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Unveiling Regional Growth Patterns: Spatial Heterogeneity and Infrastructure Quality under a Bayesian Framework in Central Java

By:
Suripto[1*)], Agus Salim[1)], Mahrus Lutfi Adi Kurniawan[1)], Uswatun Khasanah[1)], Azkal Azkiya Athfal[2)]
[1)]Faculty of Economics and Business, Ahmad Dahlan University
[2)]Faculty of Engineering, Department of Nuclear Engineering and Engineering Physics, Universitas Gadjah Mada
[*)]Corresponding Author: aulia.rahman@uin-alauddin.ac.id

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ABSTRACT: This study investigates the impact of infrastructure quality, including roads, the distribution of clean water, and electricity consumption, on regional economic growth in Central Java from 2018 to 2024. A Bayesian Panel-Data Regression model with a hierarchical structure was estimated using the Markov Chain Monte Carlo (MCMC) method, implemented in Python, to address spatial heterogeneity, lag effects, and parameter uncertainty. Model validation ultilized Posterior Predictive Checks (PPC), Bayesian R^2, R-hat statistics, and Effective Sample Size (ESS). The results indicate that past GRDP significantly influences current regional economic growth, while the direct effects of infrastructure variables are statistically insignificant. These results highlight that infrastructure quality is more important than quantity in promoting development. This study enhances empirical approaches by integrating full posterior inference with predictive validation, representing a state-of-the-art approach in regional economic analysis. The results provide strong evidence for formulating infrastructure policies that focus on long-term, sustainable Growth
Keywords: Bayesian Panel Data Regression; Spatial Heterogeneity; Markov Chain Monte Carlo (MCMC); Posterior Predictive Check (PPC)

ABSTRAK: *Penelitian ini mengkaji pengaruh kualitas infrastruktur, meliputi jalan; distribusi air bersih, dan konsumsi listrik, terhadap pertumbuhan ekonomi regional di Jawa Tengah pada periode 2018–2024. Model Bayesian Panel Data Regression dengan struktur hierarkis diestimasi menggunakan metode Markov Chain Monte Carlo (MCMC) dengan berbantuan program Python untuk menangani heterogenitas spasial, efek keterlambatan, dan ketidakpastian parameter. Validasi model dilakukan menggunakan; Posterior Predictive Check (PPC), Bayesian* R^2*, statistik R-hat, dan Effective Sample Size (ESS). Hasil penelitian menunjukkan bahwa GRDP masa lalu berpengaruh signifikan terhadap pertumbuhan ekonomi saat ini, sementara pengaruh langsung variabel infrastruktur tidak signifikan, hal ini menegaskan bahwa kualitas infrastruktur lebih penting daripada kuantitasnya. Penelitian ini memperkaya metodologi empiris dengan mengintegrasikan inferensi posterior penuh dan validasi prediktif, mewakili pendekatan terkini (state-of-the-art) dalam analisis ekonomi regional. Temuan ini memberikan bukti kuat bahwa sebaiknya perumusan kebijakan infrastruktur berbasis pertumbuhan jangka panjang.*
Kata Kunci: *Regresi Data Panel Bayesian; Heterogenitas Spasial; Markov Chain Monte Carlo (MCMC); Pemeriksaan Prediktif Posterior (PPC); Kualitas Infrastruktur*

INTRODUCTION

Regional economic growth is shaped by the availability and quality of infrastructure, particularly road networks, clean water distribution, and electricity supply. Infrastructure acts as both a production input and a catalyst that reduces logistics costs, improves mobility, and supports productivity. Evidence from China shows that aligning human capital policies with infrastructure development strengthens regional spillovers (Ross & Fleming, 2023), while strategic coordination is essential because cross-border integration is difficult in geographically fragmented regions (Gao et al., 2025; Haga, 2021). Central Java illustrates these challenges, as disparities remain between districts in road quality, where areas such as Blora, Grobogan, and Wonogiri still rely heavily on lower-class road segments, while Semarang and Kudus have more developed networks. Access to clean water also varies, with coverage in Pekalongan, Pemalang, and Purbalingga below the provincial average, and electricity consumption shows similar gaps, with industrial zones around Semarang Raya and Kudus far exceeding agrarian regions like Banjarnegara and Wonosobo. These conditions raise a critical question on whether infrastructure expansion in Central Java can effectively promote economic growth when quality, connectivity, and access remain uneven across regions.

The empirical literature shows mixed results regarding the contribution of infrastructure to economic performance. The role of infrastructure in supporting the acceleration of regional economic growth has been researched by (Khurriah & Istifadah, 2019) and (Negara, 2016) which emphasise the importance of infrastructure as the primary foundation for sustainable economic growth and fostering the absorption of resources owned by the regions, while research (Ghufron & Bustomi, 2022; Reski & Wirjodirjo, 2021) emphasised that the quality and connectivity of strategic infrastructure determines the quality of regional economic growth more than building new infrastructure just a physical expansion. Evidence of the importance of infrastructure in spurring economic growth in China was examined by (Guo et al., 2023) found that there is an overflow effect of transportation infrastructure in China on inter-provincial growth connectivity connected by the existence of infrastructure built in a multi-effect manner, while Studies (Wang et al., 2022) shows that the quality and integration of the infrastructure built is more important than the length or size of its capacity. Other research studies such as (Calderón & Servén, 2010a, 2010c) and (Foster & Briceño-Garmendia, 2010) have found that infrastructure has an important impact on increasing regional productivity, recent research such as (Banerjee et al., 2020; Iziga & Takagi, 2023) emphasised the importance of quality, governance, and equitable distribution of infrastructure as determinants of the magnitude of the impact on economic growth in a region.

Although the literature continues to advance, a significant research gap persists in understanding how infrastructure shapes regional economic growth in Indonesia's provincial contexts, particularly in Central Java, where spatial heterogeneity remains pronounced. Empirical reports from BPS indicate persistent disparities in infrastructure quality across districts; road conditions in Blora, Grobogan, and Rembang still show a high share of damaged or lower-class segments, while urban areas such as Semarang and Surakarta have more developed and well-maintained networks. Access to piped water varies widely, with coverage in Pemalang, Purbalingga, and Pekalongan consistently below the provincial average, and electricity consumption per capita in agrarian regions such as Wonosobo and Banjarnegara remains far lower than in industrial centers like Kudus and Semarang, reflecting unequal integration into productive sectors. Previous studies at the national level highlight similar disparities, noting that infrastructure gaps across Indonesian regions continue to constrain local growth potential (Khurriah & Istifadah, 2019; Nugraha et al., 2020) However, most of these studies rely on classical econometric approaches that overlook non-linearity, lag structures, and parameter uncertainty. Only a limited number of works apply Bayesian panel frameworks capable of capturing full posterior distributions and probabilistic inferences that reflect dynamic temporal processes, despite their growing relevance in modelling spatial and temporal complexities influenced by evolving infrastructure conditions (Moghbel et al., 2025; Thach, 2025).

The selection of Central Java Province as the research location is grounded in its strategic position as a major economic hub on the island of Java, connecting West Java, Yogyakarta (DIY), and East Java. Despite this strategic role, Central Java exhibits substantial intra-provincial disparities in development.

Industrial clusters in Semarang, Kudus, and Jepara contrast sharply with predominantly agrarian districts such as Banjarnegara, Blora, and Wonogiri, where infrastructure conditions remain relatively weak. BPS records show that, between 2018 and 2024, improvements in road length, clean water distribution, and electricity consumption occurred but were distributed unevenly; road quality in Blora and Grobogan remains among the lowest in the province, access to piped clean water in Pemalang and Purbalingga still falls below the provincial average, and electricity utilisation in Wonosobo and Banjarnegara remains significantly lower than in productive industrial areas. These disparities reinforce earlier observations that Central Java faces structural infrastructure challenges, which makes it an appropriate case for analysing how variations in infrastructure quality and quantity shape regional economic growth dynamics.

This study aims to fill this gap by applying *a hierarchically structured Bayesian Data Panel Regression* to analyse the relationship between infrastructure and economic growth in 35 districts/cities in Central Java during the period 2018–2024. The novelty of the research lies in the integration of spatial heterogeneity, lag effects, and parameter uncertainty in a Bayesian framework, with model validation using Posterior Predictive Checks (PPC), Bayesian R^2, R-hat statistics, and Effective Sample Size (ESS). In contrast to the previous study, this study yields more robust parameter estimation and dynamic predictive validation, thereby strengthening methodological standards in regional economic studies.

The purpose of this research is to have two main objectives. First, to assess empirically the extent to which the quality and expansion of infrastructure in Central Java Province contribute to regional economic growth by taking into account historical dependencies reflected in dynamic time elements. Second, it makes a methodological contribution by incorporating a dynamic model of the data panel, utilising Bayesian inference, to analyse regional economic dynamics and the complexity of external influences of infrastructure variables in districts/cities of the Central Java province. Through this dual contribution, the research is expected to provide policymakers with input to formulate infrastructure investment strategies that focus on quality, connectivity, and long-term sustainability, rather than just physical expansion, which can sometimes have an unreal impact on the economy (Enimola, 2011; B. Sun & Kauzen, 2023).

METHODS

This study uses panel data comprising 35 districts and cities in Central Java (i) with seven annual observations for each unit (T), forming a balanced panel for the 2018–2024 period. The primary data were obtained from official BPS publications, including Gross Regional Domestic Product (GRDP) at 2010 constant prices, road length, clean water distribution volume, electricity consumption, the number of educational facilities, and the number of healthcare facilities. Electricity, education, and health variables are included as independent variables because they represent essential components of regional productive capacity. Electricity reflects the intensity of industrial and household economic activities and often correlates with local economic performance. Education and health facilities capture human capital availability, which directly influences labour productivity and long-term growth. Their inclusion aligns with empirical studies showing that physical infrastructure and human capital jointly determine regional development outcomes (Baltagi et al., 2022; Ma et al., 2021; J. Zhang et al., 2022). All variables are transformed into natural logarithms to stabilise variance, reduce outlier influence, and allow coefficient interpretation in elasticity form.

Research Model

The model used is *Bayesian Dynamic Panel Regression* with the following basic form:

$$lnGRDP_{it} = \alpha + \beta 1 lnGRDP_{it-1} + \beta 2 lnROAD_{it} + \beta 3 lnWATER_{it} + \beta 4 lnELECTRICITY_{it} + \beta 5 lnEDUCATION_{it} + \beta 6 lnHEALTH_{it} + \varepsilon_{it} \quad (1)$$

where i indicates the district/city unit and t indicates the year of observation. Variables are used to capture the effects of economic growth dynamics (path dependence). Estimation is carried out using the Bayesian method through $lnGRDP_{it-1}$ *the Markov Chain Monte Carlo* algorithm (MCMC. The operational definition of the observed variables is summarized in Table 1 as follows:

Table 1. Operational Definition of Variables

Variable Name	Definition	Measurement Unit	Function in the Model
GRDP	GDP in Regencies/Cities in Central Java Province based on Constant Prices 2010 by Business Field	Million Rupiah (IDR)	Dependent Variable (ln_GRDP)
ROAD	Total length of regency/municipal roads	Kilometres (Km)	Independent Variable (ln_ROAD)
WATER	Total distribution of clean water	Cubic Meters (M^3)	Independent Variable (ln_WATER)
ELECTRICITY	Total electricity consumption	Kilowatt Hours (KWH)	Independent Variable (ln_ELECTRICITY)
HEALTH	Total number of healthcare facilities (such as hospitals, clinics, and community health centres) in each district/city	Number of units (count)	Independent Variable (ln_HEALTH)

Source: Processed by the author based on infrastructure and GRDP panel data from Statistics Indonesia (BPS), 2018–2024.

The assessment of the validity of the Bayesian model begins with evaluating the Goodness of Fit as well as the collective validation of the model through the Bayesian R-squared estimation and credible intervals of the model parameters. This initial step aims to determine the extent to which the model can explain the variability of observational data, as well as assess the contribution of each parameter to the dependent variables (Asgharian et al., 2017; Gelman, Goodrich, et al., 2019). After evaluating its goodness, the validation process continued with a series of diagnostic tests, including Markov chain convergence checks, practical sample size analysis, interchain variance stability, posterior predictive checks on the observed data, sensitivity analysis of prior assumptions, and autocorrelation assessment in the simulation chain. Each stage aims to ensure that the model estimation meets the principles of robustness, inferential accuracy, and validity, particularly in dealing with the complexity of dynamic panel data structures (Ahn & Hambusch, 2024; Du et al., 2022).

Estimation Approach

The approach used is Bayesian Panel Data Regression with a hierarchical structure. This method was selected because it captures spatial heterogeneity, lag effects, and parameter uncertainty more comprehensively than classical econometric approaches. Estimation relies on the Markov Chain Monte Carlo (MCMC) framework, which combines two key components: the Markov Chain mechanism, where each simulated draw depends only on the previous state to gradually approximate the target posterior distribution, and the Monte Carlo algorithm, which generates repeated random samples to approximate complex posterior moments that cannot be solved analytically. This iterative sampling process enables the model to explore the posterior distribution efficiently and yields stable estimates even under multicollinearity, temporal dependence, and dynamic interactions among infrastructure variables (Kuschnig, 2022; Y. Sun et al., 2020). Bayesian inference also integrates lag information to stabilise parameter estimates, making it particularly suitable for analysing regional dynamics involving interdependent infrastructure systems (B. Sun & Kauzen, 2023; Tadesse & Thiam, 2021). The detailed steps of the MCMC procedure used in this study, including convergence diagnostics and posterior predictive checks, are presented in the Appendix for technical reference.

Model Validation

Model validation was tested through several main steps: (i) goodness of fit evaluation using Bayesian R^2, (ii) MCMC chain convergence check with traceplot and R-hat statistics, (iii) Effective Sample Size (ESS) measurement, and (iv) Posterior Predictive Check (PPC) test to compare the actual data distribution with the model's predicted results. This validation approach follows recent Bayesian modelling research (Baltagi et al., 2022; Nguyen et al., 2022; L. Zhang et al., 2022). Technical details, including the Bayesian R^2 mathematical formulation, convergence assays, autocorrelation, and MCMC diagnostic formulas, are presented in full in the Appendix to make the main flow of discussion more concise and focus on substantive results.

RESULTS AND DISCUSSION

Table 2 presents the core results of the Bayesian Panel Data regression analysis, capturing the estimated effects of key infrastructure variables and lagged GRDP on regional economic growth across districts and municipalities in Central Java. The posterior mean and median estimates, along with the 95% credible intervals, offer a probabilistic interpretation of the modelled relationships, reflecting the uncertainty inherent in parameter estimation. The Bayesian R-squared reported in the table serves a dual function: it measures the model's goodness of fit to the observed data and simultaneously functions as an overall indicator of model significance, effectively replacing the traditional F-test commonly used in classical regression frameworks. The estimation was performed using Python, employing the Pandas library to prepare the datasets for regression analysis, manage variable transformations, and generate graphical visualisations of the relationships between infrastructure indicators and economic growth. This integration of Python's data science capabilities streamlined the analytical workflow, ensuring precision in both the estimation and the presentation of the results. Table 2 presents the finalised estimation output, which serves as the empirical foundation for interpreting the dynamic contributions of infrastructure development to regional economic growth.

Table 2. Bayesian Panel Data Regression Results with Bayesian R-squared

Variables	Posterior Mean Estimate	Posterior Median Estimate	Lower Bound (95% Credible Interval)	Upper Bound (95% Credible Interval)
const	2.4681	2.4735	1.1582	3.7521
ln-GRDP_lag	0.8643	0.864	0.7975	0.9321
ln-ROAD	-0.0203	-0.0202	-0.0514	0.0113
ln-WATER	0.01	0.0099	-0.0156	0.0366
ln-ELECTRICITY	-0.0005	-0.0005	-0.0183	0.0174
ln-EDUCATION	0.0368	0.0365	0.0042	0.0764
ln-HEALTH	0.0241	0.0240	0.0075	0.0569
Bayesian R-squared	0.879			

Source: Processed by the author based on infrastructure and GRDP panel data (BPS Indonesia, 2018–2024).

Goodness-of-Fit Evaluation

The goodness-of-fit evaluation for the Bayesian dynamic panel regression model in this study is conducted using the Bayesian R-squared as the primary indicator of goodness of fit. The obtained Bayesian R^2 value of 0.879 indicates that approximately 87.9% of the variation in the logarithm of the Gross Regional Domestic Product (GRDP) is explained by the combination of independent variables included in the model, namely lagged GRDP, road length, clean water distribution volume, electricity consumption, the number of educational facilities, and the number of healthcare facilities. Studies with classical Bayesian methods suggest that Bayesian R^2 on hierarchical models and dynamic panels provides a more informative evaluation than classical $\mathrm{R}^2_{\mathrm{Bayes}}$ (Gelman, Carlin, et al., 2019). This high goodness-of-fit suggests that the dynamic interaction of infrastructure variables significantly contributes to the variation in regional economic growth. Model accuracy in explaining variability is crucial in dynamic panel analysis, where temporal dependencies and inter-variable relationships are structurally significant factors. The Bayesian approach enables a more comprehensive evaluation by considering parameter uncertainty within a comprehensive inferential framework, resulting in a more robust interpretation compared to traditional Frequentist methods.

Overall Model Significance Testing

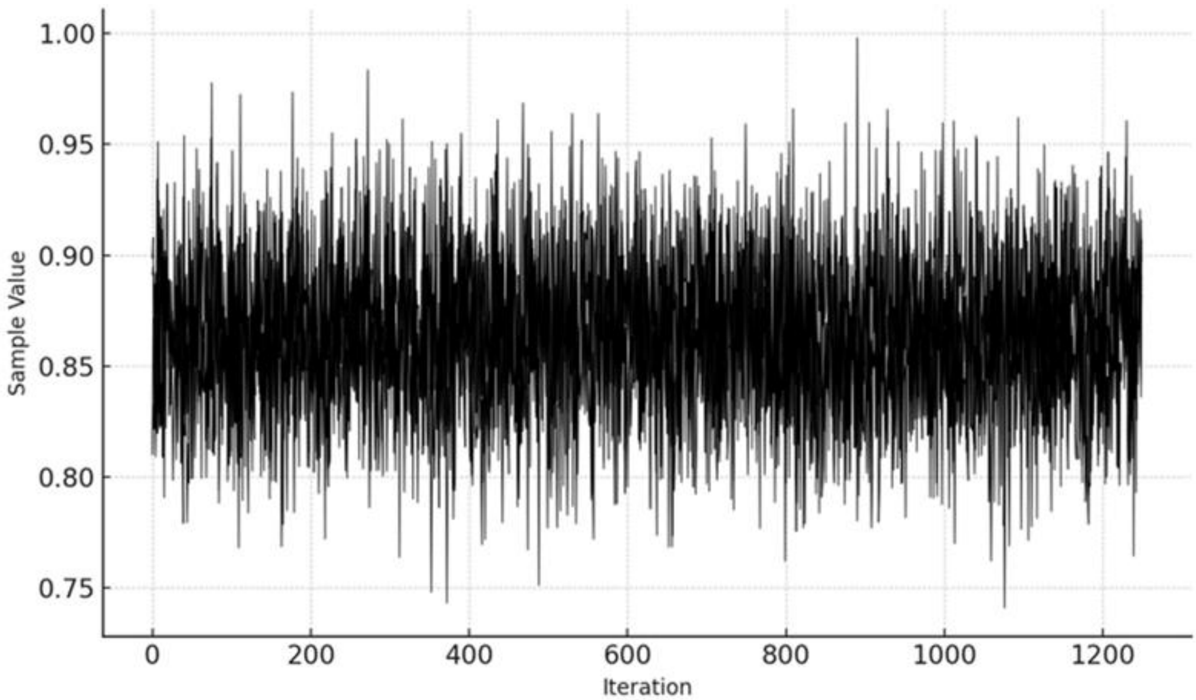
The Bayesian $\mathrm{R}^2_{\mathrm{Bayes}}$ value of 0.879 indicates that the model explains a large share of the variation in GRDP, and the pattern of credible intervals provides a clear distinction between parameters that are statistically identified and those that remain uncertain. The estimate for lagged GRDP lies entirely above zero. This outcome supports the presence of output persistence that is widely recognized in regional growth dynamics and Bayesian autoregressive models (Moral-Benito, 2013). The infrastructure indicators, which include road length, clean water distribution, and electricity consumption, have credible intervals that cross zero. This result reflects a high degree of posterior uncertainty and suggests that the marginal effects of these variables cannot be confirmed within the time span of the data. Earlier studies show that infrastructure tends to influence growth over longer periods or under institutional conditions that allow these effects to materialize more clearly (Correa et al., 2025). The education and health variables show positive posterior means, and their credible intervals lie entirely above zero. This confirms that both dimensions of human capital exert statistically significant positive effects on GRDP. The result aligns with evidence that links improvements in education and public health to higher productivity and stronger regional development (Teixeira & Queir??s, 2016). The configuration of results indicates that human capital and GRDP persistence play central roles in shaping regional economic performance within the Bayesian framework.

The overall configuration of results highlights GRDP persistence as the central driver of regional economic performance within the Bayesian framework. The infrastructure and human capital variables may require a longer temporal series or greater spatial variation before their marginal effects can be estimated with higher precision. This approach highlights that in the Bayesian framework, the assessment of overall model significance is not reliant on a single global statistic (such as an F-test) but instead on the combined interpretation of predictive strength (Bayesian R^2) and the significance of individual parameters (credible intervals). These findings are consistent with recent methodological literature that emphasises the Bayesian approach offers a richer and more reflective inferential interpretation of model uncertainty (Kruschke, 2018; Vehtari et al., 2021).

Convergence Diagnostic (MCMC Diagnostics)

Convergence evaluation in the Bayesian Panel Data model analysis is a critical step aimed at ensuring that the Markov Chain Monte Carlo (MCMC) sampling process has reached a stable and representative posterior distribution. Achieving good convergence is essential for producing valid and reliable parameter inferences that can support subsequent empirical interpretations. In this study, convergence was assessed using two primary indicators: Traceplot Analysis and the Gelman-Rubin Diagnostic (R-hat Statistic). Trace plots were employed to visualise the movement of sampled parameter values across MCMC iterations. They depict the dynamics of the sampling chains, where stationary patterns indicate good convergence, characterised by the absence of systematic upward or downward trends and consistent random fluctuations across iterations.

In this context, the trace plot displayed corresponds to the lagged GRDP parameter (ln_GRDP_lag), which was selected due to its critical role in determining the dynamics of regional economic growth within the analysed model.



Source: Processed from Bayesian Panel Data Regression Results, based on panel data (BPS Indonesia, 2018–2024).

Figure 1. Traceplot of Lag GRDP (ln_GRDP_lag).

Figure 1 illustrates the trace plot for the lagged GRDP parameter (ln_GRDP_lag) obtained through the MCMC sampling process in the Bayesian Panel Data Regression model. The sampled values exhibit random and stationary fluctuations throughout the iterations, without any discernible systematic trends. This movement pattern indicates that the sampling process successfully reached a stable posterior distribution (Albert et al., 2025; Gelman, Goodrich, et al., 2019; Vehtari et al., 2021). The even distribution of sampled values and the consistent fluctuation patterns across iterations further confirm the absence of sampling bias or non-convergence. The presence of such a stable trace plot pattern provides strong evidence that the estimation of the lagged GRDP parameter is representative of the actual posterior distribution. This stability forms a critical foundation for ensuring that the empirical inferences drawn from the model are statistically reliable (De Sisto et al., 2024; Yankey et al., 2024). Furthermore, this visual evidence from the trace plot is supported by the R-hat statistics, which approached one for all estimated parameters, reinforcing the conclusion that the Bayesian Panel Data Regression model successfully achieved full convergence.

Thus, the interpretation of the lagged GRDP coefficient and other model parameters can be conducted with a high level of confidence, strengthening the overall validity of the research findings. The selection of the lagged GRDP trace plot is based on the strategic importance of this Variable in explaining the dynamic relationship between past and present economic conditions. The trace plot for this parameter shows stable fluctuations and an even spread of sampled values across the chains, indicating that the MCMC process achieved good convergence. Additional inspections of the trace plots for all other model parameters were also conducted and exhibited similar stable patterns; however, for the sake of reporting efficiency, only the trace plot for the lagged GRDP parameter is presented here.

Adequate Sample Size (ESS)

Table 3 presents the Effective Sample Size (ESS) for each parameter estimated in the Bayesian Panel Data Regression model. ESS is used to evaluate the extent to which the Markov Chain Monte Carlo (MCMC) sampling process produces effective and independent samples. Assessing the ESS is a critical step to ensure that parameter estimations are based on a sufficiently representative number of effective samples, thereby supporting the validity of inferences within the Bayesian analytical framework.

Table 3. Effective Sample Size (ESS) for Each Parameter

Parameter	Effective Sample Size (ESS)
Intercept (const)	5000
Lag GRDP (ln-GRDP-lag)	4875.508
Road Infrastructure (ln-ROAD)	3505.328
Water Infrastructure (ln-WATER)	5000
Electricity Distribution (ln-ELECTRICITY)	4749.248
Education (ln-EDUCATION)	4988.361
Health (ln-HEALTH)	4927.544

Data Source. Processed from Bayesian panel data of infrastructure and GRDP (BPS Indonesia, 2018–2024).

Effective Sample Size (ESS) serves as a quantitative indicator to assess the number of independent samples obtained from the Markov Chain Monte Carlo (MCMC) sampling process (Armelloni et al., 2025). A higher ESS value reflects lower autocorrelation between iterations, ensuring that each sample contributes new, independent information to the parameter estimation. In the Bayesian Panel Data Regression model estimated in this study, all parameters recorded ESS values that significantly exceed the minimum standard threshold of 400 effective samples recommended in the modern Bayesian literature (Gelman, Vehtari, et al., 2021). Specifically, the intercept parameter achieved an ESS of 5000, the lagged GRDP parameter recorded an ESS of 4875.5081, road infrastructure (ln-ROAD) reached 3505.3282, water infrastructure (ln-WATER) achieved an ESS of 5000, and electricity distribution (ln-ELECTRICITY) registered an ESS of 4749.2475. These results demonstrate that the sampling process produced high-quality independent draws, ensuring the stability of credible intervals and the precision of posterior estimates. The consistently high ESS values across all parameters reinforce confidence that the MCMC sampling process operated optimally. Consequently, statistical inferences drawn from the model's results can be made with a high degree of confidence, thereby supporting the overall validity of the study's findings.

R-hat Statistic (Gelman-Rubin Diagnostic)

Table 4 presents the R-hat statistics for each parameter estimated in the Bayesian Panel Data Regression model. The R-hat statistic, also known as the Gelman-Rubin diagnostic, is a key metric for evaluating the convergence of Markov Chain Monte Carlo (MCMC) simulations. It measures the consistency between multiple MCMC chains by comparing the variance within chains to the variance between chains. Assessing R-hat values is essential to ensure that the sampling process has successfully converged to the target posterior distribution, thereby validating the reliability of the parameter estimates derived from the model.

Table 4. R-hat Statistic for Each Parameter

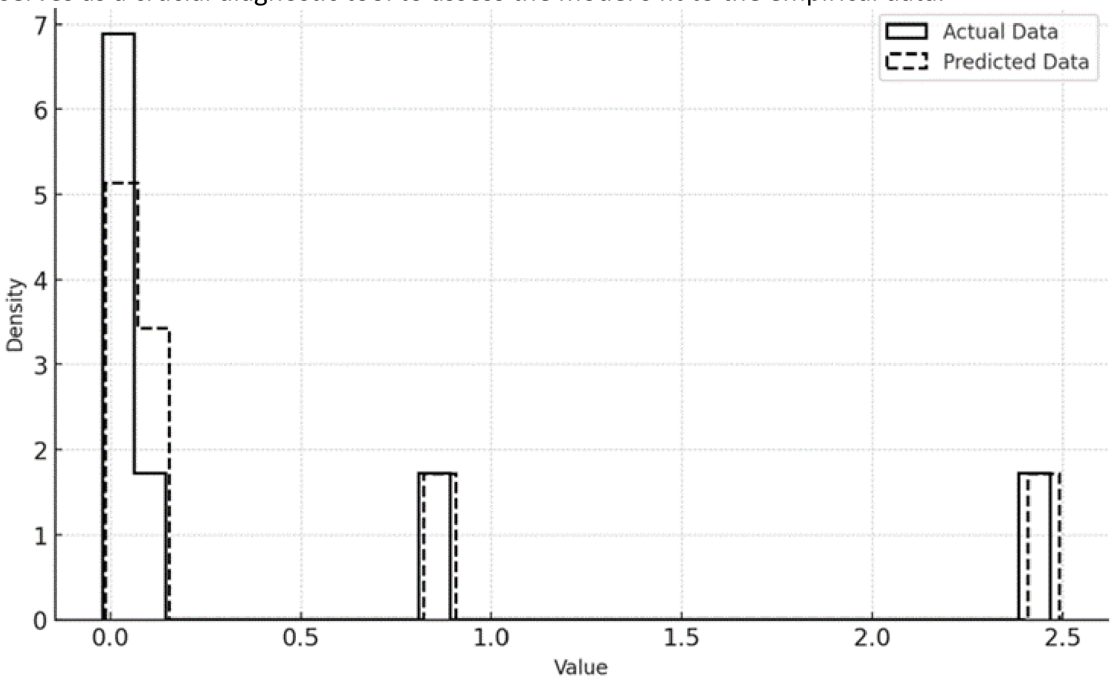
Parameter	R-hat Value
Intercept (const)	0.9997
Lag GRDP (ln-GRDP-lag)	1.0001
Road Infrastructure (ln-ROAD)	1.0002
Water Infrastructure (ln-WATER)	0.9999
Electricity Distribution (ln-ELECTRICITY)	0.9999
Education (ln-EDUCATION)	1.0000
Health (ln-HEALTH)	0.9998

Data Source. Processed from Bayesian panel data of infrastructure and GRDP (BPS Indonesia, 2018–2024).

Convergence evaluation in the Bayesian model using the R-hat statistic is a standard practice in inference analysis based on Markov Chain Monte Carlo (MCMC) methods. The R-hat statistic is specifically designed to detect discrepancies between within-chain variance and between-chain variance, aiming to assess the extent to which chains have mixed and approached the actual posterior distribution. According to De Sisto et al. (2024) and Vehtari et al. (2021), an improved version of R-hat was developed through rank normalisation and folding techniques to enhance sensitivity in detecting non-convergence. They emphasise that R-hat values below 1.1 serve as indicators of adequate convergence in Bayesian inference. Other research reinforces the requirement that R-hat values close to one are essential for sampling results to be considered a valid representation of the described sample close to its population (Amirkhiz et al., 2023). The presence of consistently low and stable R-hat values strengthens the credibility of the posterior results, making this evaluation an integral part of contemporary Bayesian Panel Data Regression analysis. Based on the estimation results presented in Table 4, all parameters exhibit R-hat values extremely close to 1, ranging between 0.9997 and 1.0002. Specifically, the intercept (const) has an R-hat value of 0.9997, the lagged GRDP (ln-GRDP-lag) shows 1.0001, road infrastructure (ln-ROAD) records 1.0002, water infrastructure (ln-WATER) is at 0.9999, and electricity distribution (ln-ELECTRICITY) stands at 0.9999. These results provide strong evidence that the MCMC sampling chains have fully converged for all parameters, validating the reliability of posterior estimates and reinforcing the robustness of the inferential conclusions drawn from the model.

Posterior Predictive Check (PPC)

Figure 2 illustrates the Posterior Predictive Check (PPC) conducted to assess the model's ability to replicate the observed data distribution. PPC is a fundamental validation tool in Bayesian analysis, providing a graphical comparison between the actual data and the data predicted by the model. By visually evaluating the similarity between the distributions of observed and predicted values, the PPC serves as a crucial diagnostic tool to assess the model's fit to the empirical data.



Source: Processed by the author based on infrastructure and GRDP panel data (BPS Indonesia, 2018–2024).

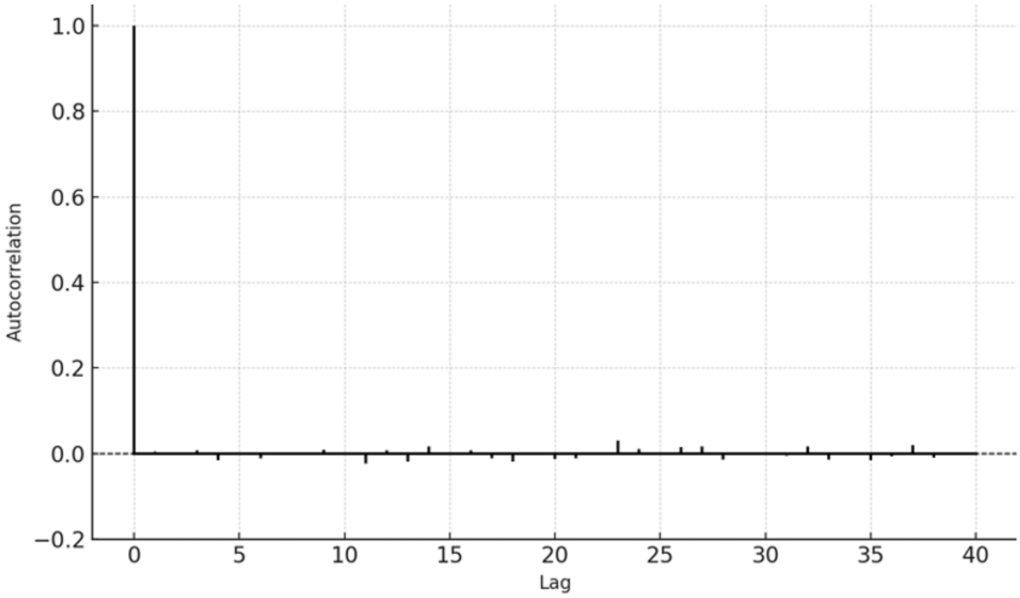
Figure 2. Posterior Predictive Check (PPC) from Bayesian Panel Data Regression (BPS Indonesia, 2018–2024).

The validity of the Bayesian Panel Data Regression model was assessed through a Posterior Predictive Check (PPC), which aimed to evaluate how well the model replicates the distributional characteristics of the observed data. The PPC process generates a predictive distribution based on posterior parameters, which is then compared against the observed data distribution to detect potential matches or mismatches between the model and the actual data.

The visualisation results presented in Figure 2 demonstrate a strong correlation between the predicted and actual data distributions. The close similarity in the shape of the density curves indicates that the model has successfully captured the main structure of the observed data. The absence of significant deviations in the distribution patterns further reinforces the evidence that the model possesses strong generalisation capabilities and is not prone to overfitting or underfitting. This quality is crucial for ensuring the statistical validity of subsequent inferences. The application of Posterior Predictive Check in this study follows the principles outlined by De Sisto et al. (2024) and N. Liu & Su (2025), who emphasise that PPC is a critical stage in the Bayesian workflow for detecting model inadequacies that traditional goodness-of-fit measures may not capture. Additional support comes from Yao et al. (2018), who advocate that Bayesian models must be validated through predictive data simulation to confirm their predictive accuracy on new data. The observed consistency between the actual and predicted distributions in this study demonstrates that the Bayesian Panel Data Regression model has successfully passed the posterior predictive validation test, allowing the results to be interpreted with high confidence.

Autocorrelation of Chains

Autocorrelation analysis is a fundamental diagnostic tool in Bayesian inference, used to evaluate the degree of dependence between successive iterations in a sampling chain. Assessing autocorrelation helps determine the efficiency of the sampling process, where lower autocorrelation levels indicate a higher number of effectively independent samples, thus improving the reliability of posterior estimates.



Source: Processed by the author based on infrastructure and GRDP panel data (BPS Indonesia, 2018–2024).

Figure 3. Autocorrelation Plot of Lagged GRDP, BPS Indonesia (2018–2024).

The autocorrelation plot in Figure 3 for the lag GRDP variable (ln-GRDP-lag) shows that the autocorrelation value decreased sharply towards zero in the first 10–20 lags. This pattern shows that the Markov Chain Monte Carlo (MCMC) chain has achieved adequate mixing and produced relatively independent samples at each iteration. The absence of persistent short-term autocorrelation indicates that each iteration provides new information for parameter inference, in line with modern Bayesian guidelines that emphasise the importance of low autocorrelation as an indicator of model quality (Chib & Carlin, 1999; Murray et al., 2022). Thus, the model is considered free of significant autocorrelation issues, and the resulting Effective Sample Size (ESS) can be seen as representing the actual number of independent samples. These findings strengthen the validity and reliability of the Bayesian Panel Data Regression model used in this study (Lanfear et al., 2016).

Interpretation of the Bayesian Panel Data Regression Model

The estimation results of the Bayesian Panel Data Regression model presented in Table 2 illustrate the dynamics of the relationship between infrastructure and GRDP growth in Central Java during the 2018–2024 period. The estimated intercept of 2.4681 has a 95 percent credible interval ranging from 1.1582 to 3.7521. This coefficient should not be interpreted as a percentage or a monetary amount because the model employs the natural logarithm of GRDP. The intercept therefore represents the baseline log-GRDP level when all explanatory variables are at their reference values, rather than a direct economic unit. Its statistical significance indicates that regional economies retain a positive underlying GRDP level even after accounting for infrastructure and other included covariates. This baseline reflects the combined contribution of structural factors such as private investment, human capital availability, technological adoption, and the effectiveness of regional fiscal management, which aligns with previous empirical findings on the determinants of regional economic performance (De Sisto et al., 2024; Nugraha et al., 2020). The result reinforces the view that regional economic development is shaped not only by infrastructure expansion but also by institutional and productive-sector capacities.

The lagged GRDP variable (ln-GRDP-lag) has a coefficient of 0.8643, with a credible interval that does not include zero, reinforcing the existence of historical dependence in regional economic growth patterns. The endogenous growth mechanism explains that past output drives future growth through repeated investment cycles, capital accumulation, improvements in productive capacity, and organisational learning (Growiec, 2022; Romer, 1986; Suparman & Muzakir, 2023). For example, the cities of Semarang and Kudus, as manufacturing hubs, exhibit sustained productive accumulation over time, where higher past output enhances the attractiveness of new investment and expands production capacity.

Although the estimated coefficient for road infrastructure is −0.0203, the 95 percent credible interval ranges from −0.0514 to 0.0113. The interval crosses zero, which means that the direction of the effect cannot be determined with statistical certainty. The posterior distribution still assigns probability to both positive and negative effects, indicating that the marginal impact of road length is not statistically identified. Therefore, the lack of significance follows directly from the Bayesian credible interval in Table 2. The lack of significance can be attributed to the fact that not all roads constructed offer sufficient quality, connectivity, or economic relevance. For instance, many road developments in Grobogan and Blora districts primarily serve local connectivity without linking major productivity centres, thus failing to stimulate trade or labour mobility effectively. This weak transmission mechanism demonstrates that road length alone is insufficient; what matters is the extent to which roads connect industrial zones, ports, and major logistics hubs (Amirkhiz et al., 2023; Yang et al., 2025).

The clean water infrastructure variable (ln-WATER) shows a small positive coefficient of 0.0100; however, its credible interval includes zero, indicating an insignificant contribution to GRDP in the short term. This insignificance can be attributed to the fact that clean water infrastructure primarily enhances the quality of life and public health in the long term, which indirectly boosts productivity (Chabibi & Sishadiyati, 2024; N. Liu & Su, 2025; Yang et al., 2025). For example, the development of clean water networks in the Banjarnegara and Purbalingga districts has led to improvements in public health; however, these improvements have not yet fully translated into measurable economic growth during the study period.

The electricity distribution variable (ln-ELECTRICITY) yields a minimal negative coefficient of -0.0005, with a credible interval that includes zero. This finding suggests that increasing electricity distribution capacity, without corresponding improvements in supply quality, network reliability, and electricity penetration into productive sectors, is insufficient to drive economic growth. In the Wonosobo and Pemalang districts, although electricity access has expanded, supply instability and frequent power outages have impeded the productivity of small industries and households (Munir et al., 2024).

The estimated coefficient for ln-EDUCATION, equal to 0.0368 with a 95 percent credible interval ranging from 0.0042 to 0.0764, indicates that the entire posterior distribution lies above zero, confirming a statistically significant and positive effect of education on regional gross regional domestic product (GRDP). Improvements in educational outcomes, workforce skills, and the availability of educated labor have been shown to enhance regional productivity by increasing labor efficiency, accelerating technology adoption, and strengthening firms' innovation capacity. This finding aligns with endogenous growth theory, which positions human capital accumulation as a central mechanism driving long-run economic expansion, with education acting as a catalyst for innovation and inter-regional knowledge diffusion (Tanjung et al., 2025). Empirical analyses across Indonesian provinces further confirm that education contributes significantly to regional growth, both directly and indirectly, through improvements in labor quality and industrial productivity. The magnitude of the coefficient (0.0368) suggests that a one-percent increase in educational attainment is associated with an approximate 0.0368-percent increase in GRDP, underscoring the role of education as a fundamental input in sustaining long-term regional economic growth dynamics.

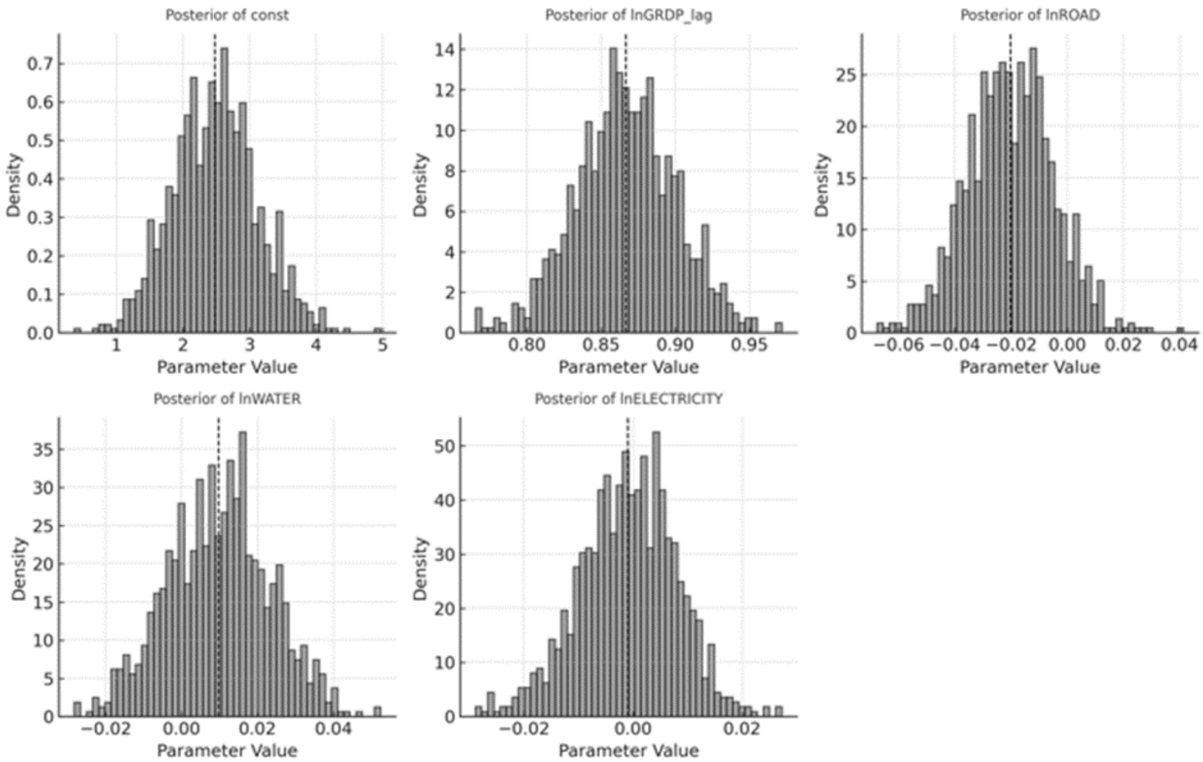
The estimated coefficient for ln-HEALTH is 0.0241, with a 95 percent credible interval ranging from 0.0075 to 0.0569, entirely above zero. This finding provides strong evidence that better public health conditions exert a statistically significant and positive impact on regional gross domestic product (GRDP). In theoretical terms, health constitutes a fundamental component of human capital that enhances labor productivity, increases participation rates, and reduces productivity losses associated with illness and absenteeism. Healthier populations contribute to higher levels of economic output through greater labor efficiency, extended working life spans, and improved adaptability to technological and structural change. Empirical evidence corroborates that health capital functions as a productive asset rather than merely a social good, serving as a catalyst for sustainable economic growth (Jiang & Wang, 2023). The magnitude of the coefficient indicates that a one-percent improvement in health indicators is associated with an approximate 0.0241-percent increase in GRDP, affirming the pivotal role of health investment in fostering long-term regional development.

Expanded and Strengthened Interpretation of Bayesian Panel Data

The estimation results of the Bayesian Panel Data Regression model presented in Table 3 provide a comprehensive overview of the contribution of infrastructure variables to regional economic growth across districts and municipalities in Central Java during the 2018–2024 period. The coefficient for the intercept is 2.4681, with a 95% credible interval ranging from 1.1582 to 3.7521. This result suggests that non-infrastructure factors play a significant role in supporting regional economic growth. Elements such as human capital, investment climate, local government policy effectiveness, technological innovation, and institutional quality emerge as critical drivers beyond physical infrastructure (Xu et al., 2025).

The lagged GRDP (ln-GRDP_lag) variable displays a coefficient of 0.8643, underscoring the strong dependence of current economic performance on historical output levels. The endogenous growth mechanism posits that past growth drives future expansion through capital accumulation, productivity enhancement, and organisational learning (Bergmann & Kalkuhl, 2025; Saidi, 2025). In the regional context of Central Java, Semarang City and Kudus Regency exemplify this path dependence, where a strong industrial base established in the past has created a cumulative snowball effect on current economic performance. The road infrastructure variable (ln-ROAD) exhibits a negative but statistically insignificant coefficient of -0.0203. This outcome highlights that merely extending road length without improving strategic connectivity, road quality, and maintenance is ineffective in driving regional growth. The experiences of Grobogan and Blora regencies illustrate that despite extensive road expansion, the lack of integration with central logistics corridors has failed to generate the necessary external economies of scale to stimulate regional acceleration.

Clean water infrastructure (ln-WATER) reveals a small positive contribution but remains statistically insignificant. This finding suggests that the primary benefits of water infrastructure are realised through long-term improvements in public health, which, in turn, enhance productivity. Infrastructure developments in Banjarnegara and Purbalingga have notably improved living standards, although the direct economic impacts remain limited within the study's time horizon. The electricity distribution variable (ln-ELECTRICITY) similarly displays a slight, negative, and statistically insignificant coefficient. Factors such as supply reliability, network quality, and electricity utilisation in productive sectors critically influence the impact of electricity infrastructure on economic growth, rather than distribution capacity (Hepp et al., 2024; Valero et al., 2025). The cases of Wonosobo and Pemalang regencies demonstrate that, although access to electricity improved, frequent supply instability undermined the gains in industrial and household productivity.

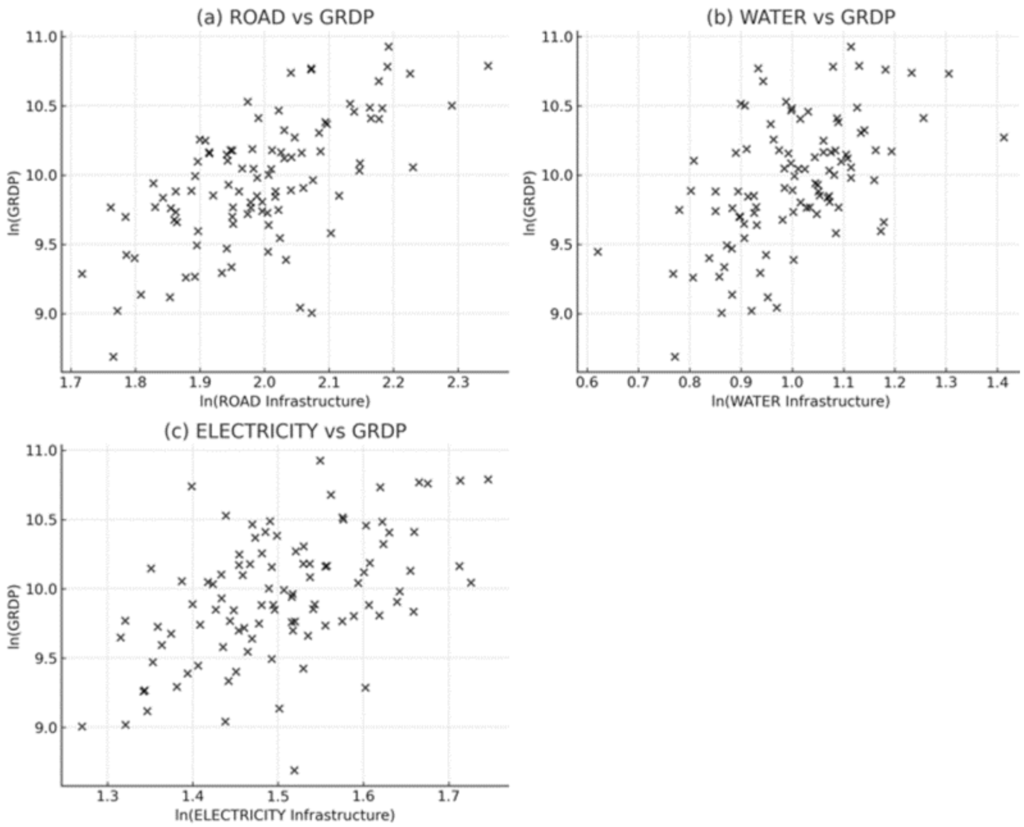


Source: Processed by the author based on infrastructure and GRDP panel data (BPS Indonesia, 2018–2024).

Figure 4. Posterior Distributions of Coefficients in Bayesian Panel Data Regression.

Figure 4 presents the posterior distributions for each coefficient estimated in the Bayesian Panel Data Regression model. Each curve represents the uncertainty associated with estimating key parameters, including the intercept, lagged GRDP, road infrastructure, clean water distribution, and electricity distribution. The posterior distributions for the intercept (const) and the lagged GRDP (ln_GRDP_lag) exhibit sharp, narrow peaks, with mean values distinguishable from zero. This pattern indicates low estimation uncertainty and strong evidence supporting the significance of these parameters in influencing GRDP growth. In particular, the narrow distribution of ln_GRDP_lag reinforces the existence of historical dependency effects (path dependence) in regional economic development, consistent with the endogenous growth framework linking historical output to capital accumulation and learning-by-doing processes (H. Liu & Liao, 2023). Conversely, the posterior distributions for ln-ROAD, ln-WATER, and ln-ELECTRICITY are wider and include zero within their ranges. This reflects greater uncertainty and suggests that the direct influence of these infrastructure variables on GRDP growth is not statistically significant at the 95% confidence level. These findings align with the broader literature, which emphasises that without improvements in quality, connectivity, and economic integration, infrastructure expansion alone may not yield substantial growth impacts (Esposito & Tedeschi, 2025).

Within the context of this study, the observed uncertainty in the distributions of infrastructure variables may be attributed to heterogeneity in infrastructure quality across districts in Central Java, as well as the influence of other dominant factors such as human capital, private investment, and local governance effectiveness. The posterior distribution analysis highlights that while infrastructure remains a crucial component in regional growth theories, its effectiveness depends critically on accessibility, quality, and functional efficiency, rather than on physical expansion alone (Foster & Briceño-Garmendia, 2010; Banerjee, Duflo, & Qian, 2020).

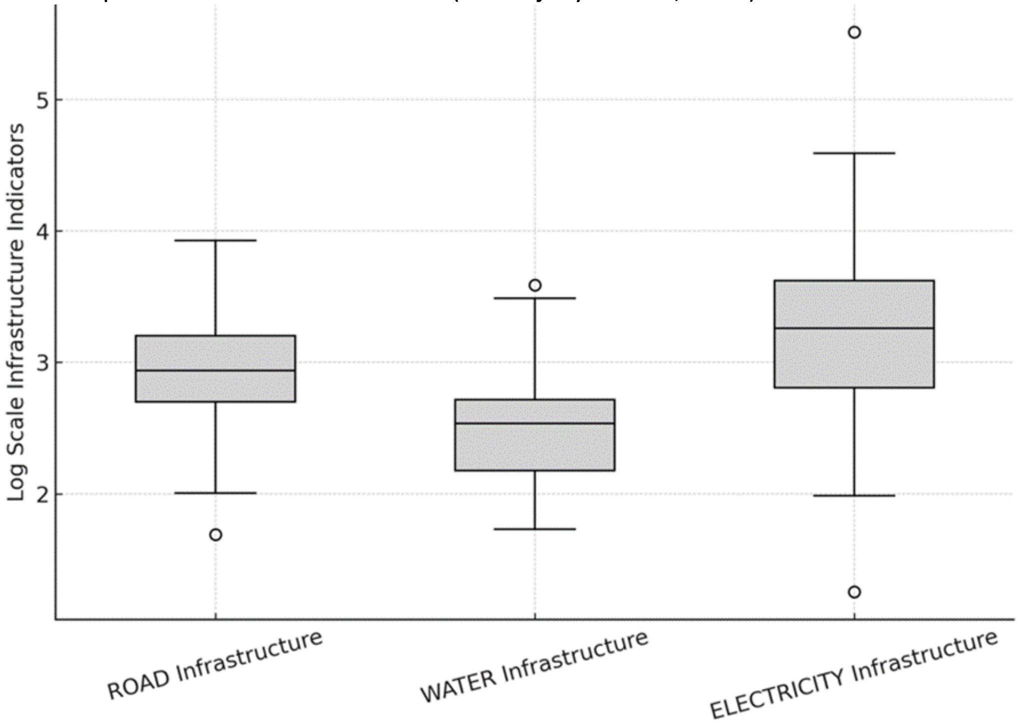


Source: Processed by the author based on infrastructure and GRDP panel data (BPS Indonesia, 2018–2024).

Figure 5. Scatter Plot of Infrastructure Quality versus GRDP in Central Java.

Figure 5 examines the relationship between infrastructure quality, as measured by road length, clean water distribution, electricity consumption, and GRDP levels, across districts in Central Java from 2018 to 2024. The scatter plots visualise the empirical patterns between infrastructure development and regional economic performance. Panel (a) illustrates the relationship between road infrastructure (ln-ROAD) and GRDP (ln-GRDP), showing a weak positive correlation with considerable dispersion around the identity line. This suggests that increases in road length do not uniformly translate into higher GRDP growth, consistent with the argument that road quality, strategic connectivity, and maintenance are more critical than sheer expansion (Iziga & Takagi, 2023). Panel (b) shows the relationship between clean water distribution (ln-WATER) and GRDP, exhibiting a slightly stronger positive pattern. This supports the view that improved access to clean water can enhance productivity and economic welfare, aligning with findings from Lestari et al. (2025) regarding the role of water infrastructure in fostering regional economic growth.

Panel (c) presents the relationship between electricity consumption (ln-ELECTRICITY) and GRDP, where a positive but heterogeneous correlation is observed. The role of reliable electricity access in enhancing industrial, household, and service sector productivity is evident, consistent with the conclusions of Ekeocha, Obasi, and Egbulonu (2022) for African economies. The three scatter plots reinforce the notion that infrastructure development contributes positively to economic growth, although the strength of the relationship varies by infrastructure type. These findings highlight that the effectiveness of infrastructure investments depends on their quality, strategic relevance, and integration with productive economic sectors (Hendajany & Wati, 2020).



Source: Processed by the author based on infrastructure and GRDP panel data (BPS Indonesia, 2018–2024).

Figure 6. Distribution of Infrastructure Quality Across Districts in Central Java.

Figure 6 illustrates the distributional disparities in infrastructure quality across districts in Central Java, based on log-transformed indicators of road length, clean water distribution, and electricity consumption. The boxplots reveal the spread, medians, interquartile ranges (IQRs), and presence of outliers for each infrastructure type. The distribution of road infrastructure (ROAD) reveals a widespread pattern, indicating significant disparities in road development among districts. Although the median is moderate, the large IQR and numerous positive outliers suggest that some districts possess substantially greater road infrastructure than others. This disparity highlights the importance of not only expanding networks but also ensuring an equitable distribution to optimise regional growth (Calderón & Servén, 2010a, 2010b).

For clean water infrastructure (WATER), the distribution appears more homogenous, with a narrower IQR and fewer outliers. This pattern suggests a more equitable distribution of clean water access among (Batrancea, Batrancea, Rus, et al., 2023) districts, which is critical for improving public health and economic productivity (Batrancea, Batrancea, Nichita, et al., 2023; Batrancea, Batrancea, Rus, et al., 2023). Figure 6 visualises the relationship between a composite infrastructure index, constructed from aggregated log-transformed indicators of road length, clean water distribution, electricity consumption, and GRDP levels across districts in Central Java. The majority of points in the scatter plot display a positive pattern, where improvements in the composite infrastructure index are associated with increases in log-GRDP values. This relationship underscores the significant connection between the development of high-quality infrastructure and regional economic growth. The finding supports the economic development theory that infrastructure acts as a productive asset, enhancing factor productivity, reducing transaction costs, and expanding investment opportunities (Calderón & Servén, 2010a; Straub, 2011). The plot reveals that integrated investments across multiple infrastructure sectors (roads, water, and electricity) generate more substantial growth effects compared to isolated sectoral development, consistent with the empirical literature, which suggests that coordinated infrastructure strategies are more effective in promoting sustained GDP growth (Ke, Dang, and Yang, 2020). A small number of outlier points deviating from the primary trend suggest the influence of moderating factors such as local governance quality, human capital capacity, and socio-economic conditions, as discussed in development disparity studies in emerging economies (Agenor, 2010).

CONCLUSIONS

This study demonstrates that regional economic growth in Central Java between 2018 and 2024 is strongly shaped by historical output dynamics, emphasizing the importance of path dependency in regional development processes. The persistence of output, reflected in significant dynamic regional spillover patterns (DRSP), illustrates an endogenous growth mechanism in which previous production outcomes influence current investment decisions, capacity expansion, and institutional learning across regions. This mechanism suggests that economic expansion is not solely determined by external shocks or short-term policy interventions but by the self-reinforcing interaction between accumulated output and adaptive regional capabilities.

The insignificance of variables such as road length, clean water distribution, and electricity consumption indicates that physical expansion alone does not guarantee economic acceleration. Instead, infrastructure quality, reliability, and interregional connectivity are more decisive determinants of sustainable growth. This finding aligns with development theory which argues that the productivity effects of infrastructure depend on operational efficiency and strategic integration within regional production systems rather than mere physical presence. Therefore, infrastructure policies should focus on quality improvement, regular maintenance, and alignment with regional value chains and production centers that support long-term competitiveness.

From a policy perspective, the results call for a shift in infrastructure planning that moves away from a quantity-driven orientation toward a quality-focused approach. Development strategies should prioritize service reliability, maintenance of existing assets, and connectivity that links industrial estates, logistics hubs, and trade centers. The integration between transportation infrastructure and industrial clusters can reduce logistics costs, increase mobility of production factors, and generate agglomeration benefits that strengthen regional competitiveness. Expanding access to clean water and electricity should emphasize stability of supply and its productive utilization to create measurable and lasting economic effects.

The practical implications highlight the need for stronger coordination between local and central governments in aligning infrastructure priorities with human resource development, industrialization, and institutional strengthening. Collaborative governance is essential to synchronize fiscal capacity, spatial planning, and innovation policies that sustain infrastructure quality and functionality.

Future research should incorporate institutional quality, digital infrastructure, and regional fiscal digitalization as moderating variables that explain differences in infrastructure effectiveness across provinces. Comparative studies among Indonesia's regions will be valuable in assessing the consistency of infrastructure's influence under different governance and technological conditions. The findings of this study provide an empirical foundation for designing infrastructure policies that emphasize quality, inclusiveness, and sustainability, ensuring that infrastructure development contributes not only to short-term growth but also to long-term structural transformation and regional resilience

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