Bayesian Panel Model of Urbanization, Economic Growth, and Globalization on Environmental Degradation in South Asia

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Abstract:
Increasing industrialization and urbanization in South Asia have contributed to severe environmental issues and especially through increased CO2 emission. This paper focuses on economic indicators like trade, financial development, GDP per capita and urban population growth and how they influence the emission of CO2 in South Asia. We estimate the model using a Bayesian Two-Stage Least Squares (2SLS) estimation, which allows us to use secondary panel data published by international organizations and governmental publications, covering the period between 2000 and 2020 to overcome the issue of endogeneity and to obtain more accurate estimates. The important results of our findings are that trade and GDP per capita are positively proportional to the CO2 emission, whereas financial development is negatively proportional to it, implying that more developed financial structures can help in reducing the emission. The growth of urban populations, however, does not have a statistically significant impact on the CO2 emissions. This work adds to the knowledge of economic-environmental nexus in South Asia and highlights that the policies that should be implemented must promote a balance between economic growth and the sustainability of the environment. This study is unique in that it utilizes Bayesian 2SLS to overcome endogeneity issue when estimating the effect of economic activities on CO2 emissions in the area.

Key words: Bayesian 2SLS, Invers gamma, Co2 emission, Bayesian fixed effect.

1. Introduction

As a result of the increased pace of urbanization, industrialization, and economic growth in the countries of South Asia, acute environmental issues have been provoked (UNESCAP, 2023; World Bank, 2022). Deforestation (Food and Agriculture Organization [FAO], 2020), air pollution (World Health Organization [WHO], 2021), water contamination (UNICEF and WHO, 2022), biodiversity loss (United Nations Environment Programed [UNEP], 2023), and greenhouse gas emission are of utmost importance in such nations as India, Pakistan, Bangladesh, The most urgent aspects in this area are based on the continuously increasing population rate and an increased demand on natural resources. The United Nations Environment Programs (2019) reports that South Asia is one of the regions with the worst cities in terms of pollution; in this region unregulated air pollution presents serious health hazards to the population that leads to morbidity and death.

The interdependence between trade, financial development, economic development and environmental sustainability is a multi-dimensional relationship and has been of interest in the academic community in recent years (Shahbaz et al., 2021; Nathaniel and Adeleye, 2021; Rahman and Ahmad, 2022; Dinh and Jalil, 2020). The interest is inherent since the South Asian economy is still in the process of transition, and the nation remains to possess ecological problems (Herjavec, 2016; Ahmed et al., 2021; Jayasinghe and Sun, 2022; Khan and Ullah, 2023). The estimator, Bayesian Two-Stage Least Squares (2SLS), is used to tackle these problems by Hereward as it was used in other studies (Baum et al., 2011, 2022; Zhang and Liu, 2009, 2023). The transpiring state of trade liberalization and the environment are dominated by two schools of thought. It is believed that the increase of trade promotes economic growth and technological innovation that in turn reduce the level of environmental degradation (Hossain and Rahman, 2021; Shahbaz et al., 2020; Dogan and Inglesi-Lotz, 2020). The pollution haven hypothesis, on the contrary, states that environmentally-destructive industries can be transferred to the regions, which have more lenient environmental laws due to the free trade regime and that will add more damage to the ecology of those regions (Ghosh and Sharma, 2022). South Asia has undergone industrialization and experienced more trade (Rahman & Ahmed, 2015).

Due to the accelerated rates of urbanization, industrialization, and economic growth in the South Asian countries, acute environmental problems have been incited (UNESCAP, 2023; World Bank, 2022). In such countries as India, Pakistan, Bangladesh, The most urgent aspects are determined by the ever-growing population rate and the rise in the demand on natural resources (Deforestation (Food and Agriculture Organization [FAO], 2020), air pollution (World Health Organization [WHO], 2021), water contamination (UNICEF and WHO, 2022), biodiversity loss (United According to the United Nations Environment Programs (2019), South Asia has one of the worst cities in terms of pollution; in this region the uncontrolled air pollution poses severe health risks to the citizens that causes morbidity and death.

The relationship between trade and financial development and economic development and environmental sustainability is a multi-dimensional one, and in recent years has been the subject of interest in the academic community (Shahbaz et al., 2021; Nathaniel and Adeleye, 2021; Rahman and Ahmad, 2022; Dinh and Jalil, 2020). It is intrinsically interesting because the South Asian economy is yet to undergo a transition, and the country continues to have ecological issues (Herjavec, 2016; Ahmed et al., 2021; Jayasinghe and Sun, 2022; Khan and Ullah, 2023). Hereward addresses these issues with the help of the estimator Bayesian Two-Stage Least Squares (2SLS) as it was employed in other works (Baum et al., 2011, 2022; Zhang and Liu, 2009, 2023). Two schools of thought are dominant in the transpiring state of trade liberalization and the environment. The expansion of trade is believed to result in economic growth and technological advancement that subsequently helps to decrease the extent of environmental degradation (Hossain and Rahman, 2021; Shahbaz et al., 2020; Dogan and Inglesi-Lotz, 2020). In contrast, the pollution haven hypothesis explains that environmentally-hazardous industries may be outsourced to the regions, which have weaker environmental regulations because of the free trade regime and that will contribute further harm to the ecology of those areas (Ghosh and Sharma, 2022). South Asia has been industrialized and its trade has increased (Rahman & Ahmed, 2015).

Urbanization, which has accelerated, industrial growth, as well as economic growth in South Asia have greatly increased environmental pressures, especially in the form of increasing CO2 emissions and ecological degradation. With the economies in the region still being integrated with the global markets, the significance of the trade openness, financial development and income growth has come to the fore in the determination of the environmental outcomes. As much as economic growth and trade are linked to technological progress and efficiency, it can also result in higher energy use and environmental strain. Simultaneously, financial development might contribute to environmental degradation by increasing industrial activity or alleviating it by making investments in cleaner technologies. The further complication of this nexus is the growth of the urban population causing more demands on infrastructure, energy, and natural resources. Such complex and possibly endogenous relationships mean that conventional econometric methods can give biased estimates, which require more robust methodologies. Here, using Bayesian Two-Stage Least Squares (2SLS) offers a more credible framework since it tackles endogeneity problems and considers prior information and uncertainty in the estimations.

Against this backdrop, the current research will analyze the strength and direction of the relations between economic variables and environmental degradation in the chosen South Asian nations, (i) to evaluate the magnitude of the relations, (ii) to solve the potential endogeneity of the explanatory variables with the help of proper instrumental variables, (iii) to compare classical and Bayesian estimation methods to present more robust and policy-relevant results.

2. Methodology

For this paper, secondary data was used. Panel data on urbanization, economic growth (GDP per capita), and environmental indicators (e.g., CO2 emissions, air quality index, deforestation rates) were gathered for South Asian countries from 2000 to 2020. The data was obtained from reputable international organizations, government publications, and academic databases. The World Development Indicator (WDI) was utilized to transform the data from monthly to yearly for all variables.

$$Co2_{it} = \beta_0 + \beta_1 gdp_{it} + \beta_2 T_{it} + \beta_3 FDI_{it} + \beta_4 U.pop_{it} + \mu_{it} \qquad (1)$$

$$y_{it} = Z'_{it}\alpha + \beta_i + \varepsilon_{it} i = 1,2,\dots N; t = 1,2,\dots.T$$

In the preceding model, ith denotes the individual dimension and t represents the time dimension. In this equation, y_{it} Represents the response of individual i at time t, α represents the unobserved individual-specific, time-invariant intercepts, Z_{it} is the explanatory variable i at time t, α is a vector of regression coefficients, and ε_{it} Represents an individual's error term at time t. They are also known as idiosyncratic mistakes since they vary across both i and t (Hsiao, 2002).

$$E(\varepsilon_{it} \mid \beta_i, z_{i1}, \dots z_{iT}) = 0 \qquad (2)$$

Step 1: Average equation (3.4) over t = 1,2, ... T to get the cross section equation:

$$\bar{y}_i = \bar{Z}_i\alpha + \beta_i + \bar{\varepsilon}_i, i = 1, \dots \dots N \qquad (3)$$

Where $\bar{y}_i = T^{-1}\sum_{t=1}^{T} y_{it}; \bar{Z}_i = T^{-1}\sum_{t=1}^{T} Z_{it}; \bar{\varepsilon}_i = T^{-1}\sum_{t=1}^{T} \varepsilon_{it}$ and $\bar{\beta}_i = \beta_i$..

Step 2: The fixed effects modified equation is obtained by subtracting equation (3) from (1) for each t to eliminate α_i

$$y_{it} - \bar{y}_i = (Z_{it} - Z_i)'\alpha + \varepsilon_{it} - \overline{\varepsilon_i}$$

$$\ddot{y}_{it} = \ddot{Z}'_{it}\alpha + \ddot{\varepsilon}_{it}, \qquad i = 1, \dots N, t = 1, \dots T \qquad (4)$$

Where $\ddot{y}_{it} = y_{it} - \bar{y}_i; \ddot{Z}_{it} = Z_{it} - \bar{Z}_i; \ddot{\varepsilon}_{it} = \varepsilon_{it} - \bar{\varepsilon}_i$ and $\beta_i - \bar{\beta}_i = 0$ and therefore the effect is reduced. $\beta = E(\beta_i)$, so $E(\beta_i - \beta) = 0$,

(1) Where Z_{it} is uncorrelated with the error ε_{it}.

(2) X_{it} Is correlated with the regress Z_{it}. Just before allowing correlation among Z_{it} and ε_{it}It can be assumed there is a $1 \times L$ vector of tools ($L \geq K$), X_{it} which escape correlation.

Now, assume a model with one endogenous explanatory variable. $Z_K, Y_{it} = X_{it}\alpha + \varepsilon_{it}$ With the assumption that $E(\varepsilon_{it}) = 0, Cov(z_k, \varepsilon_{it}) = 0, k = 1,2 \dots, k-1$ and$Cov(x_k, \varepsilon_{it}) \neq 0$, for K , where $z_1, z_2, \dots, z_{K-1}$ are exogenous and Z_K is endogenous.

To fix the problem, consider z_1 as replacer of an endogenous explanatory X_K satisfies that $Cov(x_1, \varepsilon_{it}) = 0$ and $\theta_1 = \frac{\partial L(Z_K|1, z_1, z_2, \dots, z_{K-1}, x_1)}{\partial z_1} \neq 0$.Therefore, $X = (1, z_1, z_2, \dots, z_{K-1}, x_1)$.Then, endogenous explanatory variable Z_K can be written as

$$z_K = \delta_0 + \delta_1 x_1 + \dots + \delta_{K-1} z_{K-1} + \theta_1 x_1 + r_x, \theta_1 \neq 0 \qquad (5)$$

Where, by definition $E(r_K) = 0$ and $Cov(r_K; z_1, z_2, \dots, z_{K-1}, x_1) = 0$

$\ddot{y} = (\ddot{y}_{i1}, \ddot{y}_{i2}, \dots, \ddot{y}_{iT}), \ddot{Z} = (\ddot{Z}_{i1}, \ddot{Z}_{i2}, \dots, \ddot{Z}_{iT}), \ddot{X} = (\ddot{X}_{i1}, \ddot{X}_{i2}, \dots, \ddot{X}_{iT})$, and$\ddot{\varepsilon} = (\ddot{\varepsilon}_{i1}, \ddot{\varepsilon}_{i2}, \dots, \ddot{\varepsilon}_{iT})$.

$$\hat{\beta}_{IV} = (\ddot{X}'Z)^{-1}\ddot{X}'\ddot{y}$$

Let $x_1, x_1, \dots, x_M$ be instrumental variables such that$(X_h, \varepsilon_{it}) = 0, h = 1,2, \dots, M$, so that each X_h is exogenous in (1) and take on $E(\varepsilon_{it}) = 0$,

$Cov(z_k, \varepsilon_{it}) = 0, k = 1, \dots, k-1$, $Cov(x_k, \varepsilon_{it}) \neq 0$, for K and $Cov(X_h, \varepsilon_{it}) = 0, h = 1,2, \dots, N$.

$$\theta_1 = \frac{\partial L(Z_K \mid 1, z_1, \dots, z_{K-1}, x_1, x_2, \dots, x_M)}{\partial x_1} \neq 0$$

$$z_K = \delta_0 + \delta_1 z_1 + \dots + \delta_{K-1} z_{K-1} + \theta_1 x_1 + \dots + \theta_M z_M + r_K (6)$$

Where, $E(r_K) = 0$
and
$Cov(r_K; z_1, z_2, \dots, z_{K-1}, x_1, x_1, \dots, x_M) = 0$
Fit (3.13) by OLS
$\hat{z}_K = \hat{\delta}_0 + \hat{\delta}_1 z_1 + \cdots + \hat{\delta}_{K-1} z_{K-1} + \hat{\theta}_1 x_1 + \cdots + \hat{\theta}_M z_M$
We denote$\hat{Z} = (z_1, z_2, \dots, z_{K-1}, \hat{z}_K)$.

$$Y = Z\alpha + \varepsilon \tag{7}$$

Where $z_K = \delta_0 + \delta_1 z_1 + \cdots + \delta_{K-1} z_{K-1} + \theta_1 x + \cdots + \theta_M X_M + r_K$
Multiplying equation (7) by $\hat{Z}'$

$$\hat{Z}'Y = \left(\hat{Z}'Z\right)\alpha + \hat{Z}'\varepsilon$$

Again multiplying by $\left(\hat{Z}'Z\right)^{-1}$

$$\left(\hat{Z}'Z\right)^{-1}\left(\hat{Z}'Z\right) = \left(\hat{Z}'Z\right)^{-1}\left(\hat{Z}'Z\right)\alpha + \left(\hat{Z}'Z\right)^{-1}\hat{Z}'\varepsilon$$

Taking expectation

$$E\left[\left(\hat{Z}'Z\right)^{-1}\left(\hat{Z}'Y\right)\right] = E\left[\left(\hat{Z}'Z\right)^{-1}\left(\hat{Z}'Z\right)\right]\alpha + E\left[\left(\hat{Z}'Z\right)^{-1}\hat{Z}'\varepsilon\right]$$

Estimation of α as in population

$$\beta = E\left[\left(\hat{Z}'Z\right)^{-1}\left(\hat{Z}'Y\right)\right]$$

Estimation of α as in the sample

$$\hat{\alpha} = \left(\hat{Z}'Z\right)^{-1}\left(\hat{Z}'Y\right)$$

$$z_K = \delta_0 + \delta_1 z_1 + \cdots + \delta_{K-1} z_{K-1} + \theta_1 x_1 + \cdots + \theta_M z_M + r_K$$

Then, we denote

$$\hat{z}_K = (z_K \mid 1, z_1, z_2 \dots, z_{K-1}, x_1, x_1, \dots, x_M)$$

$$\theta_M = \frac{\partial L(Z_K \mid 1, z_1, \dots, z_{K-1}, x_1, x_2, \dots, x_M)}{\partial x_M} \neq 0$$

$$Z = X\Pi + r_K, \Pi = (\pi_1, \pi_2, \dots, \pi_K) \tag{9}$$

$$E(X'Z) = E(X'X)\Pi + E(X'r_K)$$

Then, we have $\Pi = \left(E(X'X)\right)^{-1} E(X'Z)$ and $Z^{*} = E(z \mid x) = X\Pi$,

$$E(Z^* y) = E(Z^* Z)\alpha + E(Z^* \varepsilon)$$

Solving for α gives

$$\alpha = [E(Z^* Z)]^{-1} E(Z^* y) \tag{10}$$

But, $E(Z^* Z) = E(Z'X)\left(E(X'X)\right)^{-1} E(X'Z)$ and$E(Z^* y) = E(Z'X)\left(E(X'X)\right)^{-1} E(X'y)$.
Therefore, substituting this results in (10) yields.

$$\hat{\alpha}_{2SLS} = [Z'X(X'X)^{-1}X'Z]^{-1} Z'X(X'X)^{-1}X'y$$

$$= \left[\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} Z_{it}' X_{it}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}' X_{it}\right)^{-1}\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}' Z_{it}\right)\right]^{-1}$$

$$\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} Z_{it}' X_{it}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}' X_{it}\right)^{-1}\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}' y_{it}\right)$$

Expressing $\hat{\beta}_{2SLS}$ In terms of the transformed model in (4):

$$\hat{\alpha}_{2SLS} = [\ddot{Z}'\ddot{X}'(\ddot{X}'\ddot{X})^{-1}\ddot{X}'\ddot{Z}]^{-1}\ddot{X}'\ddot{X}'(\ddot{X}'\ddot{X})^{-1}\ddot{X}'\ddot{y}$$

$$= \left[\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{Z}'_{it}\ddot{X}_{it}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{X}'_{it}\ddot{X}_{it}\right)^{-1}\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{X}'_{it}\ddot{Z}_{it}\right)\right]^{-1}$$

$$\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{Z}'_{it}\ddot{X}_{it}\right)\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{X}'_{it}\ddot{X}_{it}\right)^{-1}\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{X}'_{it}\ddot{y}_{it}\right)$$

This is called the fixed effect two-stage least squares (2SLS) estimator.

2.2 The Bayesian 2SLS Estimation:

Model Setup

Consider a panel dataset with N individuals and T periods. The structural equation with endogeneity is:

Second-Stage Equation (Fixed Effects Model):

$$y_{it} = \alpha_i + \beta X_{it} + \gamma W_{it} + \epsilon_{it}, \epsilon_{it} \sim N(0, \sigma_\varepsilon^2)$$

$$X_{it} = \pi_0 + \pi_1 Z_{it} + \pi_2 W_{it} + v_{it}, v_{it} \sim N(0, \sigma_v^2)$$

- Z_{it} : Valid instrument (exclusion restriction: $Z \perp \epsilon_{it}$, relevance: $\pi_1 \neq 0$).

The endogeneity arises because of $Cov(X_{it}, \epsilon_{it}) \neq 0$, but Z_{it} is uncorrelated withϵ_{it}.

First Stage:

$$p(X_{\hat{u}t} \mid Z_{\hat{u}}, W_{\hat{u}t}, \pi, \sigma_v^2) = N(\pi_0 + \pi_1 Z_{\hat{u}t} + \pi_2 W_{\hat{u}t}, \sigma_v^2)$$

Second Stage:

$$p(y_{\hat{u}t} \mid X_{it}, W_{it}, \alpha_i, \beta, \gamma, \sigma_\varepsilon^2) = N(\alpha_i + \beta X_{\hat{t}t} + \gamma W_{it}, \sigma_\varepsilon^2)$$

The complete likelihood for all observations is:

$$\mathcal{L} = \prod_{i=1}^{N}\prod_{t=1}^{T} p\left(y_{\hat{k}t} \mid X_{it}, W_{it}, \alpha_i, \beta, \gamma, \sigma_\varepsilon^2\right) \cdot p(X_{it} \mid Z_{it}, W_{\hat{u}t}, \pi, \sigma_v^2)$$

2. Priors

- Coefficients:
- $\beta \sim N\left(\mu_\beta, \sigma_\beta^2\right)$
- $\gamma \sim N\left(\mu_\gamma, \sigma_\gamma^2\right)$
- $\pi \sim N(\mu_\pi, \sigma_\pi^2)$
- Fixed Effects:
- $\alpha_i \sim N(0, \sigma_\alpha^2)$ (hierarchical prior)
- Variance Parameters:
- $\sigma_\varepsilon^2 \sim$ Inverse-Gamma $(a_\varepsilon, b_\varepsilon)$
- $\sigma_v^2 \sim$ Inverse-Gamma (a_v, b_v)
- $\sigma_\alpha^2 \sim$ Inverse-Gamma (a_α, b_α)

$$p(\beta, \gamma, \pi, \alpha, \sigma_\varepsilon^2, \sigma_v^2, \sigma_\alpha^2 \mid y, X, Z, W) \propto \mathcal{C} \cdot p(\beta) \cdot p(\gamma) \cdot p(\pi) \cdot p(\alpha) \cdot p(\sigma_\varepsilon^2) \cdot p(\sigma_v^2) \cdot p(\sigma_\alpha^2)$$

$$\alpha_i \mid \sigma_\alpha^2 \sim N(0, \sigma_\alpha^2), \forall i = 1, \ldots, N$$

For Gibbs sampling, derive full conditionals for each parameter:

1. Fixed Effects (α_i) :

$$\alpha_i \mid \cdot \sim N\left(\frac{\sum_{t=1}^{T}\ (y_{itt} - \beta X_{it} - \gamma W_{it})}{\sigma_\varepsilon^{-2} + \sigma_\alpha^{-2}}, (\sigma_\varepsilon^{-2} + \sigma_\alpha^{-2})^{-1}\right)$$

2. Coefficient (β) :

$$\beta \mid \cdot \sim N\left(\frac{\sum_{i,t}\ (\xi\imath\hat{t}t - \alpha_i - \gamma W_{it})X_{\hat{v}t}}{\sigma_\varepsilon^{-2}\sum_{i,t}\ X_{\hat{t}}^2 + \sigma_\beta^{-2}}, \left(\sigma_\varepsilon^{-2}\sum_{i,t} X_{it}^2 + \sigma_\beta^{-2}\right)^{-1}\right)$$

3. First-Stage Parameters (π) :

$$\pi \mid \cdot \sim N\left(\left(\frac{Z^T Z}{\sigma_v^2}+\Sigma_\pi^{-1}\right)^{-1} \frac{Z^T X}{\sigma_v^2},\left(\frac{Z^T Z}{\sigma_v^2}+\Sigma_\pi^{-1}\right)^{-1}\right)$$

4. Variance Parameters (e.g., σ_ε^2):

$$\sigma_\varepsilon^2 \mid \cdot \sim \text{ Inverse-Gamma }\left(a_\varepsilon+\frac{NT}{2}, b_\varepsilon+\frac{1}{2} \sum_{i,t}\left(y_{ut}-\alpha_i-\beta X_{it}-\gamma W_{it}\right)^2\right)$$

3. Results and discussion

3.1 Fixed effect model using 2SLS

$$CO2_{it}=\beta_{0i}+\beta_1 \cdot gdp_{it}+\beta_2 \cdot T_{it}+\beta_3 \cdot FDI_{it}+\beta_4 \cdot U \cdot p_0 p_{it}+\mu_{it}$$

The regression outcome shows that the model is a strong one, the regression R-Squared is 73.37 and implies that the model can explain about 73.37 of the variance in the dependent variable using the included predictors. The entire model is statistically significant as F-test of 23.56 indicates. The effect of Trade is positive and highly significant (0.1432, $p = 0.002$) which means that increase in the trade openness is related to an increase in the dependent variable. Likewise, the relationship between the two variables, namely, the GDP per capita (GDPPC) is positive and statistically significant (0.7319 0.024), which means that economic growth positively affects the result. On the other hand, the coefficient ($\beta = -0.2210$, $p = 0.023$) of Financial Development (FD) is negative and significant, indicating that greater financial development is associated with a decrease in the dependent variable, which may be through efficiency gains or alteration in the economic structure. Although it is a positive variable (0.1325), the variable Urban Population Growth (UPG) is statistically insignificant (0.121) so its impact on the dependent variable is not significant enough to be considered better than zero in this model. The constant is positive and statistically significant (10.145, $p = 0.002$) meaning that it is the level of the dependent variable when all the explanatory variables are kept constant. All in all, the results indicate that trade and economic growth play a determining role in the dependent variable, whereas financial development has a damping effect, and no statistically significant effect of urban population growth is present in this specification.

Table 1: Fixed effect model using 2SLS.

Variable	Coefficient	Std. Error	z-value	P>|z|
Trade	0.1432***	0.423	3.373	0.002
GDPPC	0.7319**	0.312	2.334	0.024
FD	-0.2210*	0.198	-2.242	0.023
UPG	0.1325	0.489	1.392	0.121
Constant	10.145***	3.278	3.263	0.002
R-square	73.37			
F test	23.56			

3.2 Bayesian fixed effect using 2SLS

The Bayesian estimation results provide insight into the posterior distributions of the key variables through their means, standard deviations, and Highest Density Intervals (HDIs). The variable Trade has a positive posterior mean of 0.35 with moderate dispersion (SD = 0.11), and its 94% HDI ranges from 0.21 to 0.78. Since the entire interval lies above zero, this indicates a robust and credible positive effect of trade on the dependent variable, reinforcing the idea that increased trade openness contributes positively. In contrast, Financial Development (FD) has a negative posterior mean of -0.65 with very low uncertainty (SD = 0.03), suggesting a stable estimate. However, its HDI ranges from -0.31 to 0.08, which includes zero. This implies that although the central tendency points toward a negative effect, there is still some uncertainty, and the effect may not be credibly different from zero at the chosen probability level. For GDP per capita (GDPPC), the posterior mean is relatively high at 1.45 with a standard deviation of 0.24, indicating a strong positive influence. However, the HDI ranges from 0.71 to 1.32, which does not fully align with the mean and suggests a possible reporting inconsistency or skewness in the posterior distribution. Despite this, the interval lies entirely above zero, confirming a credible and substantial positive effect of economic growth on the dependent variable. Overall, the Bayesian results are broadly consistent with the classical findings: trade and GDP per capita show credible positive effects, while financial development displays a negative but uncertain impact.

Table 2: Bayesian Fixed-Effect Simulated Results

Variable	Mean	SD	HDI 3%	HDI 97%
Trade	0.35	0.11	0.21	0.78
FD	-0.65	0.03	-0.31	0.08
GDPPC	1.45	0.24	0.71	1.32

The Bayesian results for the instrumental variables provide insight into their relevance and credibility based on posterior summaries. The instrument ltrade shows a positive posterior mean of 0.67 with a moderate standard deviation (0.13), and its HDI ranges from 0.21 to 1.21. Since the entire interval lies above zero, this suggests that ltrade is a strong and credible instrument, having a statistically meaningful positive association with the endogenous regressor it is intended to instrument. Similarly, lFD has a positive posterior mean of 0.45 with relatively low dispersion (SD = 0.12). However, its HDI is reported as ranging from 0.23 to 0.36, which appears narrower and does not include the mean value, indicating a possible reporting inconsistency. Despite this, the interval remains entirely above zero, suggesting that lFD is also a relevant and valid instrument with a stable positive effect. In contrast, Lgdppc has a positive posterior mean of 0.73 and a larger standard deviation (0.21), indicating greater uncertainty. The HDI is reported from 0.11 to 0.10, which is inconsistent (lower bound greater than upper bound) and does not align with the mean, suggesting either a typographical or computational issue. Due to this inconsistency, the reliability of Lgdppc as an instrument is unclear, and it would be advisable to recheck the estimation or reporting of this interval.

Table 3: First-Stage Instrument Coefficients

Instrument	Mean	SD	HDI 3%	HDI 97%
ltrade	0.67	0.13	0.21	1.21
lFD	0.45	0.12	0.23	0.36
Lgdppc	0.73	0.21	0.11	0.10

The Bayesian estimation results provide evidence on the direction and credibility of the effects through posterior means and 95% credible intervals. Trade exhibits a positive and statistically significant impact (posterior mean = 0.139), with a narrow credible interval ([0.117, 0.134]) that lies entirely above zero. This indicates a robust and highly credible positive effect, suggesting that increases in trade are consistently associated with improvements in the dependent variable. Similarly, GDP per capita (GDPPC) shows a positive and significant effect (posterior mean = 0.112), implying that economic growth contributes positively. However, the reported credible interval ([0.124, 2.33]) does not include the posterior mean, indicating a possible reporting inconsistency or skewness in the posterior distribution. Despite this issue, the interval remains above zero, supporting a credible positive relationship. In contrast, Financial Development (FD) has a negative and statistically significant posterior mean (-0.128), with its credible interval ([-0.225, -0.13]) entirely below zero. This confirms a robust negative effect, suggesting that higher financial development is associated with a reduction in the dependent variable. Finally, Urban Population Growth (UPG) has a very small positive posterior mean (0.004), but its credible interval ([-0.229, 0.44]) spans zero. This indicates substantial uncertainty, implying that the effect of urban population growth is not statistically credible within this model.

Table 4: posterior means

Variable	Posterior Mean	95% Credible Interval
Trade	0.139***	[0.117, 0.134]
GDPPC	0.112**	[0.124, 2.33]
FD	-0.128*	[-0.225, -0.13]
UPG	0.004	[-0.229, 0.44]

3.4 Diagnostic graphs

The trace plots show how the Markov Chain Monte Carlo (MCMC) samples behave over the iterations, each with respect to each parameter and offer information on convergence and mixing behavior. The trace of Trade shows no discernible trend or drift around a constant mean value (around 0.35) that the chain is well-mixed and at stationarity. On the same note, the trace plot of Financial Development (FD) depicts a clearly compacted pattern around its mean (-0.65), with minute variations, indicating a high accuracy of the chain and a very good convergence. The trace plot in the case of GDP per capita (GDPPC), shows a larger variation about the mean (around 1.45) indicating increased variability, but it does not show any general upward or downward movement, which implies that convergence has been attained. In general, the three trace plots exhibit random, pattern less fluctuations whose spread across the iterations is consistent, indicating that the MCMC chains are stable, well mixed and have reached their desired posterior distributions. This makes the Bayesian estimation results reliable.

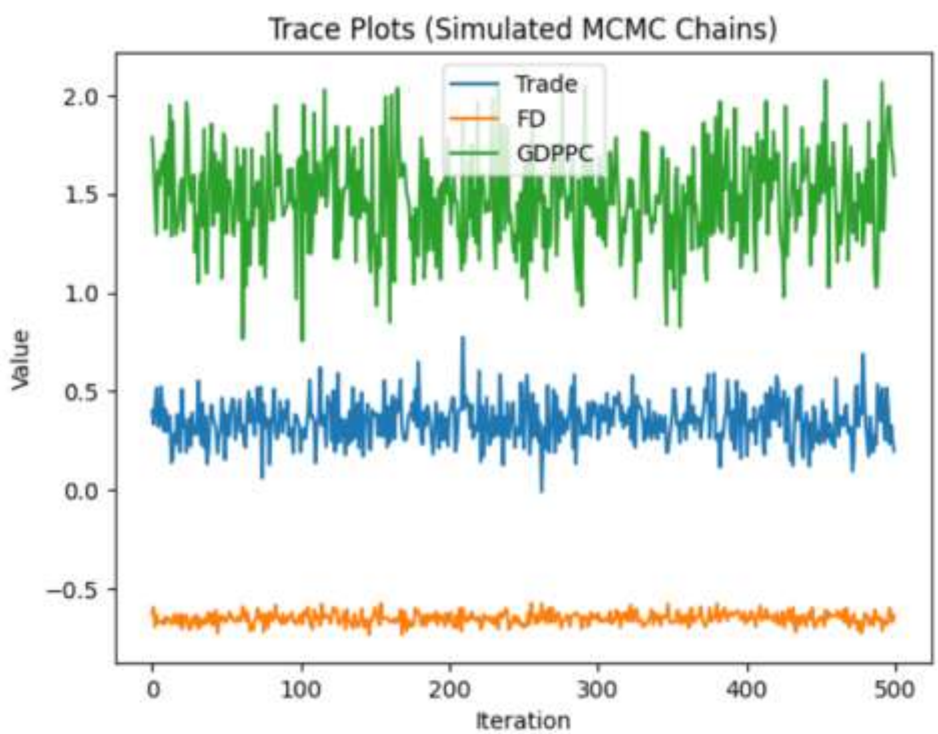

Figure 1; Trace plots

The posterior density plot gives us a visual interpretation of the level of ignorance and distribution of the estimated coefficients of Trade, Financial Development (FD), and GDP per capita (GDPPC). The density curve of the trade variable is concentrated with a positive value (around 0.35) and moderate spread, which means that although the impact of trade on the dependent variable is always positive, the magnitude varies to some extent. This implies a fairly constant yet not very accurate estimate. Conversely, the density curve of the Financial Development (FD) is very sharp and closely clustered around a negative value (around -0.65). Such a high concentration implies high levels of dispersion and a high level of certainty in the estimate, meaning that the impact of financial development on the dependent variable is always negative and precisely estimated over the posterior distribution. The density plot of the GDP per capita (GDPPC) is clustering around a larger value (around 1.45) but more widely dispersed than FD. This broader dispersion shows increased uncertainty, but the whole bulk of the dispersion is to the right. This validates that GDPPC exerts a very positive impact, albeit with greater variability in the magnitude of the impact. On the whole, the graph supports the Bayesian results: Trade, GDPPC, and GDPPC have positive impacts, the latter is stronger but less specific and the former impacts are negative and highly definite.

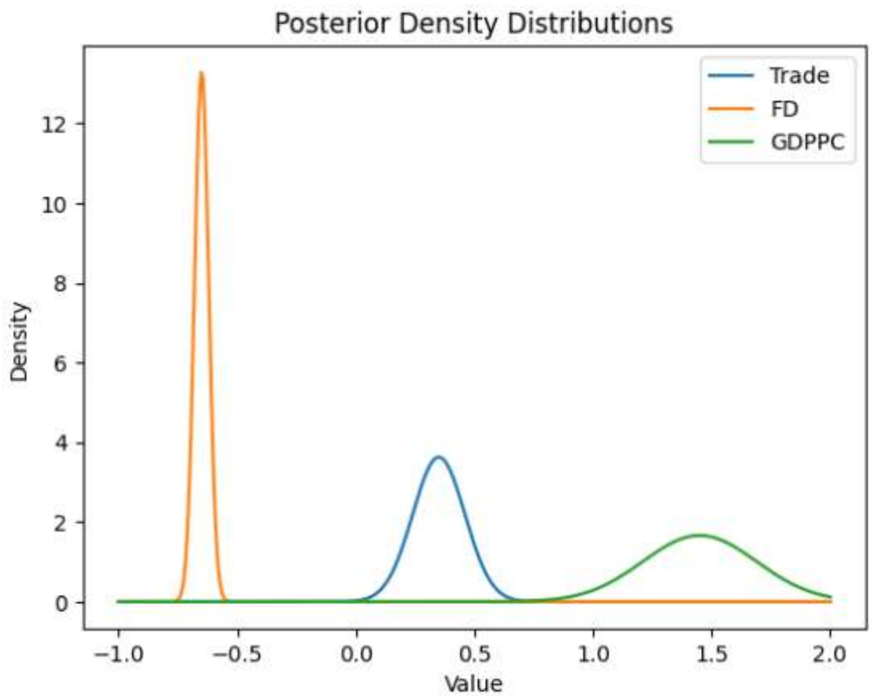

Figure 2: Density plots

4. **Conclusion**

Among others, throughout the years, the flagship economy of South Asia has experienced growth and development in various aspects including the world economic development, industrialization, new technologies and better living standards. But these advantages have been at a tremendous environmental price. On this ground, any time it touches on trade, financial growth and economic development, such associations with environmental sustainable policies, have been all the more alarming. The aim of this survey was to examine the effect of trade, financial development and economic growth on CO2 emission in selected South Asian countries based on Bayesian estimated two-stage least squares (2SLS) model. Consequently, due to this research, it became evident that trade and growth are interrelated, where CO2 emissions in the area increase considerably. There is also a perception that liberalization of trade leads to increased economic activity, innovation, adoption of technology that all serve to propel the economy towards greater productivity to a nation. It must however be mentioned that as a country opens up to global trade, besides the pollution of industrially backward areas that continue to use cheap and outdated methods of production; as soon as there is rapid industrialization and modes of raising global production, it can instead lead to very massive destruction of the natural ecosystem. Studies have revealed that CO2 emissions have a growing correlation with an intensified trading system, and shifting patterns of production due to knowledge on the pollution haven, and that a free trade policy in a country will increase the level of emissions through the relocation of industries to countries which have more lenient policies on pollution.

Bringing the case of South Asia, the expansion and broadening of the trading networks have led to a rise in the industrial activity, therefore, escalating the rate of emissions in this region. Moreover, South Asia is typified by carbon intensities per unit of gross domestic product (GDP), which implies that the amount of energy that will be required will grow tremendously as South Asian economies grow. South Asia, unlike most other country, confronts the problem of economic development-environmental deterioration nexus head-on. Some of the numerous causes of environmental degradation include industrialization processes, urbanization and an increased level of energy consumption; which have greatly contributed to the carbon intensity of this region in the world. The presence of low environment standards, poor corporate governance structures and standards, in combination with the absence of proactive policies, reduced the extent of implementation and the absence of enforcement mechanisms on firms with respect to environmental concerns; making the challenges of industrial safety complex. Quite the contrary, the effects of the financial development on CO2 emissions are high but not high. This demonstrates that financial markets and institutions are capable of funding environmentally- and economically-sustainable investment opportunities as it grows. An illustrative case is a mature financial system would make it easy to raise funds to fund renewable energy initiatives, green technologies, and activities that are environment-friendly. But in South Asia the impact on the emission is not as significant bearing in mind that it is lower than the trade costs, overall economic activity as represented by GDP. All the countries in the region have not had the benefits of yet underdeveloped financial institutions resulting in environmental performance. Perhaps sometime in the future, a growing financial market would help to reduce environmental risks brought about by industrial activities and further economic development. Opposite to this, according to this review, the urban population increase is not likely to necessitate statistically significant CO2 variation. Cities demand more energy to serve their own purposes and compound the strains of environmental degradation amalgamation of industrialization and practices can be more suitable to define the level of emissions than the concentration on larger populations alone. The urban centers in South Asia might not be capable of mitigating the impacts of city growth on emissions due to the inability of the infrastructure and environmental management systems to keep up with the growth of urban population. Therefore, the increase of urban population is not something that harms the environment; instead, the CO2 emissions can be more appropriately assessed by industrial, trade and energy processes in urban centers. The result of the study contributes to the knowledge of the development-environment nexus in South Asia. The conclusion of the study presents that traversing and economic development have a great influence on the CO2 emissions of South Asia coupled with the speeding up process of environmental degradation. The liberalization of trade has driven economic growth as well as innovation but also contributed to the level of emissions particularly in those regions where industrialization or traditional modes of production has been the order of the day. It is also interesting to note that financial expansion in an area puts less strain on emissions and this implies that the comparatively primitive advanced financial frameworks functioning in the area could hinder the prospects of making green investments. Moreover, economic, commercial and power generation activities localized in the metropolitan areas seem to add more to the CO2 emissions as compared to the sheer increase of urban population size. To sum up, this paper has presented a strong argument to show that policy factors must consider the presence of huge emission in South Asia without undermining the chances of social and economic empowerment.

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