Original Research Article

InterplayofMacroeconomicsandCO$_2$EmissionsDynamics:EvidencefromTop CO$_2$emitting Economies

Abstract

UnderstandingthedynamicconnectionbetweenmacroeconomicfactorsandCO$_2$emissionsisvital fordeveloping sustainableand environmentally conscious economic systems. Utilizing a30-year datasetfromtheWorldBank,focusingonthetop10CO$_2$-emittingnations,thestudyemploysthe Vector Error Correction Model (VECM) to capture both long-term and short-term causal relationships.Additional methods, such as Generalized Method of Moments (GMM) and fixed-effectmodels,areappliedforuncoveringsignificantrelationships.Descriptivestatisticsshowcase per capita CO$_2$emissions averaging 8.77 metric tons with notable variability. Key economic indicators,includingforestarea, foreigndirectinvestment,trade,andGDP,exhibitdynamictrends. Renewable energy consumption averages 15.02%, while energy use per capita stands at 3579.16 kg of oil equivalent. Agricultural land constitutes 32.48%, and the estimated rural population percentageisapproximately33.94%.TheVARmodelwithnineequationsisthoroughlyevaluated usingcriterialikeBIC(125.280)andHQIC(122.177),signifyingmodelfitting.Coefficientsinthe model highlight the impact of lagged values on the dependent variable, such as the statistically significant lagged CO$_2$emissions variable at lag 1. The Impulse Response Function (IRF) illustrates dynamic responses to variable shocks, while Cholesky decompositions reveal the system'sreactiontoinnovations.ForecastErrorVarianceDecomposition(FEVD)emphasizesthe heavy reliance on past values for short-term CO$_2$forecasts, with external factors gaining significance over longer horizons. This comprehensive approach enhances the understanding of variablecontributionstoforecastuncertainty,emphasizingtheimportanceofintegratingeconomic development with environmental stewardship.

Keywords: CO2 emissions; climate change; economic growth; VECM; GMM model

1. Introduction

Climate change is a significant issue of our time and is increasingly alarming on a global scale. Data provided by the International EnergyAgency reveals a concerning trend, carbon emissions worldwidehaveincreasedby40%sincetheearly1970s (IEA, 2013).Fromthe21stcenturyuntil 2019, there has been a consistent upward trajectory in global Greenhouse Gas (GHG) emissions, primarily driven by the surge in emissions from China and other emerging economies. Consequently, atmospheric concentrations of greenhouse gases have significantly risen, intensifying the natural greenhouse effect and potentially threatening life on Earth. The COVID-19pandemicledtoanotabledeviationfromthistrend,withglobalemissionsexperiencinga3.7% decrease in 2020 compared to 2019 levels. However, this interruption to the upward trend was short-lived,asglobalGHGemissionsresumedtheirascentshortlyafterthepeakofthepandemic. By 2022, emissions had rebounded to a level of 53.8 Gt CO_2eq, surpassing 2019 levels by 2.3% and 2021 levels by 1.4%.Among the various contributors to this complex phenomenon, carbon dioxide (CO_2) emissions stand out as a primary concern due to their significant impact on the Earth's climate system. Understanding the factors driving CO_2emissions is crucial for designing effective policies aimed at mitigating climate change while sustaining economic growth.

Despite extensive research on the drivers of CO_2emissions (Cole & Elliott, 2003; Dinda, 2004; Grossman & Krueger, 1995; Halkos & Paizanos, 2015; Shafik & Bandyopadhyay, 1992; Stern, 2004), the dynamic nexus between macroeconomic factors and carbon output remains a complex and understudied area. Existing literature offers conflicting insights, with some studies (Ang, 2007; Cole & Neumayer, 2004; Halicioglu, 2009)highlighting a positive correlation between economic growth and CO2 emissions, while others (Jackson, 2009; Peters & Hertwich, 2008) suggest the potential for decoupling economic development from environmental degradation. Additionally, the decrease in CO_2emissions has become a critical component of energy and economic policy strategies worldwide.

Against this backdrop, the primary objective of this study is to assess how different macroeconomic factors such as climate change, economic growth, energy consumption, agriculture, and rural development affect CO_2emissions in top CO_2-emitting nations. This study investigatestheimpactofmacroeconomicfactors onCO_2emissions,focusingonthetop10CO_2emittingcountriesnamely,China,UnitedStates,India,Russia,Japan,Korea,Iran,Indonesia,Germany, and Canada. The selection of these countries is based on their substantial contribution to global emissions and their pivotal role in shaping international climate policies. By examining therelationshipbetweenmacroeconomicindicatorsandCO_2emissionsovertime,thisstudyaims to provide valuable insights into the drivers of carbon emissions and their implications for sustainable development.

Furthermore, our study carries various implications that extend to the understanding of carbon emissions sensitivity, actions, and guidelines applicable to the general public, producers, policymakers, and government officials. As far as we know, this is the first study to assess the influence of macroeconomic factors on CO_2 emissions specifically in the top 10 CO_2emitting nations. To accurately portray the factors influencing CO2 emissions, we consider a range of indicatorsasproxiesand analyze thetop10CO_2emittingnationsglobally.Methodologically,we utilizethevectorerrorcorrectionmodel(VECM)tocapturebothlong-termandshort-termcausal relationships between dependent and independent variables, as well as the directional association betweenthem.Additionally,weemployageneralizedmethodofmoments(GMM)andfixedeffect models to uncover significant relationships between variables. Finally, we offer insightful recommendations to enhance environmental sustainability in the studied regions based on the findings of our research. Based on empirical findings, the study offers evidence-based policy recommendations to policymakers, stakeholders, and international organizations for enhancing climate resilience and fostering low-carbon transitions in high-emission economies.

2. Materialandmethods

Thedataforthisstudyweregatheredfromthe WorldBank,encompassing 30-yearperiod (1991- 2020), and focused on the top 10 CO_2-emitting countries (China, United States, India, Russia, Japan,SouthKorea,Iran,Indonesia,Germany,andCanada).Themainintuitionbehindthisstudy is to explore the role of climate change, economic growth, use of energy, agriculture, and rural developmentinthetopCO_2emissionscountries.TheCO_2emissionsareconsideredasadependent variable,andthepopulationgrowthrateandforestarearatioasproxiedforclimatechange;foreign direct investment, tradepercentagerate, gross domestic product as proxied foreconomic growth; energy use, renewableenergy consumption as proxied for energy use; and agricultural land ratio, rural population rate as proxied for agriculture and rural development are considered as independent variables.

We examine the relationship between explanatory variables and the dependent variable using VAR-typemodels,specificallyVECMandtheGrangercausalitytestproposedbyGranger(1969). This analysis allows us to explore both short-run and long-run relationships, as well as pairwise Granger causality between the variables. Additionally, we employ OLS-type models, including GMM(Hansen, 1982), and incorporate a fixed-effect model to uncover any significant relationships between the dependent variable and independent variables.

2.1 VectorErrorCorrectionModel(VECM)

VECM is a powerful tool for examining Granger causality in the context of time series data, allowing researchers to understand the dynamic relationships between variables over time. In the VECM framework, the Grangercausality test is applied to assess the causal relationship between variables. Granger causality essentially examines whether past values of one variable provide information about the future values of another variable. In the context of VECM and Granger causalitytesting,theprocedureinvolvesestimatingtheVECMandthenassessingthesignificance oflaggedvaluesinpredictingfuturevaluesofthevariables.TheGrangercausalitytestistypically conducted by comparing the restricted and unrestricted models. If the addition of lagged values significantly improves the model, it implies Granger causality.

2.2 GeneralizedMethodofMoments(GMM)

Afteridentifyingthealignmentofexplanatoryvariableswithcarbondioxideemissionsinboththe longandshortrun,weemploytheGMMstatisticalapproachtoinvestigatetheoverallsignificant connectionbetweenindependentvariablesandthedependentvariable.GMMisasemiparametric model designed to address sources of heteroskedasticity in the data (Le et al., 2016). This model proves valuable in addressing issues associated with the maximum likelihood estimator in cointegration.Additionally,itcontributestotestingtherobustnessof ourVectorErrorCorrection Model (VECM) based Impulse Response Function (IRF) results.The GMM model is essentially anOLSlinearregressionmodel,anditsequationisspecifiedasfollows:

$$\frac{1}{n}\sum_{i=1}^{n}x_i\hat{\mu}_{\rm i} = \frac{1}{n}\sum_{i=1}^{n}x_i\left(y_i - x_i\hat{\beta}\right) = 0$$

Here, $x_i$indicates thevectorofp covariates, $\mu_i$is the exogenous error term, $\beta_0$is thetrue value of p in the unknown parameters β and n is time series indices. In case of panel data, the moment condition E [(x_i, θ_0)] =0 translates to E [$x_i\mu_i$] = E[x_i(y_i− x_iβ)] = 0.

3. Results and Discussion

3.1 Descriptivestatistics

ThepercapitaCO_2emissionsstandatapproximately8.77metrictons,displayinganotablerange from 0.68 to 20.47 metric tons.The population growth rate hovers around 0.76%, with relatively lowvariabilitybetween-0.62%and2.8%.Keyaveragesinclude39.32%forforestarea(%ofland area),$51.46billionforforeigndirectinvestment,48.78%fortrade(%ofGDP),and$3.12trillion forGDP(current US$).Renewableenergyconsumption averagesat 15.02%,ranging moderately from 0.44% to 58.44% of total final energy consumption. Energy use per capita averages at 3579.16 kg of oil equivalent, with moderate variability between 316.56 and 8455.55 kg. Agricultural land constitutes an average of 32.48%, displaying moderate variability from 6.37% to61.07%.Theestimatedaveragetotalruralpopulationpercentageisapproximately33.94%,with amoderate spread from 8.22%to 74.22%.Trendlines foreach variable are presented in Figure1.

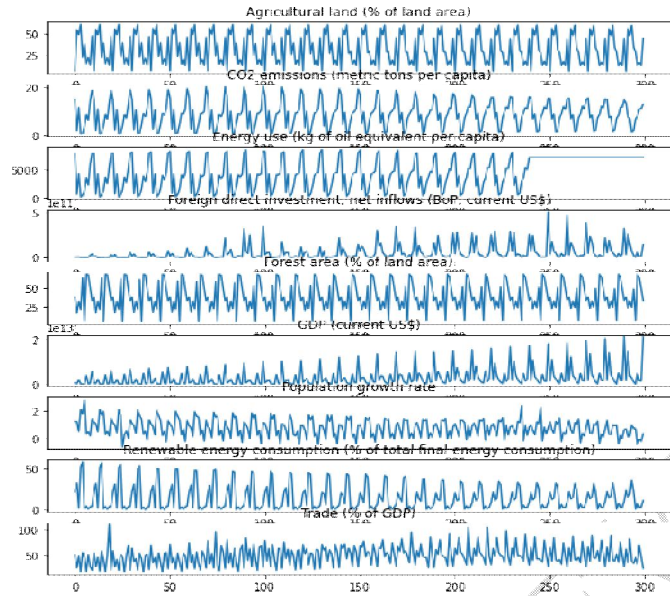

Figure1:GraphicalplotsofstudiedvariablesforthetopCO$_2$emitting countries

3.2 VAR model

The examination comprises a VAR model consisting of 9 equations. The BIC (Bayesian Information Criterion) is 125.280, utilized for model selection, with lower values indicating superior fitting models. Similarly, the HQIC (Hannan-Quinn Information Criterion) stands at 122.177, serving as an additional criterion for model selection. The Log-likelihood is -21068.8, which measures how effectively the model elucidates the observed data. The AIC (Akaike Information Criterion) is 120.10, offering another criterion for model selection, where lower values suggest improved models. Additionally, the FPE (Final Prediction Error) is 1.483, assessing the predictive performance of the model.

The coefficients indicate the impact of lagged values of variables on the current value of the dependent variable. Standard errors provide a measure of the precision of the estimate coefficients. The coefficient for the lagged CO$_2$emissions variable at lag 1 is -0.228. With a standarderrorof 0.082,thisyieldsa t-statof-2.781.Theassociatedp-valueforthiscoefficientis 0.005(lessthan0.05),indicatingthestatisticalsignificanceofthelaggedCO2emissionsvariable in forecasting current CO$_2$emissions. The model incorporates lagged values up to lag 5 for each variable, denoted by terms such as "L1" for lag 1, "L2" for lag 2, and so forth.

3.3 ImpulseResponseFunction

TheImpulseResponseFunction (IRF) helps to comprehend thedynamicresponseofvariablesin the system to a shock or innovation in one of the variables. The Cholesky one standard deviation novelties impulse response functions (IRFs) adjusted by Agricultural land (% land area), forest area(%landarea),energyuse(kgofoilequivalentpercapita)andGDP(currentUS$)againstall other remaining variables (Figure 2 to 5). The IRF is suitable for being able to elucidate the sign of the association and how long these upshots necessitate to take place.

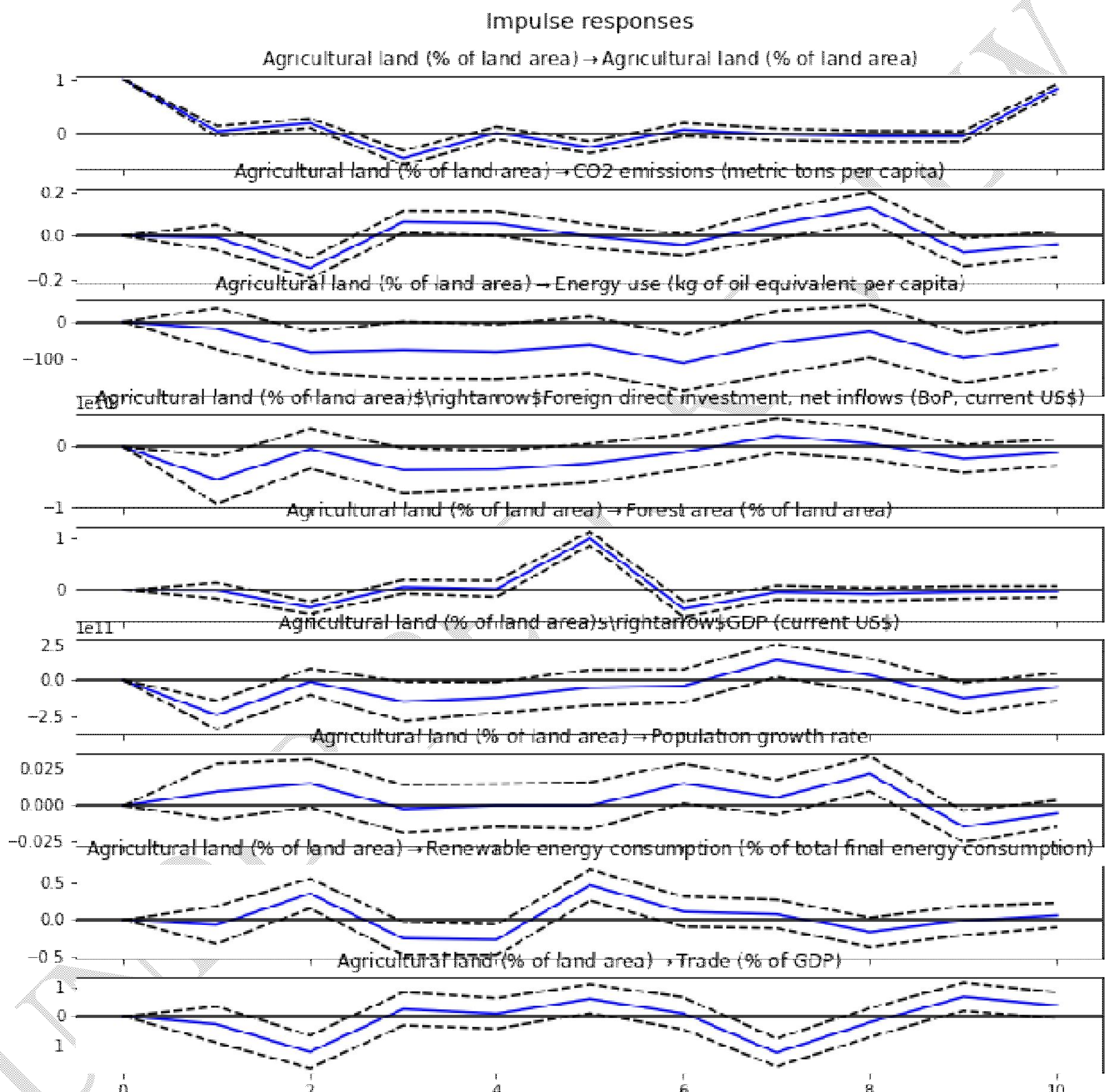

Figure2.ImpulseresponsetoCholeskyonestandard deviationof agricultural land

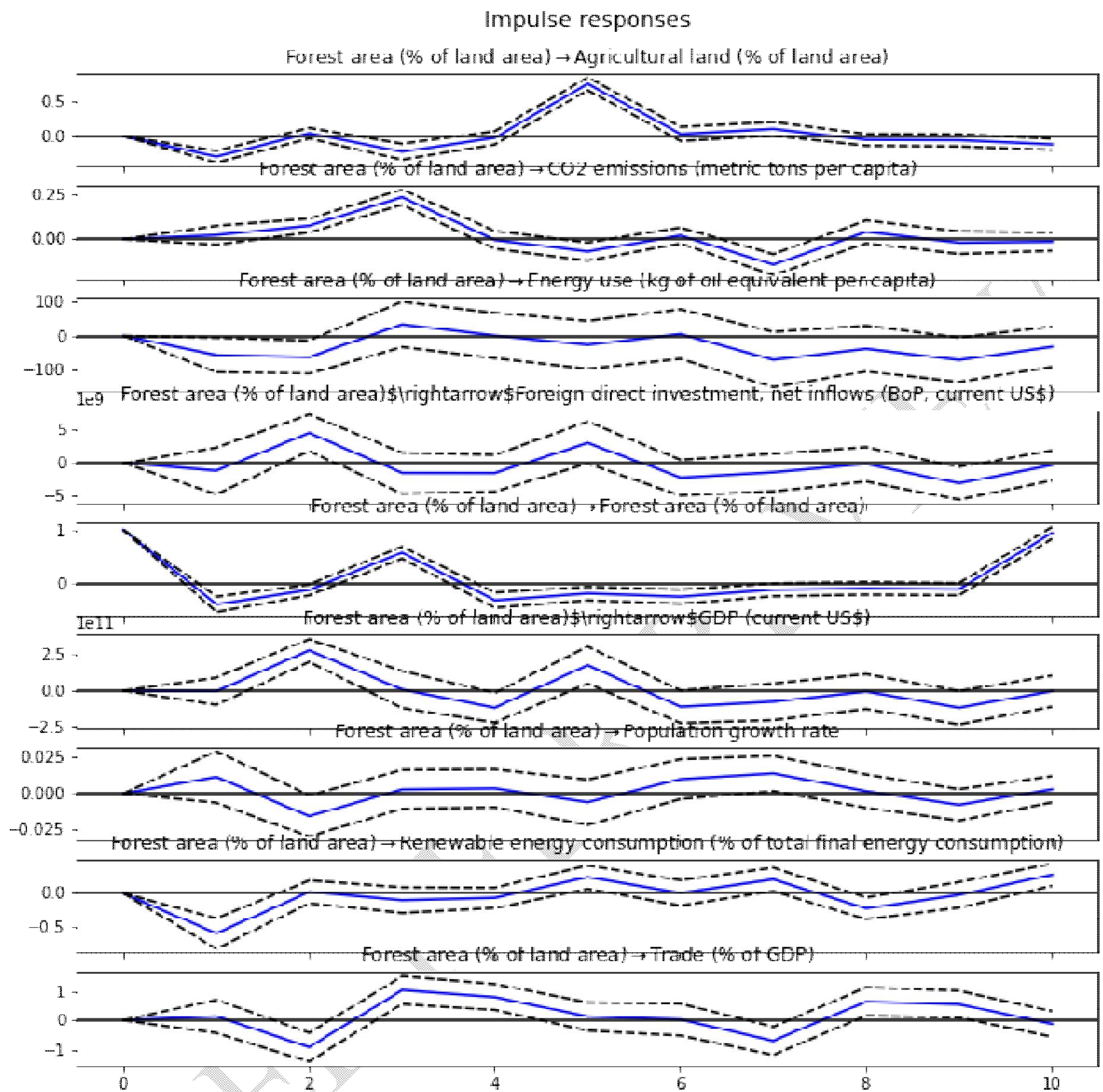

Figure3.Impulse responseto Choleskyonestandarddeviation offorest land

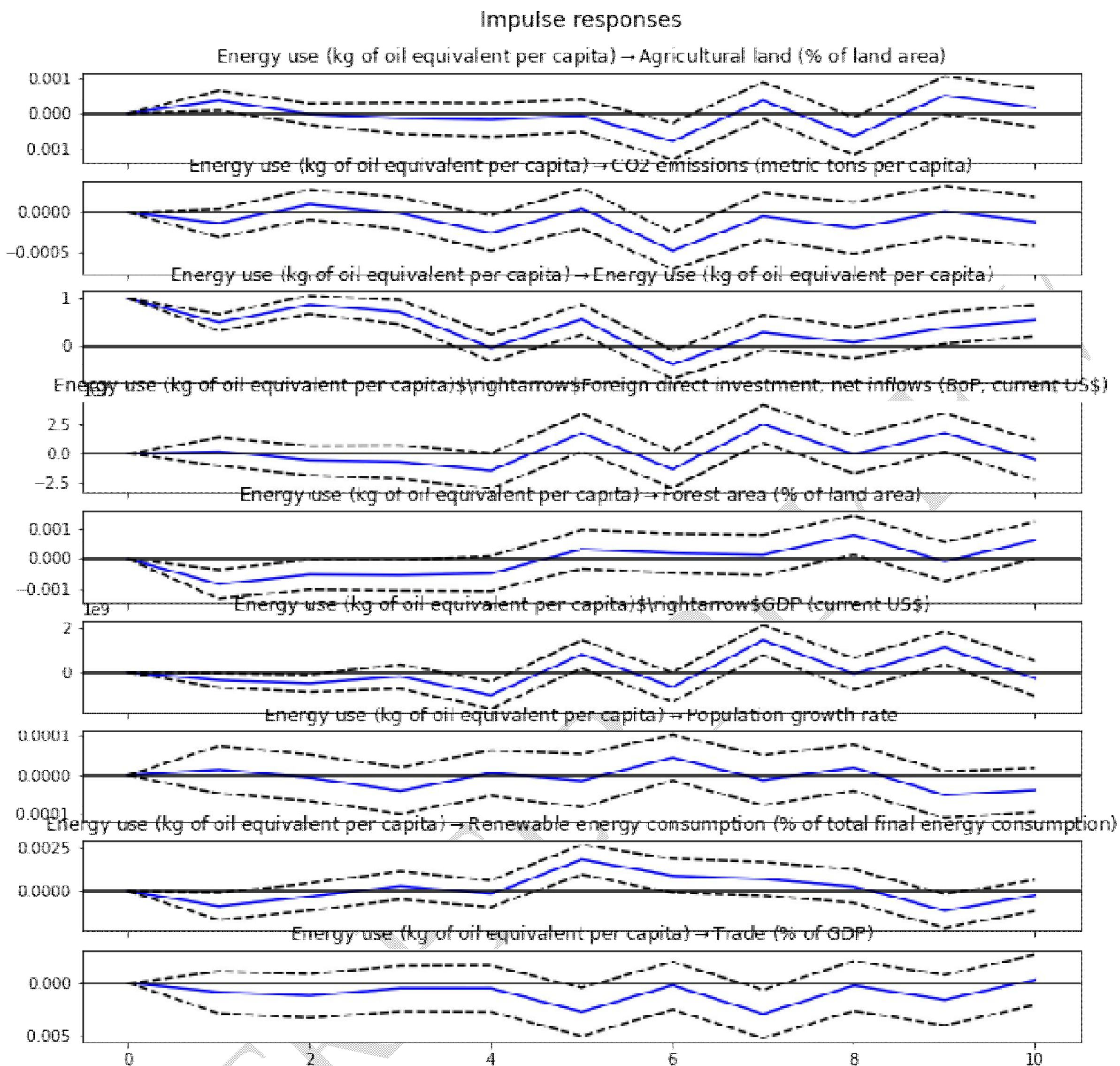

Figure4.ImpulseresponsetoCholeskyonestandarddeviationofenergyuse

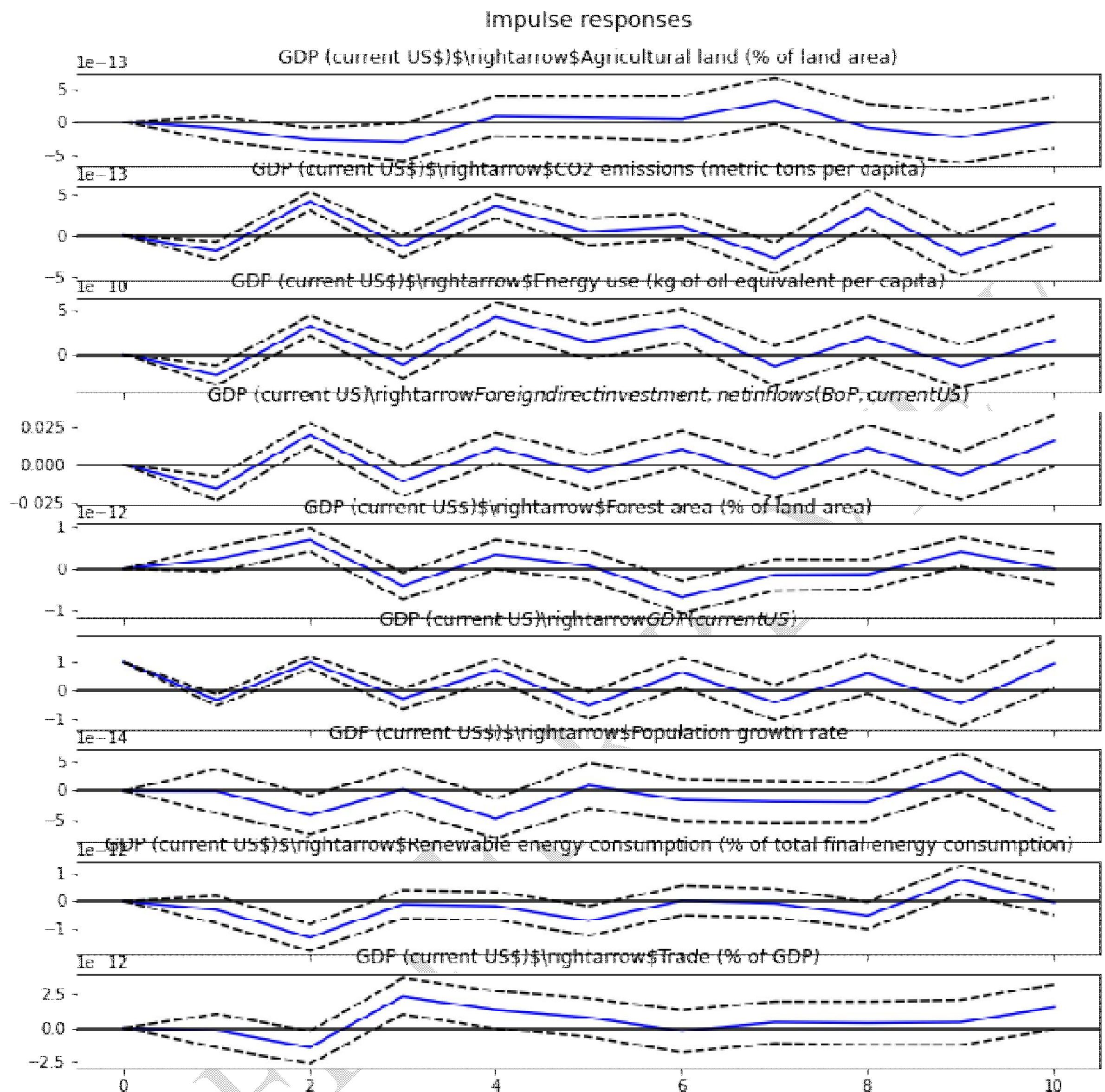

Figure5.ImpulseresponsetoCholeskyonestandarddeviationof GDP(current)

In Time Horizon 0, CO_2emissions are predominantly influenced by their historical values (92.41%),indicatingastrongrelianceonpastdataforshort-termforecasting.Othervariables,such as agricultural land, energy use, foreign direct investment, forest area, GDP, population growth rate,renewableenergyconsumption,andtrade,contributenegligibly(Figure6).Similarly,atTime Horizon 1, CO2 emissions heavily rely on their past values (84.66%), with minor contributions fromagriculturalland,forestarea,GDP,andtrade.Energyuseandforeign directinvestmentalso contribute, albeit less than CO_2emissions. In Time Horizons 3 and 4, as the forecasting period extends, dependence on CO_2emissions past values diminishes. Agricultural land, energy use, forestarea,GDP,populationgrowthrate,renewableenergyconsumption,andtradebecomemore significantcontributorstoforecasterrorvariance.Althoughforeigndirectinvestmentcontinuesto contribute, its impact decreases over time. Overall,The decomposition illustrates that while CO2 emissions' own past values are crucial for short-term forecasts, the influence of external factors increases over longer horizons. Variables like GDP, renewable energy consumption, and trade exhibit notable contributions to explaining the forecast error variance of CO_2 emissions. This information is valuable for understanding how different variables contribute to the uncertainty in forecasting CO_2emissions at various points in the future The final forecasted value of $CO_2$is presented in Figure 7.

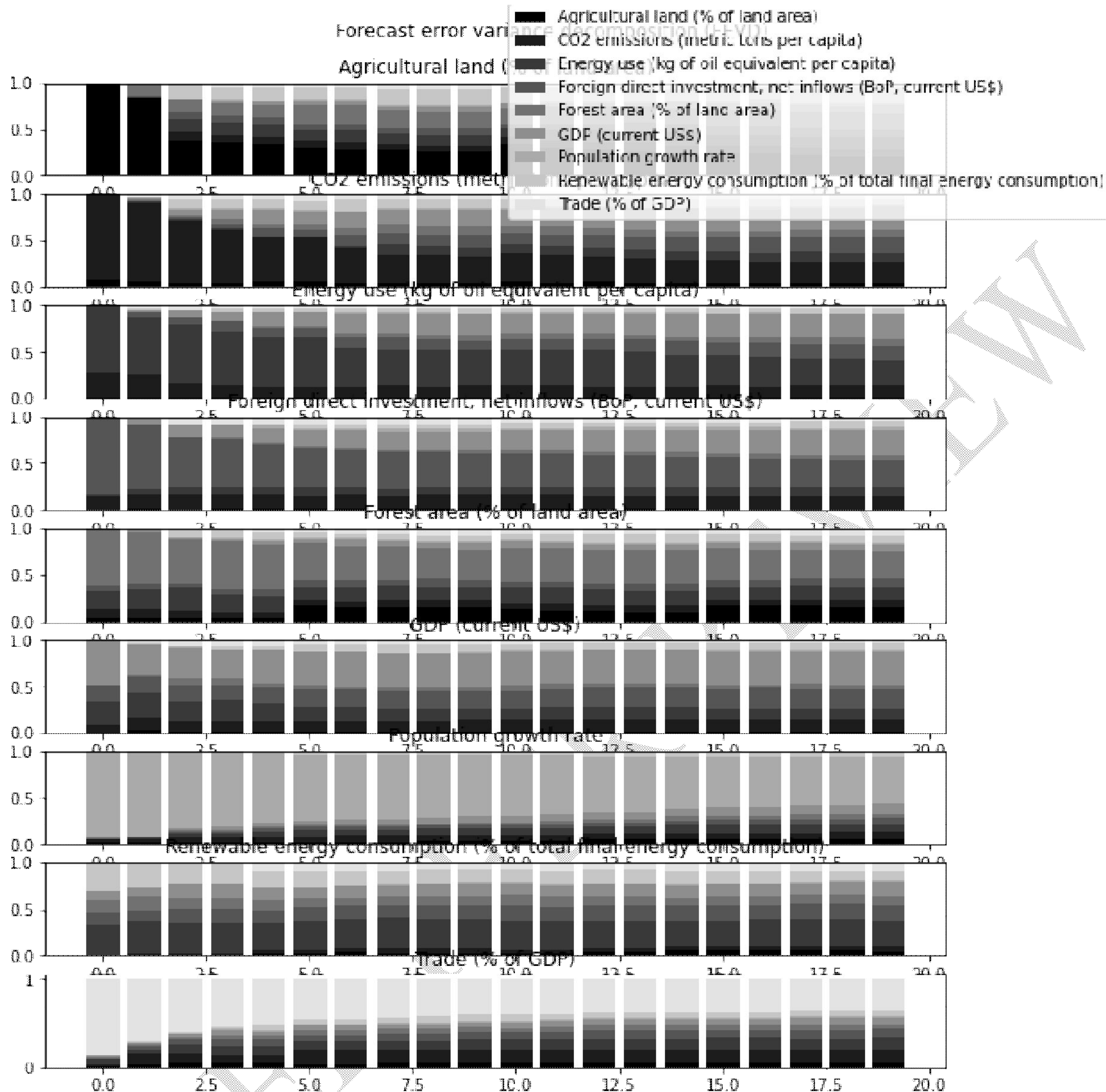

Figure6.ForecastErrorVarianceDecompositionforCO$_2$Emissions

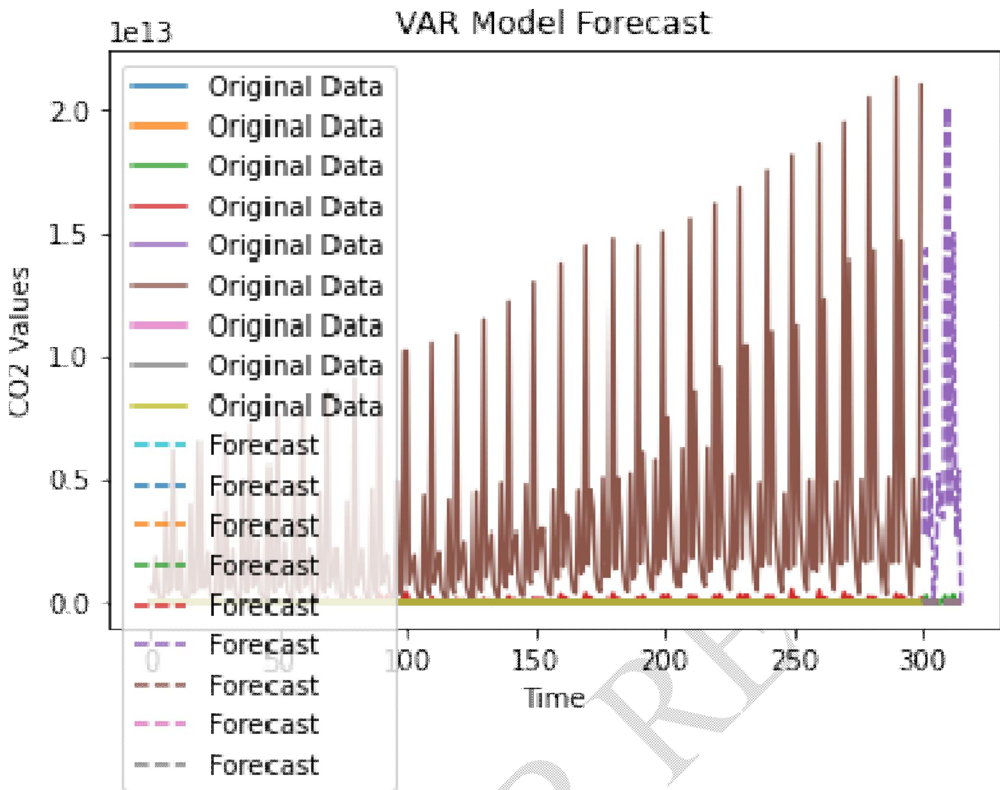

Figure7:ForecastedvalueofCO_2emissionfortheallthe data

4. Conclusion and Recommendations

This study highlights the complex interplay between macroeconomic factors and CO_2 emissions in the top 10 CO_2-emitting nations, emphasizing both short- and long-term dynamics over a 30-year period. Using methodologies such as Vector Error Correction Models (VECM), Generalized Method of Moments (GMM), and fixed-effects models, it identifies critical drivers, including GDP, energy use, renewable energy consumption, and agricultural land. The analysis reveals that while CO_2 emissions are heavily influenced by their own historical values in the short term, external macroeconomic factors such as trade, foreign direct investment, and renewable energy consumption become more significant over longer horizons. Descriptive findings, such as an average per capita CO_2 emission of 8.77 metric tons and renewable energy consumption at just 15.02%, underscore the pressing need for sustainable energy transitions and targeted interventions to mitigate climate change.

The findings present actionable insights for policymakers aiming to achieve low-carbon economic growth. Expanding renewable energy infrastructure, implementing carbon pricing mechanisms, and promoting energy-efficient technologies are essential strategies. Additionally, fostering sustainable agricultural practices, aligning trade and foreign direct investment with environmental goals, and integrating climate resilience into development planning can significantly reduce emissions. Strengthening international cooperation through multilateral agreements and technology transfers is vital for addressing global environmental challenges. These recommendations provide a roadmap for balancing economic development with environmental stewardship in the world's highest-emitting economies, contributing to a sustainable and climate-resilient future.

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Tables1:Descriptivestatisticsofthevariablesoftop10CO2emittingcountries

	CO2 emissions	PGR	FA(%of)	FDI(US$)	Trade (%GDP)	GDP(current US$)	REC(%)	EU (kg)	ALR (%)	RP(%)
Mean	8.773	0.764	39.319	51459247019	48.781	3123860417791	15.016	3579.161	32.480	33.9363
StandardError	0.313	0.037	1.120	4954735644	1.140	250392706982	0.898	151.108	1.060	1.09676
Median	9.250	0.805	36.298	15347499705	47.979	1420332039182	7.270	3708.705	29.038	25.632
Standard Deviation	5.429	0.633	19.393	85818538731	19.746	4336928903369	15.545	2595.363	18.367	18.99645
Skewness	-0.794	-0.565	-1.023	6.8	-0.170	4.863	-0.092	-1.026	0.129	0.897632
Range	0.197	0.122	0.018	2.5	0.477	2.269	1.048	0.437	54.704	66.004
Minimum	19.787	3.420	62.906	531842419557	94.854	21317232495769	58.000	8138.987	6.370735	8.218
Maximum	20.4698	2.8	68.49383	5.11E+11	110.5771	2.14E+13	58.44	8455.547	61.07447	74.222
Sum	2631.865	229.16	11795.77	1.54E+13	14634.45	9.37E+14	4504.94	1055853	9744.092	10180.89

Table2:ResultsforequationCO2emissions(metrictonsper capita)

	coefficient	std. error	t-stat	prob
const	5.643	7.949	0.710	0.478
L1.Agriculturalland(%oflandarea)	-0.007	0.029	-0.248	0.804
L1.CO2emissions(metrictonspercapita)	-0.229	0.082	-2.781	0.005
L1.Energyuse(kgofoilequivalentper capita)	0.000	0.000	-1.422	0.155
L1.Foreigndirectinvestment,netinflows(BoP,currentUS$)	0.000	0.000	1.103	0.270
L1.Forestarea(%ofland area)	0.023	0.027	0.851	0.395
L1.GDP(currentUS$)	0.000	0.000	-3.240	0.001
L1.Populationgrowthrate	-0.033	0.195	-0.167	0.867
L1.Renewableenergyconsumption(%oftotalfinalenergy consumption)	0.009	0.021	0.401	0.688
L1.Trade(%ofGDP)	-0.022	0.006	-3.725	0.000
L2.Agriculturalland(%oflandarea)	-0.195	0.027	-7.219	0.000
L2.CO2emissions(metrictonspercapita)	-0.480	0.084	-5.731	0.000
L2.Energyuse(kgofoilequivalentper capita)	0.000	0.000	0.766	0.443
L2.Foreigndirectinvestment,netinflows(BoP,current US$)	0.000	0.000	0.885	0.376
L2.Forestarea(%ofland area)	0.089	0.029	3.019	0.003
L2.GDP(currentUS$)	0.000	0.000	6.379	0.000
L2.Populationgrowthrate	-0.515	0.193	-2.666	0.008
L2.Renewableenergyconsumption(%oftotalfinal energy consumption)	-0.153	0.021	-7.430	0.000
L2.Trade(%ofGDP)	0.012	0.006	2.029	0.042
L3.Agriculturalland(%oflandarea)	0.083	0.030	2.760	0.006

L3.CO2emissions(metrictonspercapita)	-0.054	0.099	-0.547	0.584
L3.Energyuse(kgofoilequivalentper capita)	0.000	0.000	0.572	0.567
L3.Foreigndirectinvestment,netinflows(BoP,current US$)	0.000	0.000	0.152	0.880
L3.Forestarea(%ofland area)	0.179	0.022	7.974	0.000
L3.GDP(currentUS$)	0.000	0.000	1.172	0.241
L3.Populationgrowthrate	0.291	0.190	1.528	0.127
L3.Renewableenergyconsumption(%oftotalfinalenergy consumption)	-0.085	0.021	-4.026	0.000
L3.Trade(%ofGDP)	0.013	0.006	2.110	0.035
L4.Agriculturalland(%oflandarea)	0.139	0.035	3.950	0.000
L4.CO2emissions(metrictonspercapita)	0.011	0.092	0.116	0.908
L4.Energyuse(kgofoilequivalentper capita)	0.000	0.000	-0.199	0.842
L4.Foreigndirectinvestment,netinflows(BoP,current US$)	0.000	0.000	-0.110	0.912
L4.Forestarea(%ofland area)	0.081	0.019	4.174	0.000
L4.GDP(currentUS$)	0.000	0.000	-2.614	0.009
L4.Populationgrowthrate	0.137	0.197	0.698	0.485
L4.Renewableenergyconsumption(%oftotalfinalenergy consumption)	-0.076	0.018	-4.260	0.000
L4.Trade(%ofGDP)	0.001	0.006	0.219	0.827
L5.Agriculturalland(%oflandarea)	-0.031	0.038	-0.817	0.414
L5.CO2emissions(metrictonspercapita)	0.072	0.084	0.852	0.394
L5.Energyuse(kgofoilequivalentper capita)	0.000	0.000	-1.669	0.095
L5.Foreigndirectinvestment,netinflows(BoP,current US$)	0.000	0.000	-0.423	0.672
L5.Forestarea(%ofland area)	-0.041	0.029	-1.421	0.155
L5.GDP(currentUS$)	0.000	0.000	-0.924	0.356
L5.Populationgrowthrate	-0.012	0.201	-0.059	0.953
L5.Renewableenergyconsumption(%oftotalfinalenergy consumption)	0.019	0.023	0.832	0.405
L5.Trade(%ofGDP)	0.026	0.006	4.220	0.000
L5.Populationgrowthrate	-0.012	0.201	-0.059	0.953
L5.Renewableenergyconsumption(%oftotalfinalenergy consumption)	0.019	0.023	0.832	0.405
L5.Trade(%ofGDP)	0.026	0.006	4.220	0.000

Table3:forecasterrorvariancedecomposition(FEVD)forCO2emissions(metrictonsper capita)

	Agricultural land (%)	**CO2 emissions**	**Energy use(kg/ equ/ c)**	**FDInet inflows (US$)**	**Forest area (%)**	**GDP (US$)**	**Population growthrate**	**Ren.rgy cons(%)**	**Trade (% of GDP**
0	0.0759	0.9241	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.0608	0.8466	0.0173	0.0003	0.0032	0.0323	0.0000	0.0002	0.0393
2	0.0514	0.6625	0.0175	0.0263	0.0041	0.0766	0.0145	0.0813	0.0659

3	0.0465	0.5613	0.0224	0.0433	0.0517	0.1063	0.0170	0.0979	0.0535
4	0.0537	0.4821	0.0192	0.0699	0.0438	0.1617	0.0175	0.0828	0.0694