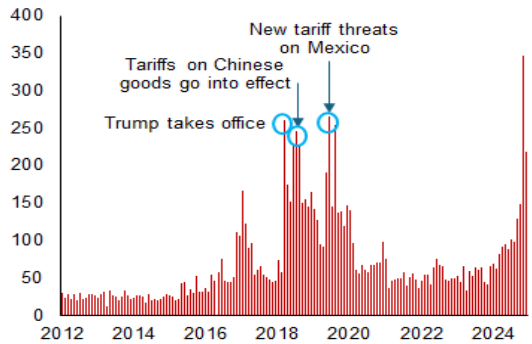
C. Increasing Trade Policy Uncertainty

Elevated trade policy uncertainty can negatively impact Hong Kong's external sector by constraining global trade. According to the U.S. Trade Policy Uncertainty (TPU) Index[11] proposed by Caldara et al. (2020), trade policy uncertainty surged significantly with the inauguration of the first Trump administration in 2017 and spiked again in late 2024, preceding the anticipated second Trump administration (Figure 10). Caldara et al. (2019) found that the increase in TPU during the first half of 2018 contributed to a 0.8 percent decline in global GDP by the first half of 2019. The slowdown in global trade could have adverse spillover effects on Hong Kong's economy, which is highly dependent on international trade. Historical trends reveal that during periods of heightened U.S. trade

[11] The TPU index is based on automated text searches of the electronic archives of seven newspapers: Boston Globe, Chicago Tribune, Guardian, Los Angeles Times, New York Times, Wall Street Journal, and Washington Post. The measure is calculated by counting the monthly frequency of articles discussing trade policy uncertainty (as a share of the total number of news articles) for each newspaper.

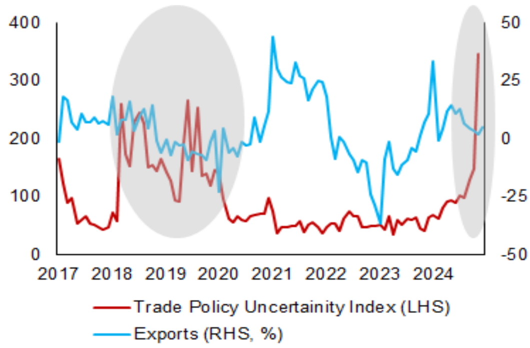
policy uncertainty, Hong Kong's exports generally declined, underscoring the vulnerability of its trade sector to external shocks[12] (Figure 11).

Figure 10. Trend of Trade Policy Uncertainty Index
(Index)



Source: Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo (2020).
Note: Data is up to the end of 2024.

Figure 11. Trade Policy Uncertainty Index and Hong Kong Export
(Index, Year on year, Percent)



Source: Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo (2020); National authorities via Haver Analytics; AMRO staff calculations.

III. Literature Review regarding LBVAR model

A low-dimensional VAR model, composed of five or fewer dependent variables, represents a typical multivariate macroeconomic time series analysis. However, the inclusion of only a limited number of macroeconomic variables can lead to omitted variable bias. From the general equilibrium perspective in macroeconomics, the determinants of a single dependent variable within the VAR model are likely to extend beyond the variables explicitly incorporated in the system. Consequently, low-dimensional VAR models inevitably face reduced predictive accuracy due to omitted variables. LBVAR addresses this limitation by analyzing more than 20 macroeconomic variables within a single model, thereby mitigating the constraints associated with low-dimensional VAR frameworks.

The LBVAR model, despite its ability to incorporate a larger number of variables, presents the drawback of requiring the estimation of a greater number of parameters. However, Banura, Giannone, and Reichlin (2010) demonstrated that this issue can be mitigated by applying Bayesian shrinkage, enabling LBVAR to achieve superior predictive accuracy compared to conventional VAR models. Bayesian shrinkage is implemented through Minnesota prior, introduced by Litterman (1986). This methodology controls overfitting by assigning a high probability to models in which each variable follows a random walk. A notable study applying the Minnesota prior to LBVAR is Banura, Giannone, and Reichlin (2010), which revealed that increasing the degree of shrinkage in proportion to the number of dependent variables effectively manages overfitting, even in large-scale models with over 20 variables. The superior predictive performance of Minnesota prior over alternative models and shrinkage techniques has been validated by various studies. Koop (2013) demonstrated that LBVAR models employing the Minnesota prior outperform those utilizing factor models or the Spike and Slab Variable Selection (SSVS) approach. Additionally, Cross et al. (2020) compared the performance of Minnesota prior, SSVS, and Global-Local priors, concluding that models based on Minnesota prior exhibited the highest predictive accuracy.

Recently, major central banks have adopted LBVAR models not only for forecasting macroeconomic variables but also for conducting scenario analyses. Crump et al. (2021) at

[12] The negative impact could be more significant and widespread, given that in February 2025, the United States imposed an additional 10 percent tariff not only on China but also on Hong Kong.

the New York Federal Reserve and Cimadomo et al. (2022) at the European Central Bank exemplify this trend.

- Crump et al. (2021) demonstrated that the LBVAR model achieves predictive performance for U.S. macroeconomic data comparable to large-scale theory-based models utilized by central banks. Furthermore, conditional forecasts were employed to conduct structural analyses of the macroeconomy and assess policy effects.

- Cimadomo et al. (2022) applied mixed-frequency data to the LBVAR model, performing nowcasting to predict current values of economic variables and demonstrating the model's capability for scenario-based analyses.

This paper utilizes the LBVAR model to project Hong Kong's GDP trajectory over the next three years and examines the impact of risk factors such as China's economic slowdown, prolonged property market adjustment in Hong Kong, and increasing global trade policy uncertainty. Section IV outlines the LBVAR model, while Section V presents the baseline projection of Hong Kong's GDP over the next three years, along with a comparison of baseline projections to hypothetical GDP growth paths under shocks from risk factors.

IV. Projection based on LBVAR model

A. Model and Methodology

This paper employs a large-scale Bayesian Vector Autoregressive (LBVAR) model with 21 dependent variables. The advantage of the LBVAR model lies in its ability to overcome the limitations of traditional small-scale VAR models, providing improved forecasts while enabling the projection of dynamic changes in each variable under researcher-designed scenario conditions. A standard VAR(p) model is generally expressed in the following form of order p:

$$y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \cdot \\ \cdot \\ \cdot \\ y_{K,t} \end{bmatrix} \mid \theta, Y_{t-1} \sim N(\Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p}, \Omega) \tag{1}$$

where, y_t is a K-vector of variables, θ is model parameter, Φ is coefficient matrix, and Ω is variance-covariance matrix. Additionally, all variables are assumed to be mean-adjusted, eliminating the need for an intercept term in the equation. In equation (1), when K is sufficiently large, specifically 20 or more, and Bayesian shrinkage is applied, the model is viewed as an LBVAR. For sufficiently large K. the size of each VAR coefficient matrix $\Phi_j (j = 1, 2, \dots, p)$ and the variance-covariance matrix is $\mathrm{K} \times \mathrm{K}$. In the Bayesian approach, specifying the model requires setting prior distributions for the model parameters. These prior distributions introduce shrinkage, addressing overfitting issues. The prior distribution for the model parameters in this paper is based on the Minnesota prior, which includes two parameters, λ and γ, that determine the degree of shrinkage. Following Giannone et al. (2015), this paper treats λ and γ as parameters and assigns prior distributions to the shrinkage parameters using a hierarchical prior distribution. The application of a hierarchical model enhances robustness by allowing the degree of shrinkage to be determined by the data rather than arbitrary values selected by the researcher. Specifically, λ and γ are assumed to be independent, scalar, and follow the inverse gamma distribution as outlined below.

$$\lambda = \text{InverseGamma}\ (\alpha_0, \delta_0 = \ \bar{\lambda}(\alpha_0 - 1))$$
$$\gamma = \text{InverseGamma}\ (\tau_0, \kappa_0 = \ \bar{\gamma}(\tau_0 - 1)) \tag{2}$$

Where, $\bar{\lambda}$ and $\bar{\gamma}$ represent the prior means of λ and γ respectively. Additionally, α_0 and τ_0 denote the degrees of freedom. The ijth element of Φ_r, denoted as $\phi_{ij}^{(r)}$, reflects the regression effect of $y_{j,t-r}$ on $y_{i,t}$. It is assumed that, given (λ, γ), $\phi_{ij}^{(r)}$ follows a normal distribution as below (3).

$$\phi_{ij}^{(r)} |\ \lambda, \gamma \sim \mathrm{N}(0,\ v_{ij}^{(r)}) \tag{3}$$

Here, $v_{ij}^{(r)}$ represents the prior variance. For all $r = 1,2,\cdots,p$, prior variance is determined by equation (4) and (5)

$$v_{ij}^{(r)} = \frac{\lambda}{r^2}\ if\ i = j \tag{4}$$
$$v_{ij}^{(r)} = \frac{\lambda}{r^2} r \frac{w_i}{w_j}\ if\ i \neq j \tag{5}$$

A key point is that λ regulates the degree of shrinkage in the prior distribution for all VAR coefficients. Since λ appears on the right-hand side of both equations (4) and (5), it is referred to as the global shrinkage parameter. In contrast, γ, which determines the prior variance only for the off-diagonal coefficients, is termed the local shrinkage parameter. Typically, both the global and local shrinkage parameters are significantly smaller than 1. Consequently, the prior variance for the off-diagonal coefficients is smaller than that of the diagonal coefficients. Additionally, as the lag r increases, the prior variance decreases, leading the prior variance to converge to zero with longer lags. Due to this characteristic, the aforementioned prior distribution is called a shrinkage prior, known for mitigating overfitting issues and enhancing model performance. The shrinkage prior utilized in this paper is designed to reflect the following two stylized empirical phenomena commonly observed in time series analysis.

- Variables with longer lags are far less likely to influence the dependent variable compared to those with shorter lags.

- Each dependent variable is more strongly affected by its own lags than by the lags of other variables. As shown in equation (5), $v_{ij}^{(r)}$ is proportional to the scale (w_i) of the dependent variable i and inversely proportional to the scale (w_j) of the variable j when $i \neq j$.

The magnitude of coefficients varies depending on the unit or scale of the independent variables. Consequently, the degree of shrinkage also differs based on the scale of the independent variables. However, adjusting the shrinkage prior distribution each time the scale of variable changes is cumbersome and impractical. Moreover, the adjustment process may introduce errors or lead to inappropriate modifications. To mitigate this, scale parameters w_i and w_j are introduced. These parameters adjust the scale of the coefficients, ensuring that the shrinkage is not sensitive to the scale of the variables. This approach enhances model robustness and simplifies implementation by reducing the need for manual corrections.

This paper estimates the AR (p) model by applying linear regression to each variable, setting the scale parameter, $w_i(i = 1,2,\cdots,K)$, as the standard error of the ith equation. Consequently, the prior distributions in equations (4) and (5) can be reformulated in matrix form, as expressed in (6).

$$\Phi_r \mid \lambda,\gamma \sim \text{Multi} - \text{Normal}\left(\Phi_{r,o} = O_{K\times K},\ V_r = \begin{bmatrix} v_{11}^{(r)} & v_{12}^{(r)} & \cdots & v_{1K}^{(r)} \\ \vdots & & \ddots & \vdots \\ v_{K1}^{(r)} & v_{K2}^{(r)} & \cdots & v_{KK}^{(r)} \end{bmatrix}\right) \tag{6}$$

Also, all coefficients in VAR,

$$\beta = vec\begin{bmatrix} \Phi_1' \\ \Phi_2' \\ \vdots \\ \Phi_p' \end{bmatrix} \tag{7}$$

The prior distribution of β can be expressed in vector form as follows:

$$\beta \mid \lambda,\gamma \sim \text{Normal}\left(\beta_o = vec\begin{bmatrix} \Phi_{1,0}' \\ \Phi_{2,0}' \\ \vdots \\ \Phi_{p,0}' \end{bmatrix},\ B_0 = diag\left(vec\begin{pmatrix} V_1' \\ V_2' \\ \vdots \\ V_P' \end{pmatrix}\right)\right) \tag{8}$$

Where, β_0 is K^2p dimensional vector and B_0 is $K^2p \times K^2p$ dimensional diagonal matrix. The variance-covariance matrix Ω is assumed to follow an inverse Wishart distribution, a widely applied conditional conjugate prior in Bayesian analysis, as described in (9)

$$\Omega \sim InverseWishart\ (v_0, R_0 = \Omega_0(v_0 - K - 1)) \tag{9}$$

Where, $\Omega_0 = diag([w_1^2, w_2^2, \cdots, w_k^2])$ is composed of scale parameters, while $E(\Omega) = \Omega_0$ represents the prior mean of Ω. Given the lack of substantial prior information about Ω, a weak prior distribution with $v_0 = K + 2$ is applied. However, despite the advantage of the LBVAR model in producing meaningful results by utilizing large datasets, it does not fully eliminate multicollinearity among variables. As a result, the prior distribution may exert greater influence on the estimation outcomes than the information contained in the data itself, representing a key limitation of the model.

B. Projection

In a Bayesian model, estimation involves deriving the joint posterior distribution of the parameters given the observed data $\{y_i\}_{i=1}^T$. According to Bayes' theorem, this can be expressed as in equation (10), which relates to the likelihood and the joint prior distribution. Here, $\pi(\cdot)$, $f(\cdot)$, θ represent the density function, likelihood function, and set of parameters respectively.

$$\pi(\theta|Y) = \frac{f(Y|\theta)}{f(Y)} \cdot \pi(\theta) \tag{10}$$

Parameter estimation involves deriving posterior distributions, which can be accomplished using Gibbs sampling, as all prior distributions are conditionally conjugated. Gibbs sampling is particularly useful in LBVAR, because it allows for the sequential sampling of parameters, which can be more computationally efficient than attempting to estimate all parameters simultaneously in high-dimensional models[13] (Joshua Chan, 2019). Let the sample size be T, and let $Y = \{y_i\}_{i=1}^{T}$ represent all observations. The parameters are sequentially updated in four blocks β, Ω, λ, and γ, corresponding from (11) to (14). During each Gibbs sampling iteration, each block is simulated from its full conditional distribution. Gibbs sampling involves iteratively drawing samples from the full conditional distributions of each parameter over n iterations. At each sampling step, the conditional parameters are set based on the values drawn in the preceding iteration. For the first iteration, however, the parameters are sampled from the prior distribution. It is well-established that the distribution of the samples generated through this process converges with the joint posterior distribution as the number of iterations increases.

$$\beta \mid Y, \Omega, \lambda, \gamma \tag{11}$$
$$\Omega \mid Y, \beta, \lambda, \gamma \tag{12}$$
$$\lambda \mid Y, \beta, \Omega, \gamma \tag{13}$$
$$\gamma \mid Y, \beta, \Omega, \lambda \tag{14}$$

Projections are performed by simulating the posterior predictive distribution, $\{y_{T+1}\}_{i=1}^{H}|Y$, from one quarter to H quarters ahead, using the given parameters. Both the parameters and the predictive distribution are sampled in each iteration of the Gibbs sampling process.

C. Scenario Analysis Methodology

This paper distinguishes itself from other LBVAR studies by forecasting the future trajectory of a target variable—Hong Kong's GDP growth—under scenario conditions. A widely used approach in scenario analysis involves examining changes in the target variable in response to standard deviation shocks to the scenario variables. This paper also adopts an intuitive and comprehensible approach by applying standard deviation shocks to each risk factor. The target variable can be selected at the researcher's discretion; in this paper, GDP is chosen as the target because it serves as the most appropriate indicator for assessing the economic impact of the assumed shocks to the selected variables. For each forecast horizon, $h = 1,2,\cdots,H$, scenario conditions for specific variables are represented as in (15). Here, $\bar{y}_{T+h}$ refers to variables for which scenarios are assumed, while $\hat{y}_{T+h}$ denotes all other variables not subjected to scenario assumptions.

$$y_{T+h} = \{\bar{y}_{T+h}, \hat{y}_{T+h}\} \tag{15}$$

In this framework, the scenario path is represented as in (16). Once the scenario path is specified, the remaining variables are treated as unobserved random variables, as expressed in (17).

$$\bar{Y}_{1:H} = \{\bar{y}_{T+1}, \bar{y}_{T+2}, \cdots, \bar{y}_{T+H}\} \tag{16}$$
$$\hat{Y}_{1:H} = \{\hat{\bar{y}}_{T+1}, \hat{y}_{T+2}, \cdots, \hat{y}_{T+H}\} \tag{17}$$

The variables corresponding to $\hat{y}_{T+h}$ are the subject of conditional forecasting. In this context, the scenario analysis results refer to $\hat{Y}_{1:H}|Y, \bar{Y}_{1:H}$ the conditional predictive distribution of $\hat{Y}_{1:H}$. Here, parameters are not included as conditions but are integrated out. This approach ensures that the conditional predictive distribution of $\hat{Y}_{1:H}$ accounts for parameter uncertainty in its estimation. This paper examines the changes in Hong Kong's

[13] Gary Koop (2013) also explores the use of Gibbs sampling for parameter estimation in LBVAR, comparing different prior specification and their impact on forecasting performance.

GDP growth over the next three years under one standard deviation shock scenarios involving key risk factors influencing Hong Kong's economy, including China's economic slowdown, the continued price adjustment in the property market, and increasing global trade policy uncertainty.

V. Baseline Projection and Measuring the Impact of Risk Factors

A. Data

This paper estimates an LBVAR model using quarterly data for 21 variables related to Hong Kong. The data set is organized into four blocks: domestic macro, labor market, financial and monetary, and external. Among the 21 variables, nine belong to the domestic macro block, representing major indicators of Hong Kong's economy. The labor market block includes four variables, such as labor force participation rates and unemployment rates. The financial and monetary block consists of four variables, including M3 growth rates and stock price changes. The external block comprises China's economic growth and the Trade Policy Uncertainty (TPU) Index. The sample period spans from Q1 2012 to Q4 2024. For variables with monthly frequency, quarterly averages are calculated for consistency[14].

Key descriptions for each variable appear in Table 1, with further data statistics details in Appendix 1.

Table 1. Description for each variable

Category	Variables	Description	Source
Domestic Macro Block	• GDP	• Real GDP, year on year change	Hong Kong Census & Statics Department
	• Consumption	• Real consumption, year on year change	
	• Investment	• Real fixed Investment, year on year change	
	• Industrial Production	• Manufacturing industrial production, year on year change	
	• Retail Sales	• All retail outlets' sales, year on year change	
	• SMEs	• Small and Medium sized Enterprise business outlook index (50>positive)	
	• CPI	• Consumer Price Index, year on year change	
	• Consumer Confidence	• Consumer confidence index (100=long term mean)	City University of Hong Kong
	• **Property**	• Residential property price, year on year change	Rating & Valuation Department
Labor Market Block	• LFP	• Labor force participation rate (SA)	Hong Kong Census & Statics Department
	• Unemployment	• Unemployment rate (SA)	Hong Kong Census & Statics Department
	• Salary	• Average salaries, year on year change	Hong Kong Census & Statics Department

[14] Despite monthly data provides higher frequency and minimize information loss, this paper utilizes quarterly data because most real economy-related variables are published on a quarterly basis. Additionally, GDP, a main indicator to be analyzed in this paper, is only available on a quarterly basis with a longer time span, making it more suitable for robust time series analysis.

	• Productivity	• Output per employed person, year on year change	Hong Kong Census & Statics Department
Financial and Monetary Block	• M3	• M3, year on year change	Hong Kong Census & Statics Department
	• Stock	• Hang Seng index, year on year change	Hang Seng Index
	• Exchange rate	• Hong Kong$/US$, year on year change	Hong Kong Monetary Authority
	• Loans	• Year on year change	Hong Kong Monetary Authority
External Block	• Exports	• Exports of goods, year on year change	Hong Kong Census & Statics Department
	• Imports	• Imports of goods, year on year change	
	• **China GDP**	• China's real GDP, year on year change	National Bureau of Statics, China
	• **TPU**	• Trade Policy Uncertainty Index	Dario Caldara et al. (2020) via Haver

Source: Authors' compilation.
Note: Red colored variables are used for scenario analysis. The variables with SA mean seasonally adjusted.

B. Baseline Projection

This section presents the projections of Hong Kong's GDP up to three years ahead based on the LBVAR model. Before delving into the results, a brief explanation of the hyperparameter tuning process for model estimation is provided.

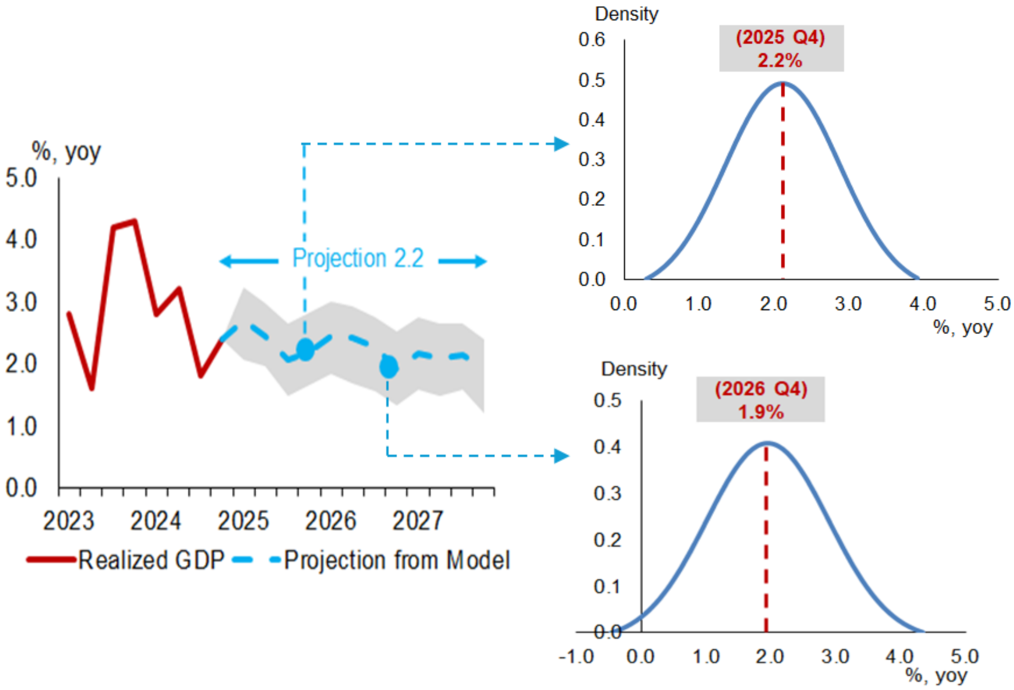
The hyperparameters determining the model specification include the hyperparameters in the prior parameter distribution, the lag order, and a COVID-19 period dummy variable. The prior distribution of the parameters governs the degree of shrinkage, which is critical for predictive accuracy. Excessive shrinkage may inadequately reflect the information in the data, reducing predictive power. Conversely, overly weak shrinkage can lead to overfitting, similarly diminishing forecast reliability. Lag order also plays a crucial role. A lag order that is too small risks omitting important variables, while a lag order that is too large can result in overfitting issues. The COVID-19 period dummy variable is introduced to capture structural changes in time series dynamics between the pandemic period and other periods. Ignoring this factor can introduce bias into parameter estimates, significantly undermining the reliability of forecasts.

This paper conducts tuning, or optimization, for the prior distribution's hyperparameters, lag order, and the COVID-19 period dummy variable. The optimization criterion is the Bayesian Information Criterion (BIC), which measures the distance between the model's predictions and actual observations by treating the entire sample period as out-of-sample data. The optimal combination of hyperparameters, determined through grid search, is $lag = 1, \alpha_0 = 40, \bar{\lambda} = 30, \tau_0 = 40, \bar{\gamma} = 30$, with the COVID-19 period dummy covering Q1 2020 to Q2 2021. Under this tuned model configuration, the posterior distributions of the parameters and the posterior predictive distributions of the dependent variables are sampled. The burn-in size is set to 1,000, and the simulation size is 5,000. The maximum inefficiency factor[15] being below

[15] After conducting posterior simulations using Gibbs sampling, it is essential to evaluate the efficiency of the sampling process. This step is critical because accurately inferring the posterior distribution requires a sufficiently large simulation size. The required size depends entirely on the sampling efficiency; inefficient sampling necessitates larger simulations. If k-order autocorrelation coefficient of the posterior sample is denoted as $\rho(k)$, the inefficiency factor can be defined as $1 + 2\sum_{k=1}^{\infty}\rho(k)$ (Chib, 2001). Generally, an inefficiency factor of 5 or less is considered acceptable.

2 indicates that all blocks rapidly converge to the target distribution during Gibbs sampling process[16].

Figure 12. Baseline Projection



Source: AMRO staff estimations.
Note: The blue dashed line represents the model's projection of GDP growth over the forecast horizon. The shaded gray area indicates the 68 percent confidence intervals, around the forecasts. The burn-in size is set to 1,000, and the simulation size is 5,000.

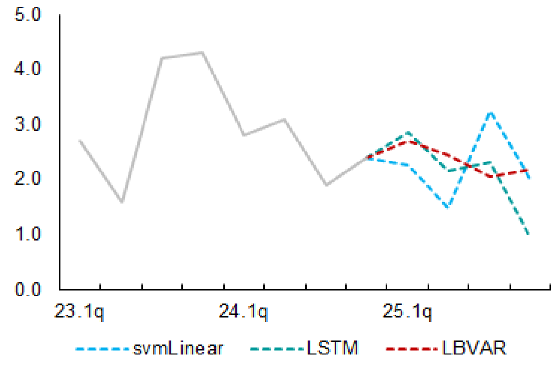
The baseline projections for Hong Kong GDP, as well as the distribution of projected growth at specific points in time (Q4 2025 and Q4 2026), based on the LBVAR model, are presented in Figure 12. The left panel of Figure 12 illustrates the baseline forecast for Hong Kong GDP over a three-year horizon. The projection results indicate that Hong Kong's GDP growth is expected to gradually decline, from the upper 2 percent range in 2023-24 to the average of mid 2 percent range in 2025-26 and further slow to lower 2 percent range in 2027. The average projected growth from 2025 to 2027 is stagnant at around 2.2 percent. This deceleration in growth reflects structural challenges arising both domestically and externally, including the slowdown of key trading partners, an aging population resulting in reduced labor productivity. Indeed, deceleration of labor productivity and exports are the main drivers for the downward trend of Hong Kong growth as presented Appendix 2[17].

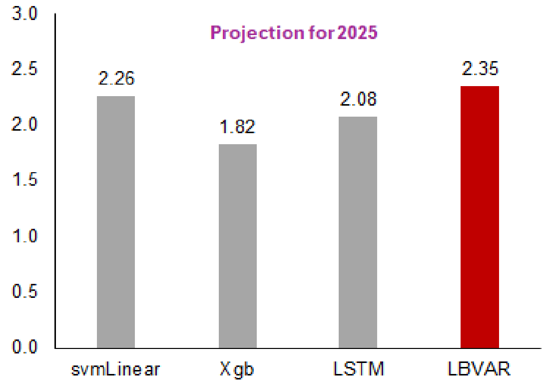
The distribution of projected growth is significant as it provides insights into Growth at Risk[18]. The right section of Figure 12 shows that for Q4 2025, the model predicts GDP growth to center around 2.2 percent, following a bell-shaped normal distribution. This reflects a moderate recovery from recent fluctuations but also highlights considerable uncertainty. For

[16] To account for the possibility that the prior distribution may be more influential due to the 48-quarter sample period starting in 2012, the analysis is extended to a 60-quarter period beginning in 2009. It is confirmed that the baseline projection remains unchanged. Additionally, even when using an alternative prior (Normal-Wishart) instead of the Minnesota prior, although the quarterly paths differ, the annual baseline forecast is preserved.
[17] The projection results for all 17 variables, excluding the three variables subjected to scenario analysis, based on the LBVAR model, can be also found in Appendix 2. To verify the robustness of the model, additional data—including lending rates, deposit rates, and the VIX—are incorporated into the estimation. It is confirmed that the projection results do not significantly differ from those obtained using the data in Table 1.
[18] Growth at Risk (GaR) framework links current macro-financial conditions to the distribution of future growth. Its main strength is its ability to assess the entire distribution of future GDP growth (in contrast to point forecasts), quantify macro-financial risks in terms of growth. (IMF 2019)

Q4 2026, the growth projection slows to 1.9 percent, signaling a potential deceleration in economic momentum after the recovery phase.

Figure 13. Projection from LBVAR and Machine Learning Models
(Year on year, Percent)





Source: AMRO staff estimates.
Note: Gray line is realized GDP growth and dotted lines represent projection from each model. Data from 2012 to 2024 is used for estimation.

The GDP projection results using the LBVAR model are broadly consistent with those obtained from other machine learning models (Figure 13[19]). Given that machine learning models tend to be more effective for short-term forecasts rather than long-term projections, a comparative analysis of 2025 forecasts between the LBVAR model and machine learning models can be conducted. The estimated annual GDP growth for Hong Kong in 2025 is 2.3 percent based on the SVM-Linear model and 2.1 percent using the LSTM[20] model. These estimates closely align with the LBVAR model's projection of 2.4 percent.

C. Measuring the Impact of Risk Factors

This section analyzes the potential impact of risk factors on Hong Kong by comparing hypothetical GDP growth paths under shocks from risk factors with the baseline projection. The key variables subject to application include China's GDP, the residential property market, and trade policy uncertainty, all of which are closely linked to Hong Kong's economy as discussed in section II. To assess the potential impact of each factor on Hong Kong's future GDP trajectory, hypothetical GDP paths are estimated by applying one standard deviation shocks to each factor. Alternative hypothetical GDP paths for Hong Kong, based on the assumption of a rapid recovery in Mainland China's economy after a period of slowdown through 2026, as well as projections assuming a recovery in the residential property market based on ARMA forecasts, are provided in Appendix 3.

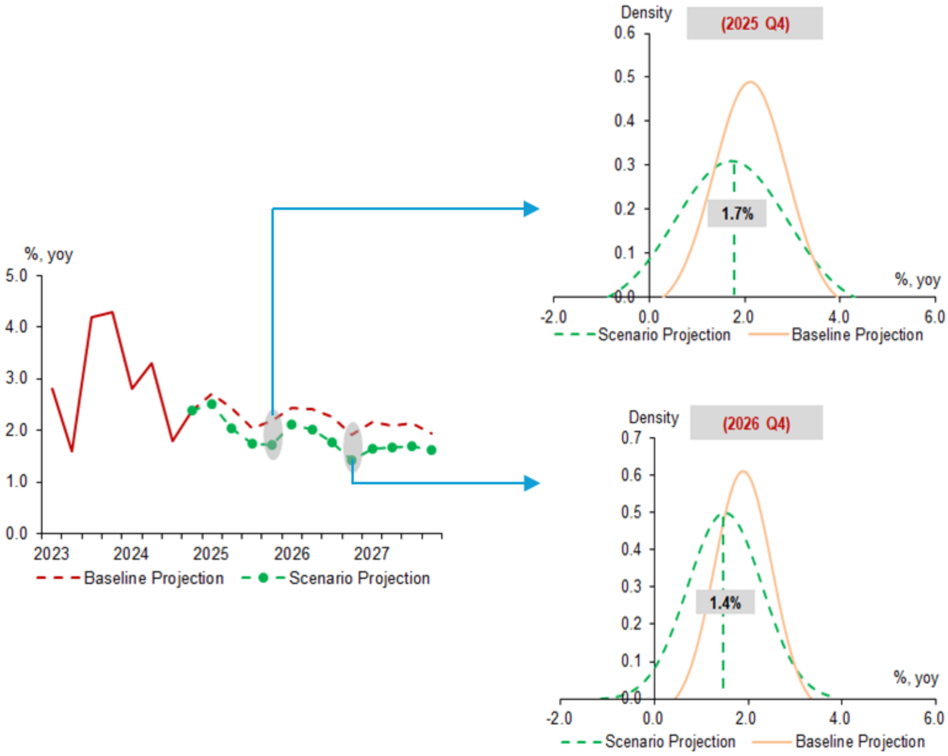
<Results>

Applying the risk of a slowdown in Mainland China's economy indicates that Hong Kong's GDP is likely to experience a more pronounced deceleration compared to the baseline projection. The analysis indicates that Hong Kong's GDP growth will remain below the baseline projection throughout 2025-2027 (Figure 14). This highlights that Hong Kong's economic slowdown could be further exacerbated under weak performance in the Chinese economy. This finding underscores that Hong Kong's future economic trajectory is highly dependent on the growth path of the Chinese economy. By specific periods, the scenario

[19] Data from Q1 2012 to Q4 2024 is utilized for estimation by assigning 70 percent of data for training set and 30 percent of data as a test set.
[20] LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) architecture designed to process and predict time series or sequential data.

analysis projects Hong Kong's GDP growth in Q4 2025 at 1.7 percent, which is lower than the baseline projection of 2.2 percent. The GDP growth for Q4 2026 is even lower at 1.4 percent (right panel in Figure 14). The projections distribution under the risk of China's slowdown indicates that the economy could face greater uncertainty in 2025 and 2026 compared to the baseline projection.

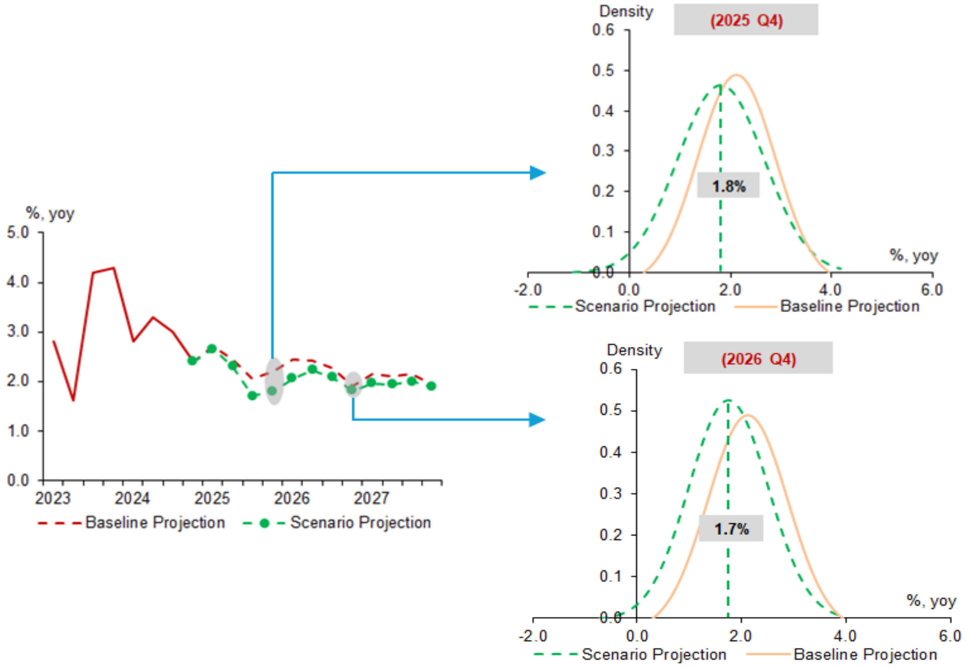
Figure 14. Projection under the Risk of China's Economic Slowdown



Source: AMRO staff estimations.
Note: The green line represents the model's projection based on the scenario. The burn-in size is 1,000, and the simulation size is 5,000.

Prolonged weakness in Hong Kong's property market is found to have a relatively limited impact on the growth trajectory (Figure 15). This outcome reflects the structural characteristics of Hong Kong's economy, which is more heavily concentrated in finance, tourism, and services rather than real estate. By specific periods, the analysis projects Hong Kong's GDP growth rate for Q4 2025 at 1.8 percent, less than the baseline projection of 2.2 percent. The GDP growth rate for Q4 2026 is projected at 1.7 percent, slightly lower than the baseline projection of 1.9 percent.

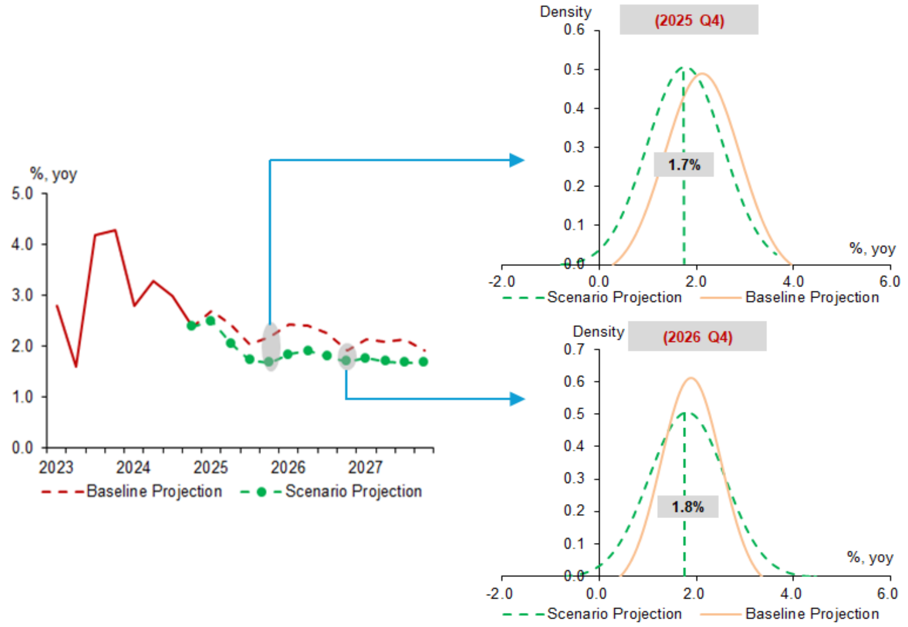
Figure 15. Projection under the Risk of Prolonged Adjustment in Property Market



Source: AMRO staff estimations.
Note: The green line represents the model's projection based on the scenario. The burn-in size is 1,000, and the simulation size is 5,000.

The risk of increasing Trade Policy Uncertainty (TPU) has a significant impact on Hong Kong's future GDP trajectory (Figure 16). As trade uncertainty rises, the Hong Kong GDP path under the trade related risk scenario is projected to remain far below the baseline through the end of 2027. The negative effects of heightened uncertainty are most pronounced in the second half of 2025. A key point under TPU risk scenario is that the projection distributions for both 2025 and 2026 include negative growth (right panel of Figure 17). This suggests that downside risks could be significantly amplified, highlighting the vulnerability of Hong Kong's economy to global trade uncertainty.

Figure 16. Projection under the Risk of Increasing TPU



Source: AMRO staff estimations.
Note: The green line represents the model's projection based on the scenario. The burn-in size is 1,000, and the simulation size is 5,000

To summarize the scenario analysis results, the risk of China's economic deceleration generates the most significant impact on Hong Kong's GDP trajectory (Table 2). Risks associated with trade policy uncertainty (TPU) are found to have a smaller, yet still significant. In contrast, property market-related risks appear to exert a relatively limited influence compared to other factors. The effects of each risk factor on Hong Kong's GDP, along with the baseline projection, are summarized in Table 2. In the event of an extreme crisis involving a deceleration of Mainland China's economy, heightened trade policy uncertainty (TPU), and prolonged weakness in the domestic property market, Hong Kong's economic performance could fall significantly below the baseline projection. Under such simultaneous shocks, the annual GDP growth rate is estimated to decline by approximately 0.8 percentage points compared to the baseline scenario.

Table 2. Projection Comparison

Period		Slow down in China's growth (A)	Increase TPU (B)	Slowdown RPP (C)	A+B+C	A+B
2025 (2.4)	Hypothetical GDP growth (%)	2.1	2.1	2.2	1.6	1.8
	Deviation from Baseline (%p)	-0.3	-0.3	-0.2	-0.8	-0.6
2026 (2.3)	Hypothetical GDP growth (%)	1.9	2.0	2.2	1.5	1.6
	Deviation from Baseline (%p)	-0.4	-0.3	-0.1	-0.8	-0.7
2027 (2.1)	Hypothetical GDP growth (%)	1.7	1.9	2.0	1.4	1.5
	Deviation from Baseline (%p)	-0.4	-0.2	-0.1	-0.7	-0.6

Source: AMRO staff estimations.
Note: RPP and TPU represent residential property price and trade policy uncertainty. The numbers in parentheses indicate baseline projection.

VI. Findings and Policy Implications

This paper employs the LBVAR model, widely utilized by major central banks, to project Hong Kong's GDP and assess the potential impact of risk factors on Hong Kong by comparing hypothetical GDP paths under various shocks, with the baseline projection. The three risk factors have significant impacts on the Hong Kong economy's growth path, although the degree of impact varies. The analysis suggests that Hong Kong's GDP could gradually decline to the low 2-percent range by 2027 if the risks were to materialize. A slowdown in Mainland China's economy is identified as having the most significant and persistent impact on Hong Kong's economic performance. Increasing trade policy uncertainty (TPU) presents a smaller yet still considerable influence. Compared to other risk factors, risks related to the property market are found to have a relatively limited effect.

The policy implications derived from the analysis include securing new growth engines, strengthening engagement with global trade partners while deepening economic integration with China, supporting the recovery of the property market, and adopting proactive fiscal policy while maintaining fiscal stability.

- **Securing New Growth Engines**: Hong Kong's concentration and overdependence on a few sectors such as finance, trade, services and tourism render it more susceptible to external and sectoral shocks. To mitigate such risks and foster resilient growth, policy should prioritize emerging, high-growth industries. Hong Kong can leverage its international financial hub status to become a leading center in green finance and fintech. In addition, recent initiatives by the Hong Kong authorities to support the AI industry represent a positive step toward securing new drivers of economic growth.

- **Enhancing Engagement with Global Trade Partners while Deepening Integration with China**: In an increasingly uncertain and rapidly evolving global economic landscape, Hong Kong should broaden and strengthen its economic connections by fostering stronger trade relationships with emerging markets in Asia, Africa, and South America, beyond its traditional trading partners. Furthermore, Hong Kong's accession to the Regional Comprehensive Economic Partnership (RCEP) is anticipated to enhance access to vibrant regional markets and integrated production networks (AMRO 2022). Strengthening economic ties within the Greater Bay Area (GBA) is crucial to leveraging the region's growth trajectory. With this, Hong Kong can serve as a key logistics and financial node for Chinese exports and imports.

- **Supporting the Recovery of the Property Market**: Sustained efforts by the authorities to support the recovery of Hong Kong's property market remain essential. Easing property-related regulations is critical to ensuring that the recent rebound in the residential property market translates into renewed economic dynamism. In this context, the Hong Kong government's initiatives to relax property-related taxation and macroprudential regulations are commendable. Furthermore, a revitalized property market can bolster government revenue, thereby enhancing the fiscal space needed to implement more effective policy measures.

- **Adopting proactive fiscal policy while maintaining fiscal stability**: The Hong Kong government could consider adopting a more proactive fiscal policy in this new era of industrial policy, where governments focus on strategic sectors and technologies to enhance national competitiveness and resilience beyond traditional globalization models. Especially during economic downturns, supporting SMEs and distressed households could provide immediate relief. Over the long term, allocating resources to strategic infrastructure and high-growth sectors might be essential. Incentivizing green innovation and digital transformation through tax relief and financial support could further enhance Hong Kong’s global position. Additionally, maintaining a stable fiscal environment is vital for attracting foreign investment, crucial for sustained economic growth.

In conclusion, while Hong Kong's economy is navigating a landscape marked by substantial uncertainties, strategically designed domestic initiatives and enhanced regional cooperation hold the potential to mitigate the risks and drive improved economic outcomes. Addressing these risks proactively involves not only tailoring policy responses to the current economic conditions but also preparing for potential future disruptions. It is important to note, however, that the actual trajectory of key factors may diverge both from the baseline and scenarios analyzed in this paper, leading to variations in Hong Kong's growth path. Therefore, it is critical that policy efforts include continuous monitoring of economic indicators and flexible policy adjustments to respond effectively to both expected and unforeseen challenges. Furthermore, long-term projections beyond the next three years are essential for a comprehensive understanding of the city's economic future, which is identified as a subject for future research.

Appendix 1. Statistics of Data

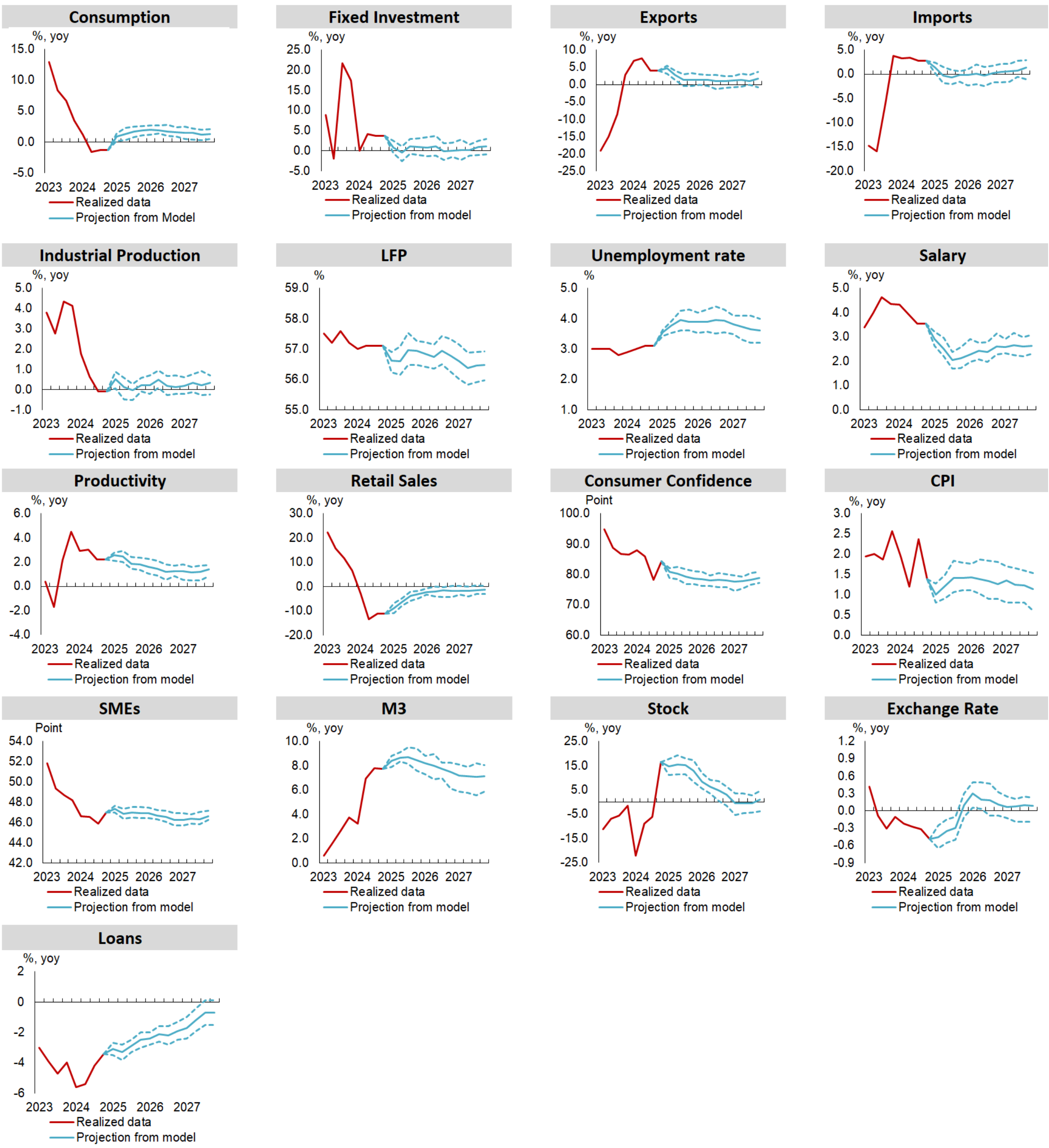
Table A1. 1. Main Statistics of Data (2012Q1 – 2024Q4)

	Mean	Std. Dev.	Min.	Max.	Num. Obs.
HK Domestic Macro Block					
GDP	1.48	3.55	-9.40	8.20	52
Consumption	2.17	5.00	-14.50	12.20	52
Investment	0.14	9.43	-21.10	21.90	52
IP	0.27	2.78	-7.50	7.71	52
Retail Sales	-0.73	11.44	-37.08	22.18	52
Consumer Confidence	78.67	9.84	52.80	94.80	52
CPI	2.51	1.36	-1.76	5.35	52
SMEs	47.86	2.56	38.47	51.87	52
RPP	4.43	10.65	-13.56	28.23	52
Labor Market Block					
LFP	59.91	1.45	56.90	61.40	52
Unemployment	3.60	1.00	2.70	6.70	52
Salary	3.09	1.93	-1.44	6.94	52
Productivity	1.18	2.92	-6.44	12.03	52
Financial and Monetary Block					
M3	6.78	3.96	0.61	14.56	52
Stock	0.62	16.32	-30.13	34.59	52
Exchange Rate	0.02	0.46	-1.14	1.04	52
Loans	6.02	7.08	-5.63	19.55	52
External Block					
Exports	1.24	9.16	-24.90	30.40	52
Imports	1.07	9.04	-23.00	23.00	52
China GDP	6.26	2.91	-6.80	18.90	52
TPU	71.24	52.85	20.78	237.40	52

Appendix 2. Projection results for the variables used for LBVAR

The main text primarily presents projections for the target variable, Hong Kong GDP, while (Figure A2.1) displays the LBVAR projection results for the remaining variables, excluding the target variable and the scenario variables.

Figure A2. 1. Baseline Projection for Each Variable



Source: AMRO staff estimations.
Note: The light blue line represents the model's projection of each variable over the forecast horizon. The dotted light blue lines indicate the 68 percent confidence intervals. The burn-in size is set to 1,000, and the simulation size is 5,000.

Appendix 3. Alternative hypothetical GDP paths for Hong Kong

Alternative hypothetical GDP paths for Hong Kong, based on the assumption of a rapid recovery in Mainland China's economy after a period of slowdown through 2026 is presented in Figure A3.1. The impact of changes in the property market on GDP, based on projections from the ARMA model, is presented in Figure A3.2.

Figure A3. 1. Alternative GDP Projection based on China's fast Recovery

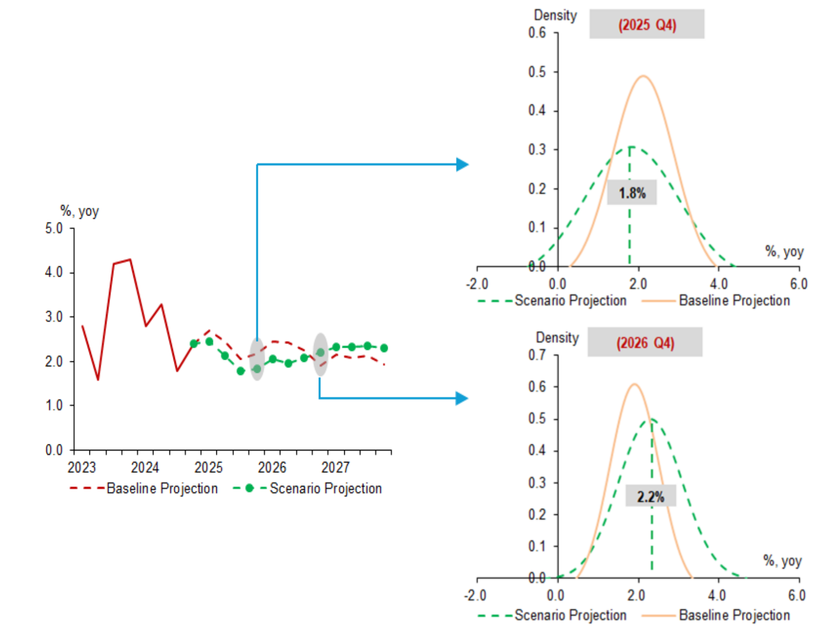
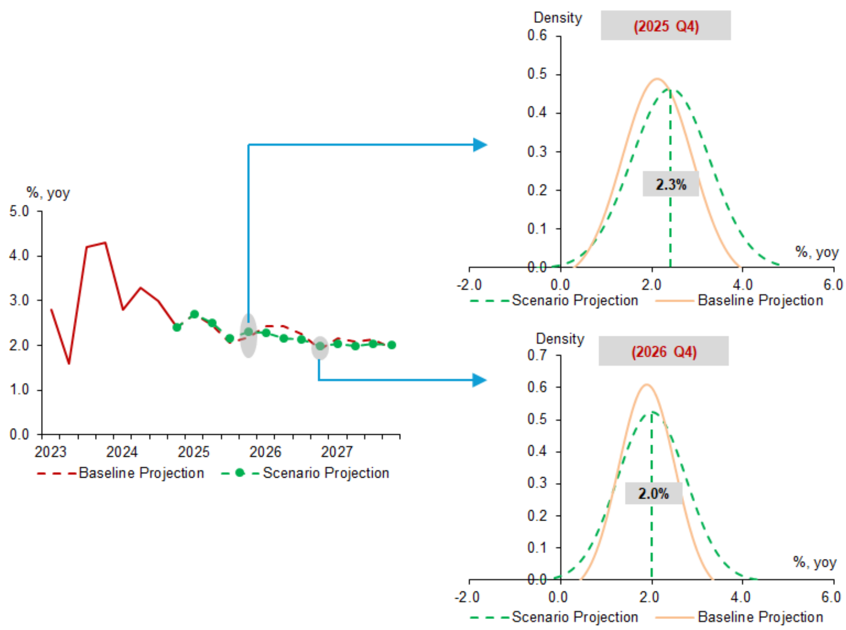


Figure A3. 2. Alternative GDP Projection based on Residential Property path from ARMA



Source: AMRO staff estimations.
Note: The green line represents the model's projection based on the scenario. The burn-in size is 1,000, and the simulation size is 5,000.

Appendix 4. Procedure to Forecast using ARMA Model

Following Box and Jenkins (1976), the series y_t follows ARMA (p, 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 ARMA 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 ARMA 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 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 paper applies to the maximum likelihood estimation method.

Use the fitted model to make forecasts. The ARMA 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 paper forecasts real estate prices up to 24 months from the end of 2024, utilizing twenty ARMA models.

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

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

Then,

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

The s period ahead forecasts would be

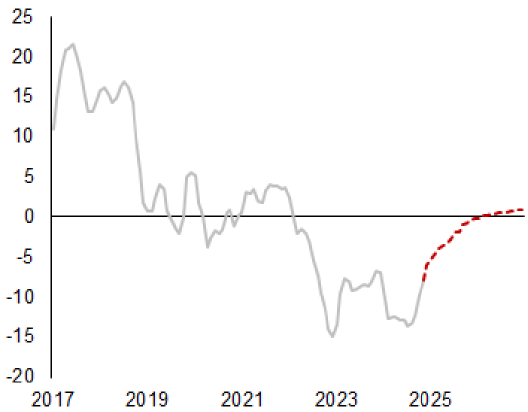
$$(\widehat{Y_{t+s|t}} - \boldsymbol{\mu}) = \boldsymbol{\phi_1}\left(\boldsymbol{\widehat{Y}_{t+s-1|t}} - \boldsymbol{\mu}\right) + \boldsymbol{\phi_2}\left(\boldsymbol{\widehat{Y}_{t+s-2|t}} - \boldsymbol{\mu}\right) + \cdots + \boldsymbol{\phi_p}\left(\boldsymbol{\widehat{Y}_{t+s-p|t}} - \boldsymbol{\mu}\right)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

For s = 1, 2, 3, ..., q

The projection for residential property prices over the next 24 months, based on data from January 2017 to December 2024, is presented in Figure A4.1. AIC values of candidate models used in the analysis are compared in Figure A4.2.

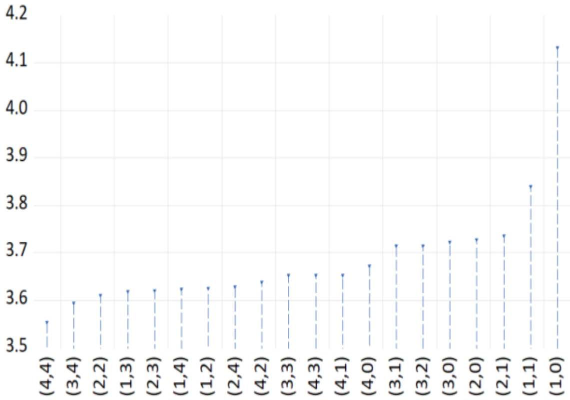
Figure A4. 1. Residential Property Price Projection

(Year on year, Percent)



Source: AMRO staff estimates.
Note: Red dotted line is projection using ARMA (4,4) model.

Figure A4. 2. Comparison of AIC Criteria among different Models
(p, q)



Source: AMRO staff estimates.
Note: AIC is shown as the top 20 models.

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