PARAMETER
JURNAL MATEMATIKA, STATISTIKA DAN TERAPANNYA

e-ISSN. 2829-6303
Vol. 04, No. 3, December 2025
Page 551-562

Forecasting Regional Economic Growth Using TVARX: Model Accuracy Evaluation in Banten Province

Amelia Vega[1], Muhammad Fajar[2*], Hendro Prayitno[3], Erya Afrianus[4]

[1]Statistics Department, Faculty of Science and Mathematics, University of Diponegoro, Semarang, 50275, Jawa Tengah, Indonesia
[2,3]Badan Pusat Statistik,
Dr. Sutomo 6 – 8 St, Jakarta Pusat, 10710, DKI Jakarta, Indonesia
[4]Pusdiklat Badan Pusat Statistik,
Raya Jagakarsa 70 St, Lenteng Agung, Jakarta Selatan, 12620 DKI Jakarta Indonesia

***E-mail Correspondence Author:** *mfajar@bps.go.id*

Abstract
Forecasting regional economic performance is essential for supporting timely and responsive policy planning. This study aims to forecast the Gross Regional Domestic Product at constant prices (GRDP) in Banten Province for the second to fourth quarters of 2025 using the Time-Varying Autoregressive model with Exogenous Variables (TVARX). The model incorporates household final consumption expenditure, gross fixed capital formation, exchange rates, and export values as exogenous variables. Model performance was evaluated by comparing combinations of training-testing data proportions (90:10, 80:20, 70:30, and 60:40) and two estimation approaches (local constant and local linear), using the Mean Absolute Percentage Error (MAPE) as the predictive accuracy metric. All variables were transformed into logarithmic form and differenced to ensure stationarity. The results indicate that the model using a 90:10 data split and the local linear estimation approach yielded the most accurate prediction, with the lowest MAPE value of 0.6%. The best-performing model was then applied to forecast out-of-sample GRDP CP for the next three quarters, with its year-on-year growth subsequently analyzed. These findings are expected to serve as a basis for data-driven economic analysis and support macroeconomic planning that is responsive to short-term structural dynamics.

Keywords: *Forecasting, GRDP, time series analysis, TVARX,*

: https://doi.org/10.30598/parameterv4i3pp551-562

Research Ariticle Open Acces
Email: jurnalparameter@gmail.com
Homepage: https://ojs3.unpatti.ac.id/index.php/parameter

Submitted: August 2025
Accepted: December 2025

1. INTRODUCTION

Gross Regional Domestic Product (GRDP) is one of the most important macroeconomic indicators for assessing regional economic performance over a given period, measured in both current prices and constant prices. Conceptually, GRDP represents the total gross value added generated by all final goods and services produced by economic units within a region during a specific time frame [1]. Among these measures, GRDP at constant prices is widely regarded as the most reliable indicator for economic growth analysis because it reflects real economic dynamics after removing inflationary effects. Accurate forecasting of constant price GRDP is therefore essential not only for understanding future economic trajectories but also for supporting anticipatory, responsive, and evidence-based regional economic policymaking. Despite its strategic importance, methodological advancements in regional GRDP forecasting, particularly those that accommodate structural changes and evolving economic relationships, remain limited in the existing literature.

In modeling and forecasting GRDP dynamics at constant prices, several exogenous macroeconomic variables play a crucial role, including Household Final Consumption Expenditure, gross fixed capital formation, exchange rates, and export values. Household consumption captures domestic demand and purchasing power, while gross fixed capital formation reflects long-term investment behavior. Exchange rates influence the competitiveness of imports and exports, and export values represent a region's integration into global markets. Although these variables are theoretically and empirically linked to GRDP movements, most existing studies incorporate them within static or linear modeling frameworks, thereby implicitly assuming stable relationships over time. Such assumptions may be unrealistic in the presence of economic shocks, policy interventions, and structural transformations. Economic and financial processes are inherently dynamic and subject to continuous change. As highlighted by Blasque et al. [2], economic outcomes are influenced by evolving agent behavior, endogenous and exogenous shocks, institutional changes, and shifting market conditions. Consequently, time series models that allow parameters to vary over time are increasingly necessary. In this context, the Time-Varying Autoregressive (TVAR) model offers a flexible framework capable of capturing structural dynamics and time-dependent relationships. Unlike conventional autoregressive models with fixed coefficients, the TVAR model allows parameters to evolve in response to changing economic conditions, making it particularly suitable for analyzing nonstationary and structurally evolving economies [3].

Although the TVAR model has been applied in various macroeconomic and financial studies, such as analyzing the transmission of monetary policy in the United States [4], examining the time-varying effects of economic policy uncertainty [5], and assessing the impact of oil revenues on economic growth in developing countries [6], its application remains largely confined to national-level or financial-market analyses. More importantly, the extension of the TVAR framework to explicitly incorporate exogenous variables through a TVARX specification has received very limited attention, especially in the context of regional economic forecasting.

This study addresses a clear gap in the literature by systematically developing and applying a TVARX framework for regional GRDP forecasting. To the best of the authors' knowledge, no previous study has comprehensively examined the performance of TVARX models in forecasting constant price GRDP at the regional level, compared the effectiveness of local constant and local linear estimation methods within a TVARX setting, and evaluated the sensitivity of forecasting accuracy to different training and testing data partition strategies. Existing studies typically focus on either model development or empirical application, but rarely investigate how estimation approaches and data-splitting schemes jointly affect predictive performance. This methodological dimension constitutes a key novelty of the present research.

Furthermore, while local constant estimation is computationally straightforward, it may fail to adapt to abrupt local changes in economic dynamics. In contrast, local linear estimation has been shown to reduce bias and more effectively capture smooth parameter evolution driven by localized data behavior [7], [8]. However, empirical evidence comparing these approaches within a TVARX framework, particularly for regional macroeconomic forecasting, remains scarce. Likewise, the choice of training data proportion is often treated as a technical detail rather than a substantive modeling decision, despite its critical implications for underfitting and overfitting risks. This study explicitly addresses these unresolved methodological issues.

The empirical application focuses on Banten Province, which provides a compelling case study due to its open economic structure, strong dependence on manufacturing exports, and high exposure to global economic fluctuations. Banten's economy is characterized by rapid industrial expansion, intensive export and import activities, and ongoing infrastructure development, which make it particularly vulnerable to structural shifts and external shocks [1]. These characteristics underscore the relevance of using a modeling framework capable of capturing time-varying relationships and evolving economic dynamics, an aspect that has been largely overlooked in previous regional studies.

Based on this background, the primary objective of this study is to forecast the constant price GRDP of Banten Province for the first through fourth quarters of 2025 using a TVARX model that delivers optimal predictive accuracy. Model performance is rigorously evaluated using the Mean Absolute Percentage Error (MAPE), while alternative combinations of estimation methods, namely local constant and local linear approaches, and different training and testing data proportions are systematically compared. By integrating methodological innovation with regional economic application, this study offers a novel and robust contribution to the literature on regional macroeconomic forecasting and time-varying econometric modeling.

2. METHOD

2.1 Data and Variables

Table 1. Scenarios of Training and Testing Data Split

Data Proportion	Training Period	Number of Training Data	Testing Period	Number. of Testing Data
90:10	2010Q1-2023Q3	55	2023Q4-2025Q1	6
80:20	2010Q1-2022Q1	49	2022Q2-2025Q1	12
70:30	2010Q1-2020Q3	43	2020Q4-2025Q1	18
60:40	2010Q1-2019Q1	37	2019Q2-2025Q1	24

The data utilized in this study consists of quarterly time series data spanning from the first quarter of 2010 to the first quarter of 2025, totaling 61 observations. The variables analyzed include Gross Regional Domestic Product at constant prices (GRDP) as endogenous variable (y), and household final consumption expenditure (HFCE), gross fixed capital formation (GFCF), the exchange rate of the rupiah against the USD and export values as exogenous variables. All data were transformed into logarithmic form.

The model was tested using R Studio across several scenarios based on different proportions of training and testing data, namely 90:10, 80:20, 70:30, and 60:40. The data splitting scenarios are presented in **Table 1.**

2.2 Time-varying Autoregressive with Exogenous Variables

The fundamental model of time series analysis begins with the AR model, which represents the current value of an endogenous variable as a function of its own past values. Mathematically, a p-order AR model is expressed in **Equation (1)** **[9]**.

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-1} + \varepsilon_t \tag{1}$$

In many economic contexts, the endogenous variable y_t is not only influenced by its own past values, but also by external factors outside the system, known as exogenous variables. Therefore, the AR model is extended into the Autoregressive model with exogenous variables (ARX). The ARX model is formulated in **Equation (2)** **[10]**.

$$y_t = + \sum_{i=1}^{p} \alpha_i y_{t-1} + \sum_{j=1}^{q} \beta_j x_{j,t} + \varepsilon_t \tag{2}$$

The ARX model still assumes that the regression coefficients (α_i, β_j) remain constant over time. To address this limitation, the model is further extended to the Time-Varying Autoregressive model with exogenous variables (TVARX), in which the parameters are allowed to evolve over time in a flexible manner. An intercept term $(\alpha_0(t))$, which is also time-varying, is added to capture shifts in the baseline level of the endogenous variable that are not explained by lagged values or exogenous inputs. The TVARX model of order p with q exogenous variables is expressed in **Equation (3)**.

$$y_t = \alpha_0(t) + \sum_{i=1}^{p} \alpha_i(t) y_{t-1} + \sum_{j=1}^{q} \beta_j(t) x_{j,t} + \varepsilon_t \tag{3}$$

The TVARX model represents the value of the endogenous variable y_t s a combination of a time-varying intercept, contributions from its own lagged values, and the influence of exogenous variables. Mathematically, the model incorporates a time-varying intercept $\alpha_0(t)$ to capture dynamic baseline shifts in the modeled process. The autoregressive component is modeled using lagged values of y_t, each multiplied by a time-varying coefficient $\alpha_i(t)$ which reflects the temporal internal dynamics of the variable. The model also accounts for the effect of exogenous variables $x_{j,t}$ through time-varying coefficients $\beta_j(t)$, enabling adaptive responsiveness to external changes. The entire structure is completed with an error term ε_t , representing random disturbances not explained by the model. Parameter estimation in the TVARX model is carried out using the nonparametric local constant and local linear approaches, as proposed by Gao et al. **[11]**.

2.3 Mean Absolute Percentage Error (MAPE)

Mean absolute percentage error (MAPE) is one of the most widely used metrics for evaluating forecast accuracy in both academic research and practical applications. MAPE is scale-independent, making it suitable for comparing forecast performance across different datasets or measurement units, and is straightforward to interpret in percentage terms. It is defined as the average of the absolute percentage errors (APE), where each error represents the absolute difference between the actual and forecast values relative to the actual value. The MAPE formula is defined in Equation (4) [12].

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\% \tag{4}$$

where t denotes the time period, n is the number of observations, y_t represents the actual value and $\hat{y}_t$ denotes the forecast value.

A lower MAPE value indicates better forecast accuracy, with a value of zero representing a perfect forecast. Common interpretative guidelines suggest that a MAPE below 10% denotes highly accurate forecasting, between 10%–20% denotes good forecasting, 20%–50% denotes reasonable forecasting, and above 50% indicates inaccurate forecasting [13].

2.4 Research Procedure

This research process aims to develop and evaluate a predictive model of constant price GDRP using the TVARX approach. The entire procedure is carried out through the following stages:

1. The data is divided into four training and testing proportion scenarios: 90:10, 80:20, 70:30, and 60:40. The data is transformed into a logarithmic form to stabilize variance, followed by first-order differencing.
2. The optimal lag is determined for each training data proportion scenario using the Akaike Information Criterion (AIC).
3. The TVARX model is constructed based on combinations of different data proportions and two estimation approaches: local constant and local linear. An intercept is included in the model, and estimation is conducted using the default bandwidth. To avoid overfitting, a block of training data is set aside as cross-validation data to obtain more generalized parameters.
4. Time-varying parameter estimation is conducted using the kernel smoothing method according to the chosen estimation approach. These estimation results are visualized in coefficient-over-time plots to illustrate the dynamic relationship between constant price GRDP and the exogenous variables.
5. The prediction accuracy of each model is compared based on the MAPE value, which is used to determine the best model configuration based on data proportion and estimation method.
6. The best model, based on the lowest MAPE value, is used to perform out-of-sample forecasting of Banten Province's constant price GRDP for the next three quarters: Q2 to Q4 of 2025. The prediction results are also used to calculate the year-on-year growth of the constant price GRDP.

3. RESULTS AND DISCUSSION

Stationarity testing was conducted using the Augmented Dickey-Fuller (ADF) test at the level form. Based on Table 2, all variables at the level form have p-values exceeding the significance level ($\alpha = 5\%$) indicating non-stationarity. After first differencing, all variables have p-values below $\alpha = 5\%$, meaning that the data have achieved stationarity at the first difference. Therefore, to maintain model stability and interpretability, these variables were transformed into log-differenced form.

Table 2. **Results of the ADF Test**

Variables	p-value of based on Data Level	p-value based on Data 1st Difference
Constant Price GRDP	0.622	0.0013
HFCE	0.697	0.0160
GFCF	0.956	0.0180
Exchange Rates	0.317	0.0100
Export Values	0.057	0.0170

Table 3. **The Optimal Lag Length**

Data proportion	The Optimal Lag Length
90:10	Lag 2
80:20	Lag 2
70:30	Lag 2
60:40	Lag 5

The optimal lag length was determined based on the training data using the AIC due to its computational simplicity and its ability to prevent overfitting by balancing estimation quality and model complexity. AIC is widely used in the practice of modeling VAR and its extensions to determine the appropriate lag length [14]. The result of optimal lag selection is presented in Table 3.

The TVARX model in this study was estimated using the logarithmic and differenced form GRDP at constant prices as the endogenous variable, along with four exogenous variables: HFCE, GFCF, exchange rates and export values. Two nonparametric estimation approaches—local constant and local linear—were explored, along with various scenarios for splitting the data into training and testing sets. The optimal lag length was determined prior to model estimation, and an intercept term was included in the specification. Bandwidth selection followed the default procedure, allowing the method to automatically adjust smoothing levels according to the underlying data structure. To prevent overfitting and improve parameter generalizability, a block of data was reserved for cross-validation. The general form of the TVARX model is expressed as follows:

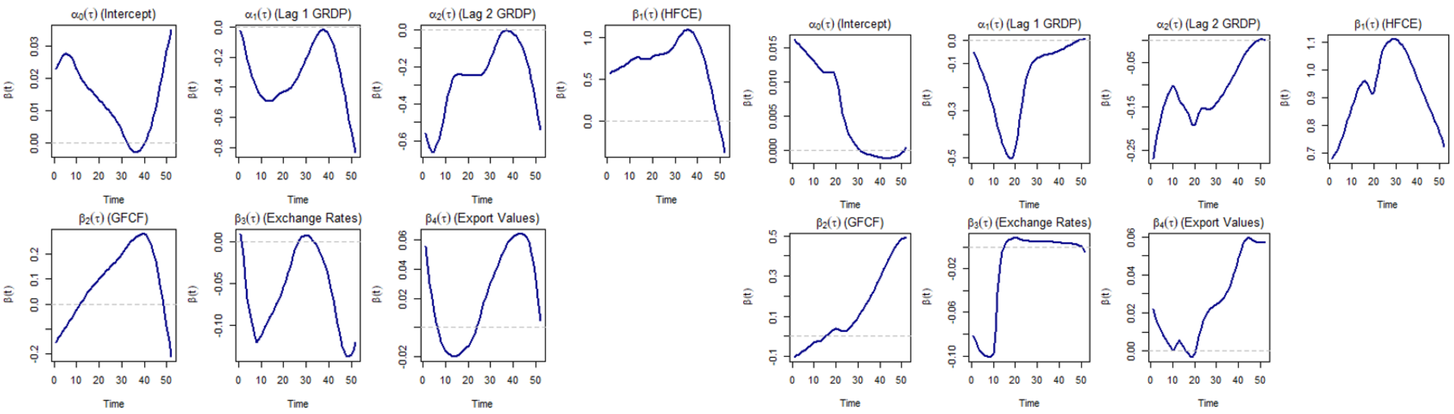
- Model with data proportions 90:10, 80:20, 70:30

$$\Delta logy_t = \alpha_{0,t} + \alpha_{1,t}\Delta logy_{t-1} + \alpha_{2,t}\Delta logy_{t-2} + \beta_{1,t}\Delta logx_{1,t} + \beta_{2,t}\Delta logx_{2,t} + \beta_{3,t}\Delta logx_{3,t} + \beta_{4,t}\Delta logx_{4,t} + \varepsilon_t$$

- Model with data proportion 60:40

$$\Delta logy_t = \alpha_{0,t} + \alpha_{1,t}\Delta logy_{t-1} + \alpha_{2,t}\Delta logy_{t-2} + \alpha_{3,t}\Delta logy_{t-3} + \alpha_{4,t}\Delta logy_{t-4} + \alpha_{5,t}\Delta logy_{t-5} + \beta_{1,t}\Delta logx_{1,t} + \beta_{2,t}\Delta logx_{2,t} + \beta_{3,t}\Delta logx_{3,t} + \beta_{4,t}\Delta logx_{4,t} + \varepsilon_t$$

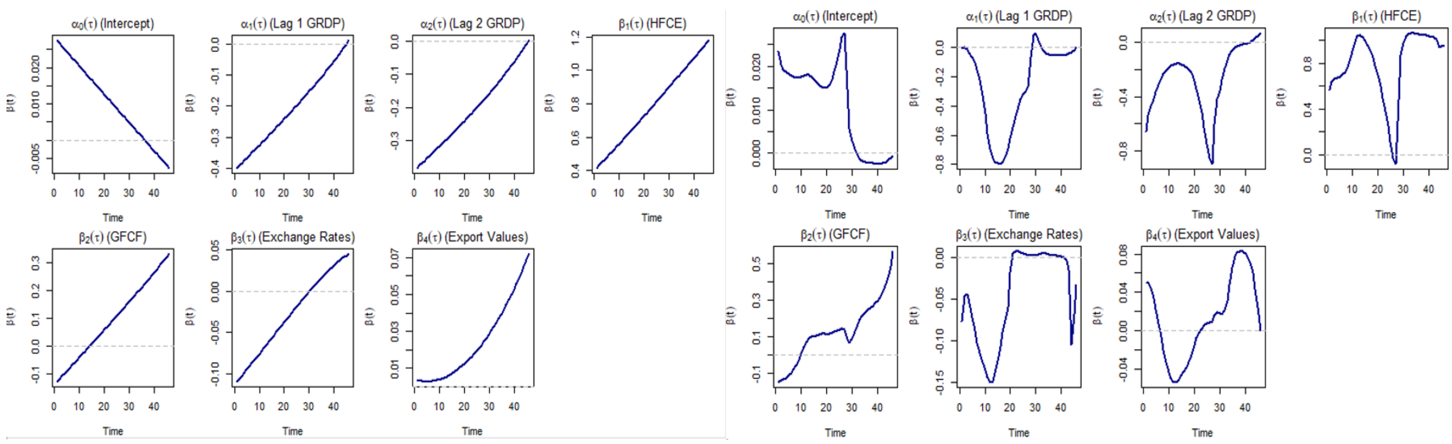
where, y_t denotes the log-differenced GRDP at constant prices, $\alpha_{0,t}$ represents the time-varying intercept, $\alpha_{p,t}\Delta logy_{t-p}$ are the time-varying autoregressive coefficients for lags $p = 1, 2, \dots, 5$, $\beta_{q,t}\,\Delta logx_{q,t}$ are the time-varying coefficients associated with the exogenous variables $q = 1, 2, 3, 4$, namely x_1 for HFCE, x_2 for GFCF, x_3 for the exchange rates, x_4 for export values, and ε_t denotes the error term.



(a) (b)

Figure 1: (a). Coefficient Plot Using Local Linear Estimation with 90:10 Data Split, (b). Coefficient Plot Using Local Constant Estimation with 90:10 Data Split.

The TVARX model allows each regression parameter in the model to vary over time, thereby capturing structural dynamics in the relationships among economic variables. **Figure 1 – 4** display plots of time-varying coefficients for each variable in the models built using different proportions of training and testing data, as well as two estimation approaches. These coefficients represent the relationships between the GRDP at constant prices and its past values ($\alpha(\tau)$), as well as with the exogenous variables—HFCE, GFCF, exchange rates, and export values ($\beta(\tau)$).

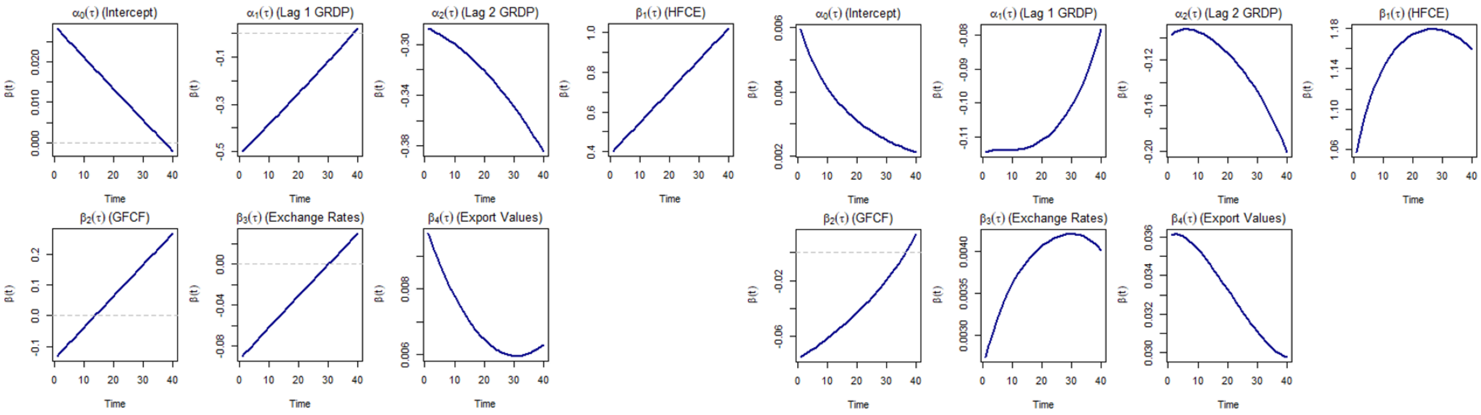


(a) (b)

Figure 2: (a). Coefficient Plot Using Local Linear Estimation with 80:20 Data Split, (b). Coefficient Plot Using Local Constant Estimation with 80:20 Data Split.

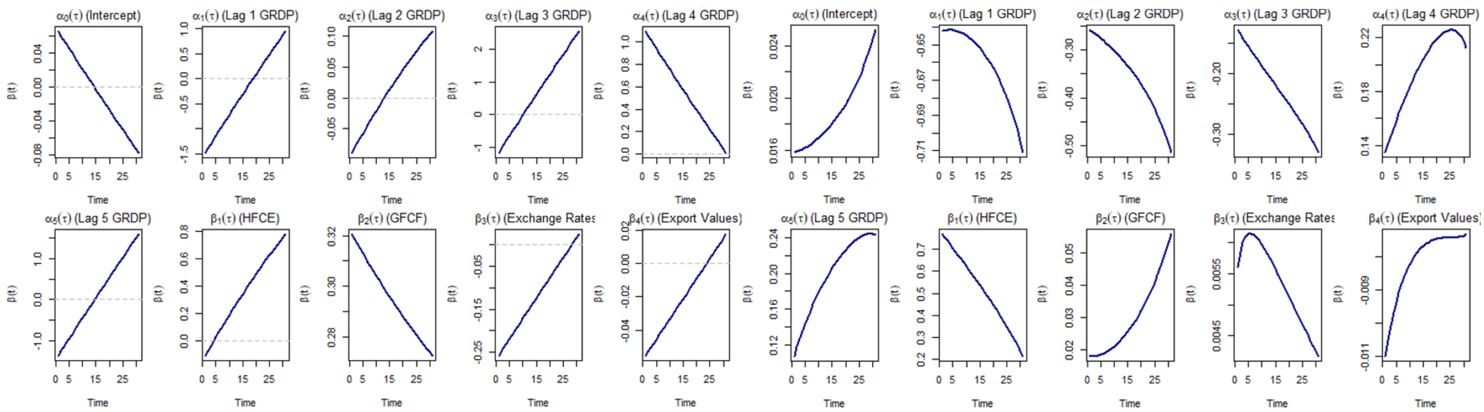
The coefficient plots indicate that the relationship between the exogenous variables and the constant price GRDP variable is not constant but changes over the observation period. The resulting patterns tend to exhibit increasing or decreasing trends depending on the variable being analyzed.

A comparison between the local constant and local linear estimation methods reveals significant differences in coefficient patterns. The local constant estimation produces more static and less flexible coefficient patterns, making it insufficiently sensitive to capturing local trend shifts. In contrast, the local linear approach yields smoother and more dynamic results, allowing for better detection of structural changes in the data over time. Overall, both methods indicate that the relationships among variables evolve gradually rather than randomly.



(a) (b)

Figure 3: (a). Coefficient Plot Using Local Linear Estimation with 70:30 Data Split, (b). Coefficient Plot Using Local Constant Estimation with 70:30 Data Split.



(a) (b)

Figure 4: (a). Coefficient Plot Using Local Linear Estimation with 60:40 Data Split, (b). Coefficient Plot Using Local Constant Estimation with 60:40 Data Split.

The predictive accuracy of the TVARX model is evaluated based on the MAPE Values. Table 4 presents the MAPE values based on different data split scenarios and the two estimation approaches.

Table 4. MAPE Values Generated from the TVARX Model by Training-Testing Sample Proportion

Data Proportion	MAPE	
	Local Linier	Local Constant
90:10	0,6%	1,01%
80:20	1,21%	1,31%
70:30	1,22%	1,04%
60:40	3,92%	1,44%

Based on the predictive accuracy evaluation results presented in Table 4, the TVARX model estimated using the local linear approach yields lower MAPE values compared to the local constant approach under training data proportions of 90:10 and

80:20. This suggests that when the training data proportion is large, the local linear approach is more effective in capturing the dynamic changes in the model parameters. Conversely, at smaller training data proportions, such as 70:30 and 60:40, the local constant approach demonstrates better predictive accuracy as reflected by its lower MAPE values compared to local linear.

This discrepancy reflects the inherent characteristics of each estimation method. The local linear approach has the advantage of edge bias correction and is capable of representing gradual parameter changes over time when supported by a sufficient amount of data [7]. However, in cases with limited data availability, this approach may become less stable, making the local constant approach—which is simpler and exhibits lower estimation variance—more optimal [15].

Table 5. Forecast and Year-on-Year Growth of GRDP at Constant Prices in Banten Province

Quarter	Forecast	Year-on-Year Growth of GRDP
Q2: 2025	138754118	5,05%
Q3: 2025	139921703	4,92%
Q4: 2025	141538252	4,19%

The choice of an appropriate estimation method should therefore consider the proportion of training data employed. The local linear approach is more suitable when a large volume of training data is available, while the local constant approach is preferable for smaller data proportions. Overall, the 90:10 data proportion combined with the local linear estimation yields the smallest MAPE value, and thus can be regarded as the most accurate configuration for forecasting the GRDP at constant prices of Banten Province using the TVARX model.

Using this most accurate model, an out-of-sample forecast was conducted for Banten Province's constant price GRDP for the second to fourth quarters of 2025. The forecasting process employed a rolling estimation approach. Annual growth rates for each quarter were also computed. This forecast aims to provide an initial overview of the region's short-term economic outlook, as well as to serve as an external validation of the model's performance in capturing recent economic dynamics. The forecasting results are presented in Table 5.

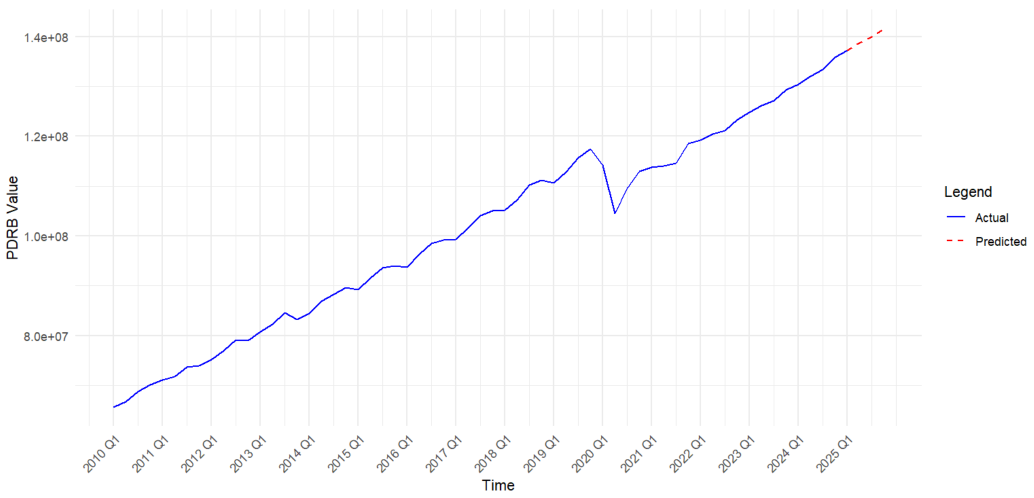


Figure 5. Plot of Actual and Forecasted GRDP at Constant Prices in Banten Province

In terms of level, the forecasted values of real Gross Regional Domestic Product (GRDP) in Banten Province exhibit a consistent quarterly upward trend, reflecting an absolute expansion of economic activity. However, from the perspective of year-on-year (Y-o-Y) growth, a gradual deceleration is observed—from 5.05% in Q2 to 4.92% in Q3, and further declining to 4.19% in Q4. This projected decline in annual growth rates, despite the continuous increase in output levels, suggests a relative weakening in the pace of economic expansion compared to the same quarters in the previous year. In macroeconomic terms, such a divergence between output levels and growth rates typically occurs when economic activity increases at a slower pace than in the corresponding period of the previous year [16].

This downward trend in growth warrants attention from policymakers, particularly in the context of maintaining regional economic resilience and stability. Several policy implications emerge:

1. Fiscal stimulus should be strategically concentrated in 2025:Q3 and 2025:Q4 to sustain economic momentum through the end of the year. Timely and targeted public expenditure has been empirically shown to have a countercyclical effect during periods of slowing growth [17].
2. Diversification of the economic base is essential, particularly by strengthening the role of trade, modern agriculture, and productive services. Reducing the province's dependency on capital-intensive and externally sensitive industrial sectors enhances its capacity to absorb external shocks [18].
3. Accelerating the realization of the regional government budget, especially capital and social spending, can stimulate aggregate demand and generate local multiplier effects. Empirical studies indicate that public investment plays a crucial role in stimulating short-term output and supporting long-term productivity [19].
4. Continuous monitoring of external indicators—such as global commodity prices, interest rate trends, and export dynamics—is critical. As an open industrial province, Banten is particularly exposed to international market fluctuations, which can significantly affect its production structure and trade performance [20].

These measures are consistent with regional development strategies that emphasize adaptive policy responses to structural and cyclical dynamics in subnational economies [21]. Strengthening institutional capacity to implement and monitor such policies is equally vital to ensure sustained and inclusive growth.

The visualization of the GRDP forecast at constant prices is presented to provide a graphical illustration of the model's capability in capturing the historical pattern of the data. This visualization is presented in **Figure 5.**

4. CONCLUSION

The application of the TVARX model in this study has successfully accommodated time-varying parameter dynamics to model and forecast the constant price GRDP of Banten Province. Based on the evaluation of various training-testing data proportions and two estimation approaches—local constant and local linear—it was found that the 90:10 data split with the local linear estimation yielded the highest prediction accuracy, with a MAPE of 0.6%. This finding indicates that utilizing the majority of historical data for model training, along with an estimation method that adapts more effectively to local dynamics (i.e., local linear), enhances the predictive performance of the TVARX model in projecting GRDP values in Banten Province.

The best-performing model was subsequently employed for out-of-sample forecasting over the next three quarters. The resulting projections may serve as an initial reference in formulating region-specific, data-driven economic strategies and policies. Practically, this study contributes a responsive time series modeling framework for forecasting regional macroeconomic indicators. Future research may expand upon this study by incorporating a broader set of exogenous variables, implementing more optimal bandwidth selection methods, and testing the applicability of the TVARX model across different regions or economic sectors. Furthermore, this model has the potential to serve as a supporting tool in evidence-based economic planning, offering not only quantitatively accurate forecasts but also sensitivity to economic uncertainty dynamics.

Funding Information

Authors state no funding involved.

Conflict Of Interest Statement

Authors state no conflict of interest.

Data Availability

The data used in this study are derived from open sources and are publicly accessible. The GRDP at constant prices, HFCE (Household Final Consumption Expenditure), GFCF (Gross Fixed Capital Formation), and export values were obtained from the Badan Pusat Statistik Banten Province (https://banten.bps.go.id). *In addition*, exchange rate data were accessed through the Bank Indonesia portal (https://www.bi.go.id).

REFERENCES

[1] Badan Pusat Statistik Provinsi Banten, "Buku Saku Produk Domestik Regional Bruto (PDRB) Provinsi Banten, PDRB Kabupaten/Kota se-Provinsi Banten, PDRB Provinsi se-Pulau Jawa, dan PDB Indonesia 2023 and 2024," Badan Pusat Statistik Provinsi Banten, Serang, 2025.

[2] F. Blasques, A. C. Harvey, S. J. Koopman and A. Lucas, "Time-Varying Parameters in Econometrics: The editor's foreword," *Journal of Econometric,* vol. 237, no. 2, pp. 1-3, 2023.

[3] Z. Jia, W. Li, Y. Jiang and X. Liu, "The Use of Minimization Solvers for Optimizing Time-Varying Autoregressive Models and Their Applications in Finance," *Mathematics,* vol. 13, no. 14, pp. 1-20, 2025.

[4] P. Paul, "The Time-Varying Effect of Monetary Policy on Asset Prices," *The Review of Economics and Statistics,* vol. 102, no. 4, pp. 690-704, 2020.

[5] G. Plesa, "State-Dependent and Time-Varying Effects of Monetary Policy," *Eastern European Economics,* pp. 1-24, 2025.

[6] D. O. Olayungbo, "Effects of oil export revenue on economic growth in Nigeria: A time varying analysis of resource curse," *Resources Policy,* vol. 64, 2019.

[7] J. Fan and I. Gijbels, Local Polynomial Modelling and Its Applications, New York: CHAPMAN & HALL/CRC, 1996.

[8] D. Kristensen and Y. J. Lee, "Local Polynomial Estimation of Time-Varying Parameters in Nonlinear Models," *arXiv,* pp. 1-42, 2023.

[9] G. E. P. Box, G. M. Jenkins, G. C. Reinsel and G. M. Ljung, Time Series Analysis : Forecasting and Control, New Jersey: John Wiley & Sons, Inc., 2016.

[10] P. Qin, R. Nishii, T. Nakagawa and T. Nakamoto, "ARX Models for Time-Varying Systems Estimated by Recursive Penalized Weighted Least Squares Method," *Journal of Math-for-industry,* vol. 2, no. A, pp. 109-144, 2010.

[11] J. Gao, P. Silvapulle and D. Li, "Nonparametric Estimation and Forecasting for Time-Varying Coefficient Realized Volatility Models," *Journal of Business & Economic Statistics,* vol. 34, no. 1, pp. 1-39, 2016.

[12] R. F. Byrne, "Beyond Traditional Time-Series: Using Demand Sensing to Improve Forecasts in Volatile Times," *Journal of Business Forecasting,* vol. 31, no. 2, p. 13, 2012.

[13] C. D. Lewis, "Industrial and business forecasting methods," *Journal of Forecasting,* vol. 2, no. 2, pp. 194-196, 1982.

[14] H. Lütkepohl, New Introduction to Multiple Time Series Analysis, New York: Springer, 2005.

[15] I. Gijbels, A. Pope and M. P. Wand, "Understanding Exponential Smoothing via Kernel Regression," *Journal of the Royal Statistical Society,* vol. 61, no. 1, pp. 39-50, 1999.

[16] O. Blanchard and D. R. Johnson, Macroeconomics (7th ed.), New York: Pearson, 2017.

[17] A. J. Auerbach and Y. Gorodnichenko, "Measuring the Output Responses to Fiscal Policy," *American Economic Journal: Economic Policy,* vol. 4, no. 2, pp. 1-27, 2012.

[18] R. Hausmann, J. Hwang and D. Rodrik, "What You Export Matters," *Journal of Economic Growth,* vol. 12, no. 1, pp. 1-25, 2007.

[19] R. J. Barro and X. Sala-i-Martin, Economic Growth (2nd ed.), Cambridge: MIT Press, 2004.

[20] D. Rodrik, "Who Needs Capital-Account Convertibility?," in *Essays in International Finance*, Princeton University, 1998.

[21] World Bank, "Reshaping Economic Geography," World Development Report, 2009.