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CO2 Emission, Energy Use, Urbanization, and Economic Growth and 2-Trilemma: A New Machine Learning Algorithm

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Abstract

The study purposes to discover the association among CO2 emissions (CO2), energy use, and GDP in Pakistan. The data type is time series, with a time span of 1991–2021. The different econometric techniques structural breaks, VECM, ARDL, and D2C algorithms used along with the machine learning experiment. As well, two models were employed in this study. In model 1, Among the anticipated variables of GDP per capita, energy use per capita, and CO2 emissions, cointegration exists. Therefore, the outcomes of model 1 show that energy use per capita and CO2 emissions have a statistically significant and positive impact on GDP per capita. In mode 2, long-run associations exist along with positive and negative signs. The estimated coefficient of urbanization comes with a negative sign. The fact that urbanization is statistically significant means urbanization has effects on targeted variables such as GDP per capita. Having statistical significance, energy use per capita negatively influences GDP per capita. In the case of Pakistan, both explanatory variables have a negative association with the targeted variable. The robustness used to check the results' validity of the D2C algorithm.

Keyword- *CO2 emissions,* Economic Growth

Introduction

Higher energy consumption is a result of economic growth, primarily from industries and manufacturing, which, in turn, increases the proportion of CO2 emissions in the troposphere. As countries develop and industries expand, their energy demands rise significantly. Most companies require energy to function, contributing to the overall increase in energy usage (Hossain, 2011). Furthermore, manufacturing and industrialization play a crucial role in boosting the country's GDP. In developing economies, the processes of urbanization, CO2 emissions, and economic growth are intricately connected. Urbanization leads to rapid population growth and increased energy consumption, primarily from fossil fuels, resulting in higher CO2 emissions.

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Simultaneously, economic growth in urban areas drives industrial activities and energy demand, further contributing to CO_2 emissions. While urbanization can spur economic development by attracting investments and fostering innovation, it also presents environmental challenges. Developing economies appearance, the task of balancing economic growth with sustainable urban planning and emissions reduction, necessitating international cooperation and support to achieve a more sustainable and prosperous future (Ahmad and Zhao, 2019; Chen et al., 2022; Sufyanullah eta l., 2022).

Pakistan is also a developing country where urbanization and CO_2 emissions increase simultaneously. As urbanization progresses in the country, there is an increase in CO_2 emissions due to enlarged energy consumption, primarily from fossil fuels, to support the growing urban population's needs. Urban areas, being centres of economic activity, drive industrial growth and higher energy demands, contributing to CO_2 emissions. Like in 2013–14, Pakistan's primary energy supply comprised gas (46.3%), oil (34.4%), hydro (11.4%), coal (5.4%), nuclear (1.8%), and LPG (0.5%), with 0.1% from imported power. However, in the following five years, the energy sector underwent a transition, and by 2019–20, the contribution shifted to gas (35%), oil (26%), hydro (8%), coal (15%), nuclear (3.5%), and LPG (1%). Additionally, LNG and renewable energy accounted for 11% and 1%, respectively. This shift reflects the changing energy landscape in Pakistan, with a gradual move towards diversified and cleaner energy sources[1] (Butt et al., 2021). In 2018–19, oil accounted for 27% of Pakistan's total primary energy needs, with a consumption of approximately 19.2 million tonnes. This represented a significant decrease compared to the period between 2013–14 and 2016–17, when the share of oil in energy consumption was around 37%, ranging from 21.2 to 25.6 million tonnes. The drop in oil consumption was primarily due to a shift away from its use in power generation, as coal became the dominant fuel source for energy growth during that time (Economy Survey of Pakistan, 2020).

[1] State of Industry Report 2020.pdf (nepra.org.pk)

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CO_2 emissions in Pakistan are closely tied to its energy use. It is largely determined by economic growth, industrial activities, and urbanization. Reducing CO_2 emissions requires a shift away from heavy dependence on fossil fuels and a greater adoption of renewable energy sources and energy-efficient practices. These efforts are crucial to mitigating the impact of climate change and promoting sustainable development in the country (Mirza and Kanwal, 2017).

Economy of Pakistan has been steadily growing, leading to an increase in energy demand. Energy is essential for powering industries, transportation, commercial establishments, and residential areas. As the economy expands, the demand for energy also rises. Therefore, Pakistan has heavily relied on fossil fuels, particularly natural gas and oil, to meet its energy needs. Fossil fuels have been the dominant sources of energy for electricity generation, industrial processes, and transportation. For instance, natural gas is widely used in power plants and as a fuel for vehicles, while oil is used in transportation and as a source of energy in various industries (Irfan et al., 2019). Industries in Pakistan, such as cement, textiles, and manufacturing, also contribute significantly to CO_2 emissions.

These industries often rely on fossil fuels for their energy needs and emit CO_2 during their production processes. Pakistan's transport sector is heavily reliant on petroleum-based fuels like gasoline and diesel. Vehicles, including cars, trucks, and motorcycles, contribute significantly to CO_2 emissions as they burn these fuels for transportation purposes. As Pakistan's urban centers grow due to population migration from rural areas, the energy demand in residential buildings increases. Urban households consume electricity and other forms of energy for lighting, heating, cooling, and appliances (Reheem et al., 2022).

Urbanization in Pakistan has resulted in significant CO_2 emissions and has had various impacts on the environment and society. As more people migrate to urban areas, the demand for energy increases, leading to a higher dependance on fossil fuels for electricity generation, transportation, and industries. The expanding urban infrastructure and construction also contribute to increased emissions. The rise in CO_2 emissions exacerbates air pollution and accelerates climate change, leading to adverse impacts such as extreme weather, increase sea level and temperatures. Additionally, urban centers experience a higher concentration of pollution, which poses health risks to the population. The effects of climate change and pollution can also affect agricultural productivity, water resources, and public health, thereby posing challenges to sustainable development and the well-being of Pakistan's urban communities. Efforts to mitigate CO2 emissions through sustainable urban planning, promoting renewable energy, and improving public transportation are crucial to addressing the environmental and social consequences of urbanization in Pakistan (Abbasi et al., 2021; Bosah et al., 2021).

Literature Review

Sufyanullah et al. (2022) Examined the significant influence of the economic disparity between urban and rural inhabitants in developing nations on CO2 emissions. In the context of Pakistan, the research investigated the impact of urbanization on CO2 emissions. The econometric approaches ARDL and VECM are used for short- and long-run cointegration and causality. The study results show that CO2 emissions increase with urbanization. Furthermore, the VECM analysis indicated a one-way causal connection from urbanization to CO2 emissions in the short run, with economic growth being a contributing factor to CO2 emissions. Therefore, government intervention is crucial in implementing energy-efficient and environmentally sustainable measures to mitigate CO2 emissions and enhance the overall environment.

Zheng et al., (2022) The effects of technological innovation and institutional quality on sectoral energy consumption in Pakistan were explored through a comprehensive study. Ten variables were examined, encompassing urbanization, household consumption expenditure, electricity consumption in different sectors, and technological innovation, among others, spanning the years 1980 to 2019. The research employed innovative methodologies, including the Novel Dynamic ARDL approach, Cumulative Fourier Frequency Domain Causality analysis, and estimation of structural breaks. Notably, the findings indicated that energy consumption in the agricultural, commercial, and industrial sectors wielded a more substantial influence compared to the residential sector. Technological innovation in the commercial and industrial sectors leads to increased energy efficiency and environmental openness. Public-private partnerships benefit commercial activities, while improved institutional performance enhances industrial productivity. Household consumption and expenditure significantly influence the residential sector.

Rehman and Rehman, (2022), Centered on the analysis of CO2 emissions-induced environmental degradation, the study evaluated the effects of urbanization, population growth, GDP per capita, and energy use on CO2 emissions across five densely populated Asian nations: China, India, Indonesia, Pakistan, and Bangladesh. Grey relational analysis (GRA) and the conservative minimax approach were used for the time period 2001–2014. The study identified India as a major contributor to carbon emissions due to population growth and economic development. China and Pakistan are found to have emissions driven by energy use and urbanization, respectively.

Khan et al. (2021) Investigated were the interconnections among diverse elements encompassing Pakistan's agricultural product exports, industrialization, urbanization, transportation, energy consumption, and carbon emissions. The analysis incorporated time-series data spanning from 1976 to 2017. Employing the econometric methodology of ARDL, the study unveiled both short-term and enduring correlations between the specified factors. Moreover, the Granger causality test was employed to ascertain the directions of causality. The study results showed that the bound test confirmed cointegration at a 1% significance level. In the long run, energy consumption has a positive impact on agricultural product exports, while urbanization, transportation, and carbon emissions lead to a decrease in exports. During the immediate timeframe, industrialization, transportation, and energy consumption contribute to the advancement of agricultural product exports. Conversely, urbanization and carbon emissions exert a counteractive influence. The research proposed fostering sustainable agricultural product exports in Pakistan through measures like promoting sustainable agricultural practices, adopting renewable energy sources, implementing low carbon emission technologies, and cultivating an environmentally conscious portfolio.

Mehmood and Mansoor, (2021) Explored the correlation between urbanization and CO2 emissions across East Asian and Pacific nations. The study encompassed natural time series data spanning from 1982 to 2014. Employing the econometric techniques of Zivot-Andrews and ARDL, the research findings demonstrated a noteworthy reduction in CO2 emissions due to urbanization in countries such as China, Japan, Hong Kong, and Mongolia. Conversely, an increase in CO2 emissions was observed in Singapore, Macao, and South Korea. The study recommended specific policy measures for Singapore, Macao, and South Korea, urging the advancement of green energy initiatives within their urban landscapes for the sake of sustainable development. Additionally, the study highlighted the necessity for policymakers in the region to reconsider their trade and urbanization strategies as a means to foster a healthier and more sustainable environment.

Pan et al. (2023) investigated the adverse impact of rapid and unplanned urbanization in developing countries, including Pakistan. The data is a time series and was used from 1985 to 2021. The study used ARDL and NARDL models with Granger causality to examine short- and long-term relationships between the variables. The findings revealed that carbon emissions are heightened by energy consumption and technological factors, while economic growth and trade exert a diminishing impact. Urbanization, on the other hand, elicits a varied influence on emissions. showing both increasing and decreasing trends insignificantly. Granger causality analysis identified urbanization and technology as critical determinants of carbon emissions. The study suggested that the state implement policies that promote low-carbon technology adoption through international trade and address urbanization and energy demand to minimize carbon dioxide emissions in Pakistan.

Ali et al., (2019) Studied how urbanization affects carbon dioxide emissions in Pakistan using data collected over the years from 1972 to 2014. The econometric approach of the ARDL bound test for co-integration analysis and the VECM model for causal analysis were used. The findings showed that there is a connection between urbanization and carbon emissions, and this relationship holds true over both the long and short periods. Parallel, urbanization was found to cause an increase in carbon emissions. The study suggested that the government implement a public urban transportation system to reduce vehicular emissions in urban areas and encourage the adoption of green technology in industrial and residential sectors. Furthermore, the study proposed an educational campaign to raise awareness and train people in environmental mitigation and adaptation strategies to combat environmental degradation.

Azam et al., (2016) The researchers looked at how urbanization and other things affect harm to the environment. They checked the amount of carbon dioxide released in four countries: India, Bangladesh, Sri Lanka, and Pakistan, all part of the South Asian Association for Regional Cooperation (SAARC). They used annual time series data from 1982 to 2013 and employed the statistical approach of least squares for parameter estimation. The findings indicated that the effect of cities growing on the environment was different in each country. In Bangladesh and India, urbanization is significantly negatively correlated with environmental degradation. However, in Sri Lanka, the impact is significantly positive, and in Pakistan, it is insignificantly positive during the study period. The study suggested that policymakers develop appropriate long-term urban planning policies to effectively mitigate CO2 emissions and environmental pollution.

Methodology

In this session trying to find the relationship, cause and effect between and among the variables. For these purposes, used two econometric approaches used for two different models.

CO2 is CO2 emissions (in metric tons per capita); GDPpc is per capita GDP (in 2000 US$), and ENGUpc is per capita energy use (in kg of oil equivalent), URB is urbanization (Population in the largest city (% of urban population)

$GDP_{pc} = f\,(CO2 + ENGU_{pc})$ … Eq (1)

$GDP_{pc} = f\,(URB + ENGU_{pc})$ … Eq (2)

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Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$

Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$

Table.1 Descriptive statistics

Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$			
	GDP_{pc}	$ENGU_{pc}$	CO2
Mean	1171.426	452.9847	0.747823
Median	1175.437	460.2391	0.758995
Maximum	1497.987	500.4320	0.956345
Minimum	924.6347	397.0965	0.544419
Std. Dev.	175.6428	24.41985	0.107044
Skewness	0.367252	-0.602550	-0.011401
Kurtosis	1.876382	3.051506	2.292552
Jarque-Bera	2.327600	1.879272	0.647128
Probability	0.312297	0.390770	0.723566
Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$			
	GDPPC	**URBAN**	**ENGUPC**
Mean	1171.426	20.59121	452.9847
Median	1175.437	20.43444	460.2391
Maximum	1497.987	21.71408	500.4320
Minimum	924.6347	19.60394	397.0965
Std. Dev.	175.6428	0.697733	24.41985
Skewness	0.367252	0.304865	-0.602550
Kurtosis	1.876382	1.605458	3.051506
Jarque-Bera	2.327600	2.992169	1.879272
Probability	0.312297	0.224006	0.390770

The descriptive statistics results of both the model display in table 1. In the model1, The GDP_{pc} means is 1171. 426 While $ENGU_{pc}$ and CO2 mean values are 452.9847 and 0.747823. Median refers to the middle value of the data and in this particular table, the Median value of GDPpc, ENGUpc, and CO2 are 1175.437, 460.2391, and 0.758995

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respectively. Maximum and minimum represents the highest and lowest value of the model. The maximum value of GDPpc is 1497.987 while the minimum value of the same variable is 924.6347. The Maximum and minimum values of ENGUpc are 500.9320 and 397.0965 singly. Therefore, CO2 holds the minimum value of the model which is 0.956345. The standard deviation shows the departure of data from the average mean. In the aforementioned table, std. dev. of GDPpc is 175.6428 while ENGUpc and CO2 clasp 24.51985 and 0.107044 correspondingly. In this case, the normality is measured in two ways skewness and kurtosis. The skewness measures the degree of asymmetry of the series. If the value of skewed is zero it means that the particular variable is normally skewed. Similarly, the greater and less than zero indicates positive and negative skewed respectively. The skewness value of GDPpc is 0.367252 means the value is greater than zero, thus indicating positively skewed. Besides, the ENGUpc and CO2 values are less than zero which refers to a negative skewed. Therefore, Kurtosis measures the flatness or peakedness of the distribution of the series.

The decision value is 3. If the kurtosis value is 3 it means a Mesokurtic curve or normal curve. If greater than 3 it indicates Platykurtic and less than 3 shows leptokurtic. Jarque-Bera test was employed to check the normality of distribution. In the above table, The P-value of all the specific variables >0.05, thus H_0 accept and it means variables are normally distributed. In the model2, the mean value of GDPpc, URBAN, and ENGUpc are 1171.426, 20.5912,1, and 452.9847 respectively. The URBAN median value is lowest from ENGUpc (460.2391) and GDPpc (1175.437). The Maximum value is GDPpc while the minimum value of URBAN is 19.60394. The S.D value of URBAN is 0.697733 while 24.419885 and 175.6428 of ENGUpc and GDPpc correspondingly. The GDPpc and URBAN are fairly symmetrical (normally distributed) because the value of skewness lies at (-0.5 to +0.5) while ENGUpc is negatively skewed. Therefore, GDPpc and URBAN are Leptokurtic because 1.87 and 1.60 < 3. But ENGUpc is mesokurtic (3.05 = 3). The Jarque-Bera test value of all variables is >0.05, meaning that accept H_0 and H_0: Distribution is normal.

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Table 2 Correlation Matrix

Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$			
	GDPPC	ENGUPC	CO2
GDPPC	1		
ENGUPC	0.6828	1	
CO2	0.7320	0.7977	1
Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$			
	GDPPC	**URBAN**	**ENGUPC**
GDPPC	1		
URBAN	0.72162	1	
ENGUPC	0.68284	0.79246	1

Table 2 represents the outcomes of the association between variables. In particular table, GDPpc and ENGUpc holds a significant and positive association. The GDPpc and CO2 are positive and strong significant association. ENGUpc and Co2 are also a strong association. The result of model is representing the association between variables i.e., GDPpc and URBAN have negative and strong associations. Urbanization (URBAN) has held a negative association with ENGUpc. Besides, GDPpc and ENGUpc have a significant and positive association. In the case of Sub-Saharan Africa, Urbanization has a +ve effect on GDP per capita (Hytenget, 2011).

The Table 3. ADF and PP outcomes

Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$								
ADF								
Variables	**$T_{-statistics}$**	**$C.V_{at5\%}$**	**P_{value}**	**O-of-I***	**$T_{-statistics}$**	**$C.V_{at5\%}$**	**P_{value}**	**O-of-I***
CO2	-1.15443	-2.9639	0.6805	I (0)	-5.0682	-2.9677	0.0003	I (1)
$ENGU_{pc}$	-2.4604	-2.9639	0.1349	I (0)	-4.1576	-2.9677	0.0031	I (1)
GDP_{pc}	1.4419	-1.9533	0.9593	I (0)	-2.1462	-1.9529	0.0328	I (1)
PP								
CO2	-1.1544	-2.9639	0.6805	I (0)	-5.0682	-2.9677	.0003	I (1)
$ENGU_{pc}$	-2.4604	-2.9639	0.1349	I (0)	-4.1576	-2.9677	0.0031	I (1)

GDP_{pc}	1.4419	-1.9533	0.9593	I (0)	-2.1462	-1.9529	0.0328	I (1)

ADF and PP results reveal on Table 3. The tests employed to check the variable's mean and variance are constant [stationary] or not [non-stationary]. In above table, The CO2 emission p-value is 0.6805 [>0.05], under p-value [>0.05] means particular variable is not stationary. Thus, CO2 is not-stationary at I (0) under both the tests ADF and PP unit root test. Thus, it converted into the first difference. Then, after covertness, the variable is stationary at I(1). The p-value of GDPpc is 0.1349 [ADF and PP] which is >0.05. Thus, we cannot reject H_0 rather we accept H_0 and our H_0 CO2 is non-stationary. The ENGUpc is also non-stationary I (0) in both tests while ENGUpc is stationary at I (1). Therefore, the GDPpc p-value is 0.9593 (In both ADF and PP) the value is (>0.05). while the same variable is stationary at I (1). We conclude that all variables CO2, ENGUpc, and GDPpc are not at I (0) while stationary at I (1).

Table 4

Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$							
Level							
Variable	$Za_{t\text{-}s}$	Za*	BY	$Za_{t\text{-}s}$	Za**	BY	Stationary/Non-stationary
GDP_{pc}	-4.10	-4.93	1997	-3.88	-4.42	2000	Non-stationary
$ENGU_{pc}$	-2.46	-4.93	2003	-3.14	-4.42	2007	Non-stationary
CO2	-4.54	-4.93	2012	-4.21	-4.42	2008	Non-stationary
First Difference							
GDP_{pc}	-5.47	-4.93	1999	-5.21	-4.42	2008	Stationary
$ENGU_{pc}$	7.35	-4.93	2004	-6.59	-4.42	1998	Stationary
CO2	-5.06	-4.93	2007	-4.69	-4.42	2010	Stationary

ZA* and ZA** indicate breath with intercept and trend value at 5% as well as I I and BY and t-s refer to break year, absolute value, and t-statistics of zivot Andrew respectively.

Table 4, recommend to we check the structural break in specific variable under the given data. Thus, the Zivot and Andrews (1992) test were performed and variables are non-stationary at a level while I(1). The Za-test outcomes confirm economic theory; shock have existed and structural breaks. In specific, the outcomes are point-able to 3 main financial, political, and natural shocks that effects on CO2 emission, energy use and economic growth. The 1st shock occurred in 1998. The crisis happened after the first nuclear test on 28 May 1998. Pakistan's economy experienced a financial crisis in late 1998. Despite some encouraging signs like ongoing agricultural development and low inflation, the macroeconomic situation significantly worsened after May 1998, nuclear test of both the countries. At the end of November 1998, about $400 million exchange reserves reduced[2].

The ADF, IMF, Export-Import Bank of Japan, and other communities stopped all assistance to Pakistan[3]. IMF Stopped $226 million, signified 3rd tranche of the $1.6 billion relief package, and $293 million was stopped by the US Export-Import Bank, ADF also stopped $2 billion guaranteed during 1998–2000[4] (Khan, 2009). The second shock is noted in 2007-08. The 2008, world financial crisis hugely affected Pakistan's economy which was even now in front of highly macroeconomic imbalances and disparities. The global crises pushed the economy of Pakistan into a financial crisis. Macroeconomic indicators of economic growth have revealed very bad performance. The GDP growth extremely declined. GDP which was noted at 5% in 2007FY reduced by 0.40% in 2008FY (Mughal et al., 2015). The third shock recorded at 2010. The ADF and WB estimated that the floods damaged infrastructure, crops, and homes, along with extra direct and indirect fatalities. Pakistani officials rejected the sum and asserted that direct and indirect losses were more closely associated with $43 billion. Therefore, flood effected over 2.4m hectares of arable land, destroyed more than 2m homes and more than 21m masses to flee their birthplaces (Fair, 2011)

[2] Pakistan: 1998 Country Report on Economic Policy and Trade Practices (state.gov).
[3] Pakistan Declares a Moratorium on Nuclear Tests, Releases Budget - WSJ
[4] Pakistan Debt Crisis of 1998: Fueled by Nuclear Power and Political Instability | machetemag | Customer Experience, Culture, Strategy

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Table 5 ADF, PP, and KPSS unit root tests' outcomes

Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$								
ADF								
	Level				First Difference			
Variables	T-statistics	$C.V_{at5\%}$	P_{value}	decision	T-statistics	$C.V_{at5\%}$	P_{value}	decision
GDP_{pc}	1.4419	-1.9533	0.9593^{NS}	I (0)	-2.1462	-1.9529	0.0328^{S}	I (1)
URBN	-2.3015	-1.9533	0.0231^{S}	I (0)	-	-	-	-
$ENGU_{pc}$	-2.4604	-2.9639	0.1349^{NS}	I (0)	-4.1576	-2.9677	0.0031^{S}	I (1)
PP								
GDP_{pc}	1.4419	-1.9533	0.9593^{NS}	I (0)	-2.1462	-1.9529	0.0328	I (1)
URBN	-5.7975	-1.9524	0.0000	I (0)	-	-	-	-
$ENGU_{pc}$	-2.4604	-2.9639	0.1349^{NS}	I (0)	-4.1576	-2.9677	0.0031^{S}	I (1)

$C.V_{at5\%}$ indicates the critical value at the 5% level.

Table 5 shows the outcomes of ADF, PP, and unit root tests. In the above table the ADF and PP unit root tests, the variables GDPpc and ENGUpc p-value is <0.05, we cannot accept H_0 rather we accept H_A and H_A (series is stationary), while URBAN is stationary at I (1).

Table 6 Lag Order Selection Criteria

Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-246.1574	NA	5823.887	17.18327	17.32472	17.22757
1	-153.8086	159.2221*	18.66699	11.43508	12.00086*	11.61227*
2	-143.8897	15.04944	17.94346*	11.37170*	12.36181	11.68179
Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$						
Lag	LogL	LR	FPE	AIC	SC	HQ

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0	-279.0642	NA	238021.0	20.89364	21.03763	20.93646
1	-152.2808	216.0013	38.93556	12.16895	12.74488	12.34020
2	-125.6879	39.39687*	10.89681*	10.86577*	11.87365*	11.16547*
3	-117.2998	10.56283	12.28472	10.91110	12.35091	11.33923
4	-111.0731	6.457354	17.52221	11.11652	12.98829	11.67310

* Indicates lag order selected by the criterion

The lag normally represents to eve-changing of time based on a specific period and its plays a significant role in prediction. Generally, 1 and 2 lags for annual data while 8 lags for quarterly data are considered suitable lags. (Liew 2004). The AIC value is 11.37179* which is the lowest as compared to others. Thus, lag 2 is appropriate in this study under both the models (Model1 and model2).

Table 7 Johansen's co-integration tests

Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$				
Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob****
None *	0.816989	74.63391	29.79707	0.0000
At most 1 *	0.593268	30.48045	15.49471	0.0001
At most 2	0.238697	7.090806	3.841466	0.0077
TT shows 3 cointegrating eqn(s) at the 0.05 level				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Pro**
None *	0.816989	44.15347	21.13162	0.0000
At most 1 *	0.593268	23.38964	14.26460	0.0014

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At most 2 *	0.238697	7.090806	3.841466	0.0077
Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$				
LR Cointegration GDP per capita.				
GDPPC = -139.1198 + 1.935194ENGUPC + 25.23461CO2				
S. D		(0.73310)	(5.22093)	
$T_{\text{-statistics value}}$		[2.63974]	[4.83335] *	
Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level				

****$T_{\text{-statistics}}$=Co-efficient/Standard Error

Table 8 displays the result of the cointegration tests. The cointegration test is employed if all variables are at I (1) (Johansen, 1995). When cointegration exists, we employed ECM if one endogenous variable (Toda and Yammoto, 1995; Tuaneh and Wiri, 2018) and ECM if more than one endogenous variable (Granger, 1988, Johansen and Juselius, 1990, Johansen, 1988, Engle and Granger 1987). Through the Maximum eigenvalue and trace test to check the specific variable is cointegrated or not. The above table shows the 3 cointegrated or long-run associations that exist among particular variables GDP_{PC}, $ENGU_{PC,}$ and CO2. Therefore, in the same table, shows that the ENGU per capita and CO2 have developed as significant causes of GDP per capita, with t-value (of 2.63974 and 4.8335) with positive sing. The ENGUper capita and CO2 both have a statistically significant and positive impact on GDP per capita. When ENGU per capita and CO2 emission increase by one unit our GDP per capita also increases by 1.935194 and 25.23451 US$.

Table 8 short-run VECM result

Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$			
	Eq.1 D (GDPPC)	**Eq. D (ENGUPC)**	**Eq. D (CO2)**
Constant	-9.467047[-1.08052]	-11.70290* [-4.82886]	-0.017928 [-0.26261]
Eq.1 D ($GDPPC_{t-1}$)	0.844457* [2.390390]	0.323327* [3.30876]	0.000631 [0.22938]

Eq.2 D ($ENGUPC_{t-1}$)	-1.740471* [-2.17604]	-0.893290* [-4.03761]	0.002867 [0.45998]
Eq. D ($CO2_{t-1}$)	374.1126* [3.16505]	203.9549* [6.23798]	-0.701478 [-0.76166]
ECT_{t-1}	-0.171617* [-3.308930]	-0.093705* [-6.53161]	2.03E-05 [0.05031] (0.9607**)
R_2	0.773185	0.848662	0.600504
Adj.R2	0.527468	0.684713	0.167716
Sum sq. resids	3305.904	252.9458	0.200701
S.E. equation	16.59795	4.591167	0.129326
F-statistic	3.146654	5.176381	1.387525
Akaike AIC	8.760169	6.189879	-0.949235
Schwarz SC	9.437606	6.867315	-0.271798

* and **refer to statistically-significance, and P-value respectively.

Table 9 shows the VECM short-run outcomes. From eq.1 all regressor variables are establishing a significant short-run association with the response variable. The ECT value is negative and significant which indicates a significant long-term association existed among GDP per capita, ENGU per capita, and CO2 emissions. The coefficient of ECT is -0.171617 [$_{t\text{-statistics}}$-3.308930] which indicates with low speed of adjustment towards convergence to equilibrium (Long-run equilibrium). This specified, when there was at all disturbance in the system in the long run, in a very small period merely 17% correction to disequilibrium would occur. The Eq.2 ECT value is negative -0.09 as well as statistically significant [$_{t\text{-statistics}}$-6.53161]. In Eq.3, the ECT value of ENGU per capita is neither negative nor statistically significant. When the ECM (or ECT) is statistically significant [T-statistics >1.96, or p-value <0.05] but the coefficient with a positive sign, indicates that in the event of a disturbance, it means divergence from equilibrium, rendering the entire system incapable of returning to equilibrium. Therefore, if ECT is neither negative nor significant like Eq.3 it divergent from equilibrium and never achieves long-run equilibrium.

Table 9 VAR Granger Causality/Block Exogeneity Wald

Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$			
GDPpc =f (ENGUpc, CO2)			
Excluded	Chi-sq	Df	Prob.
CO2	4.341629	2	0.1141
ENGUPC	6.466608	2	0.0394
All	6.941696	4	0.1390
ENGUpc=f (GDPpc, CO2)			
CO2	0.567110	2	0.7531
GDPPC	5.335137	2	0.0694
All	5.855562	4	0.2102
CO2 =f (ENGUpc, GDPpc)			
ENGUPC	2.463719	2	0.2917
GDPPC	14.99194	2	0.0006
All	15.16766	4	0.0044

Table 10 shows the VAR Granger Causality of GDPpc, ENGUpc, and CO2 emissions. In the first model p-value of ENGUpc (p-value 0.1141) is >0.05 meaning that we accept H_0. But the value of CO2 (p-value 0.0394) is <0.05, meaning that the specific variables ENGUpc is significant. In other words, ENGUpc cause of GDPpc. In the second model, CO2 emissions and GDPpc both are not a cause of ENGUpc because the p-value of both variables is>0.05. therefore, in model 3, ENGUpc (p-value 0.2917) is not a cause of CO2 while GDPpc causes CO2 emissions because p-value <0.05 means we accept H_A and our H_A GDPpc is the cause of CO2 emission. In all models, model 3 is significant, or ENGUpc and GDPpc both are the cause of CO2 emission.

Table 10 Bound Test

Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$		
F-Statistics	7.369509	
Significance	I0 Bound	I1 Bound
10%	3.17	4.14

5%	3.79	4.85
2.5%	4.41	5.52
1%	5.15	6.36

The ARDL was established by (Pesaran et al., 1996; Pesaran and Shin 1998; Pesaran et al., 2001) and the bound test for cointegration is constructed on the Wald-test (F-stat). The two critical values of cointegration were established by Pesaran et al., (2001). If the F-statistics value is less than l0 (lower bound), meaning that cointegration does not exist between or among specific variables. If the F-statistics value is higher than I1bound (in other words, reject H_0), means cointegration exists among the variables. If the Wald-test F-statistics value fall the I0 and I1 bound, then the results are inconclusive means that the association between variables cannot be determined. Table 11 displays the outcome of the bound test, the F-statistics value is 7.369509 higher than I0 (3.79) and I1 bound (4.85) at 5%.

Table 11 ECT and Long-run Coefficients Results

$GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$				
Cointegrating Form				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDPPC(-1))	0.364125	0.204789	1.778048	0.0892
D(URBAN)	143.384401	96.657075	1.483434	0.1521
D(ENGUPC)	1.241498	0.547512	2.267525	0.0335
Cointeq(-1)	-0.174684	0.063313	-2.759030	0.0115
Cointeq = GDPPC - (-28.79362*URBAN - 0.7909*ENGUPC + 755.84771)				
F-statistic	5.601127	R^2		0.756794
Prob(F-statistic)	0.000796	Durbin-Watson stat		2.141367
Long Run Coefficients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
URBAN	-28.7936156	53.025632	-5.430132	0.0000
ENGUPC	-33.23319	15.28418	-2.174352	0.0425

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C	75.58477092	163.5789330	4.620691	0.0001

Table 12 shows the ECT and Long-run ARDL results. The p-value of F-statistics is 0.0007 (<0.05) indicates our entire explanatory variables jointly effect our targeted variable. R2 value is 0.75 means 75% variation in model explain by our explanatory variable. The value of DW is 2.14 also shown the model is free from autocorrelation. The ECT value is -0.174684 which negative and significant (0.01) means short-run convergence to the long-run equilibrium. The estimated coefficient of urbanization comes along with negative sign. The urbanization is statistically significant means urbanization effects on targeted variable GDP per capita. When the urbanization raises 1 unit the GDP per capita decline $28.79US. The energy use per capita is also statistically significant (p-value 0.0001). So, when the ENGU per capita increases 1 unit the GDP per capita decline $33.23. In case of Pakistan, both explanatory variables are negative association with targeted variable.

Table 12 Diagnostic tests

Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$			
Breusch-Godfrey Serial Correlation LM Test			
F-statistic	2.149862	Prob. F (2,21)	0.1414
Obs*R²	4.928591	Prob. X^2 (2)	0.0851
Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	2.266405	Prob. F (5,23)	0.0817
Obs*R²	9.572075	Prob. X^2 (5)	0.0883
SE-SS	3.518752	Prob. X^2 (5)	0.6206
Normality: Jarque-Bera Test			
-	-	Jarque-Bera	1.553778
-	-	Prob.	0.459834

The ARDL is considered effective if a model is free from diagnostic tests, i.e., Heteroscedasticity, serial correction and the model is normal. Table 13 indicates three basic diagnostic tests, normality, heteroscedasticity, and serial correlation. The χ^2-value of F-statistics is 0.08 (>0.05), thus rejecting H_0 and H_0: no serial correlation in the particular model. The model is also free from heteroscedasticity because χ^2-value of F-

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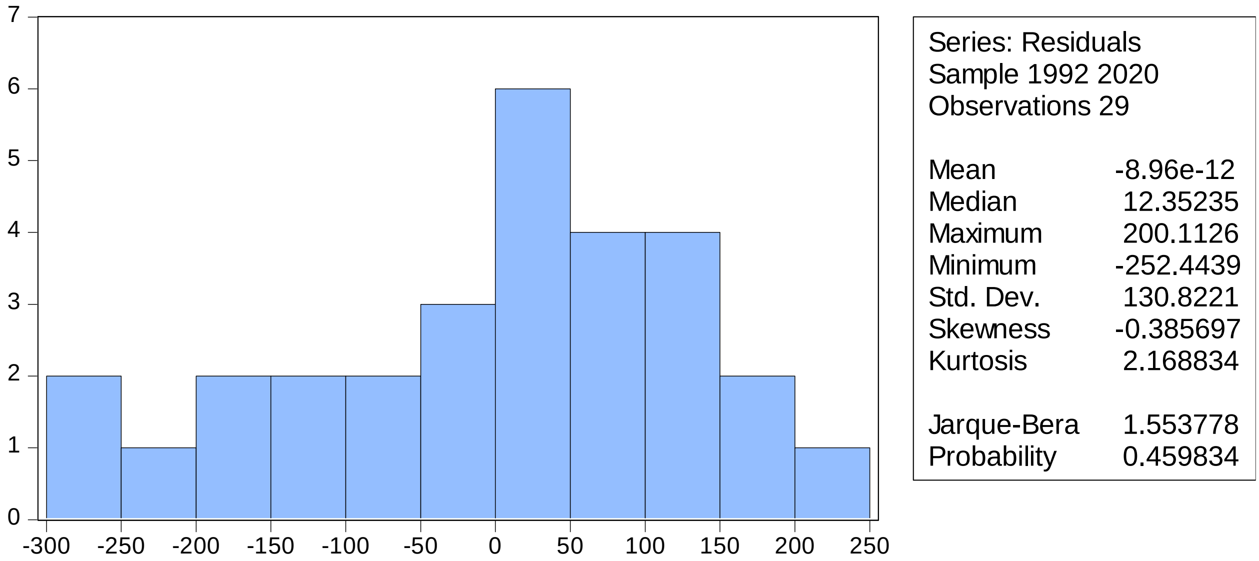
statistics 0.08 (>0.05), so reject H_0 and H_0: The model is homoskedasticity. Therefore, the condition of normality is also fulfilled, for the reason that Jarque-Bera p-value is 0.45 which is >0.05 (Fig. 2). Thus, accept H_0 and H_0: the specific model is normal.



Stability Test

The stability of a model is checked through CUSUM and CUSUM-squares tests. Figures 3 and 4 show the outcomes of CUSUM and CUSUM-squares respectively. The blue line falls within the read lies (5% significant level).

Figure 3

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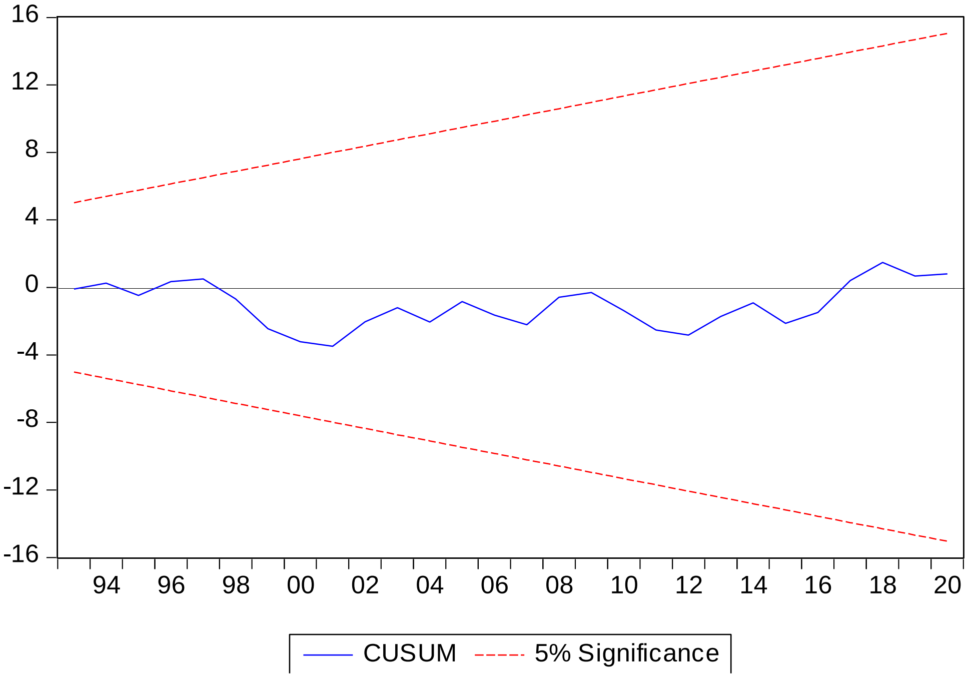
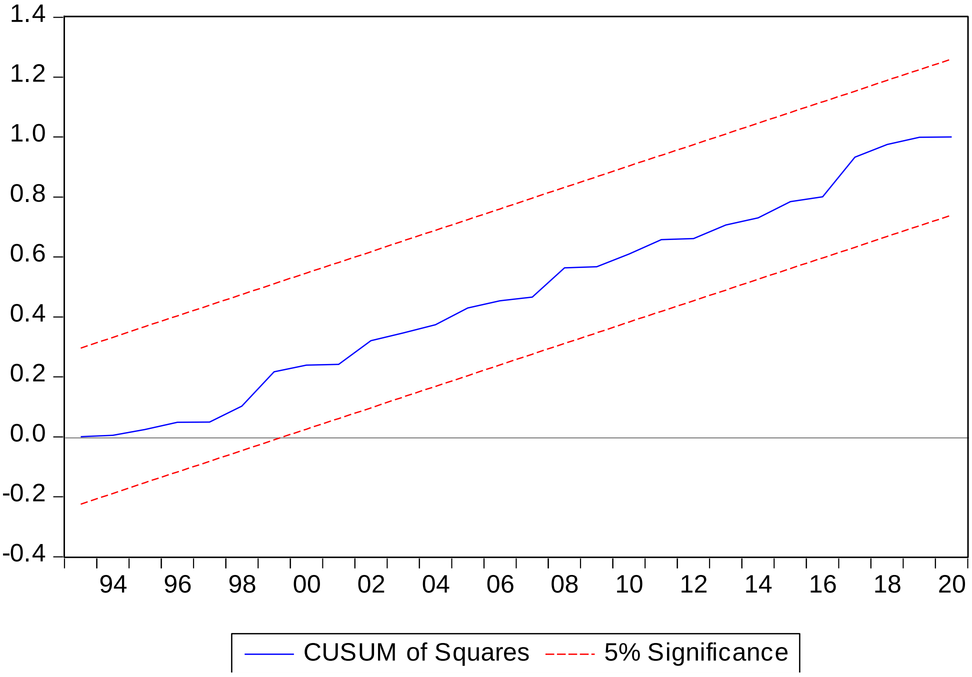


Figure 4



A MACHINE LEARNING APPROACH: D2C ALGORITHM

A necessary but not sufficient condition for causation is statistical dependency (Spirtes et al., 1989; Dul, 2016; Magazzino, 2021; Wunsch et al., 2022). In contract automated algorithm-based models of causality inference, on the other hand, have consistently demonstrated accuracy in reconstructing causality models across a wide range of

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applications. Based on this presumption, we develop an ML D2C model. To examine whether there is a direct causal relationship between n > 2 variables, supervised ML is used. This method makes use of the asymmetries in some conditional interactions between two variables in Markov networks that are causally coupled. In a multivariate setting, our D2C technique allows for the existence of a direct causal relationship between two variables, generating a collection of relationship characteristics based on asymmetric forms of the multivariate dependence. To determine whether the econometric model produced sufficient results for our conclusions, it is necessary to employ this model. We employ the same dataset that was created for the prior time series study.

To investigate the causal association between our mentioned variables, we accomplish the following mathematical steps:

$$GDPPC = g;\ CO2 = c;\ ENGU = e \ldots \qquad (a)$$

$$GDPPC = g;\ URB = u;\ ENGU = e \ldots \qquad (b)$$

Fig.1 and 2. Casual Models. Sources our elaborations in EeD and UeD for model1 and model2 respectively.

$$Pg\ (c,e) = Pg\ (c,w) if\ (c \perp\!\!\!\perp e|g) \qquad (1a)$$

$$Pg\ (u,e) = Pg\ (u,w), if\ (u \perp\!\!\!\perp e|g) \qquad (1b)$$

to estimate $Pg\ (c)$ and $Pg\ (u)$ in the causal model 1 and 2 respectively.

$$Pg, e(c) = Pg\ (c|e), if\ (c \perp\!\!\!\perp e|g) \qquad (2a)$$

$$Pg, e(u) = Pg\ (u|e), if\ (u \perp\!\!\!\perp e|g) \qquad (2b)$$

$$Pg\ (c) = \sum_{e} (pg(c|e)\ Pg\ (c)\ Pg \qquad (3a)$$

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$$Pg\ (u) = \sum_{e} (pg(u|e)\ Pg\ (u)\ Pg \tag{3b}$$

$$(c \perp\!\!\!\perp e|g) \to pg\ (c|e) = pg, c\ (e) \to pg, e(c) = p \tag{4a}$$

$$(u \perp\!\!\!\perp e|g) \to pg\ (u|e) = pg, u\ (e) \to pg, e(u) = p \tag{4b}$$

$$Pe\ (c) = \sum_{g} (pe(c,e)\ Pe\ (g) \tag{5a}$$

$$Pe\ (u) = \sum_{g} (pe(u,e)\ Pe\ (g) \tag{5b}$$

A graphical illustration is given in Fig 1 and 2

$$Pg\ (c) = \sum_{e} \left(\sum_{g} P(c,g,e)\ p\ (g) \right) P\ (e|g)$$

$$\to p\ g(c)\ \sum_{T} \left(\sum_{g} P(c|g,T)\ p\ (g) \right) P\ (T|g) \tag{6a}$$

$$Pg\ (u) = \sum_{e} \left(\sum_{g} P(u,g,e)\ p\ (g) \right) P\ (e|g)$$

$$\to p\ g(u)\ \sum_{T} \left(\sum_{g} P(u|g,T)\ p\ (g) \right) P\ (T|g) \tag{6b}$$

Where 't' is representing time series

We can now construct the identifiability algorithm. Fig. 2 and Fig. 3 sub-assemblies provide a summary for both the models. Any causal effect's identifiability can be determined by an algorithm depicted in the pictures. Additionally, it can produce a distribution for intervention. If there is a measurable effect, it is required. Now, the sub-graph of fig 3 and 4 can write the algorithm-form (Shpitser and Pearl, 2006)

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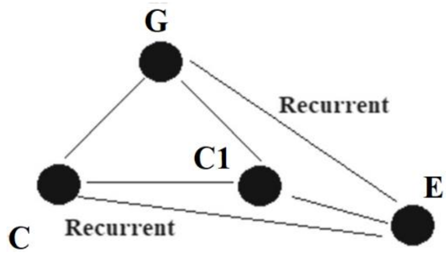
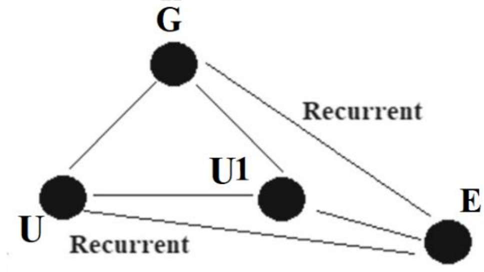
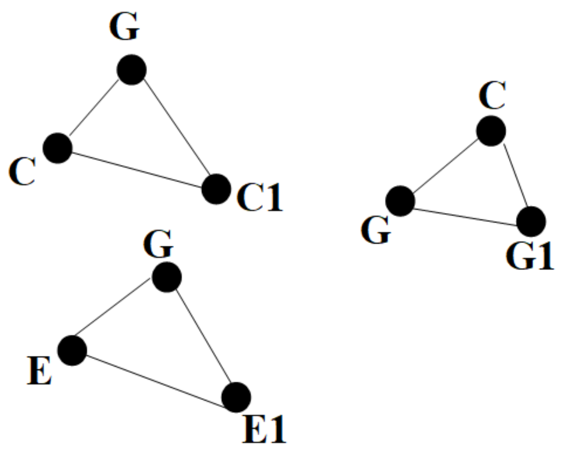
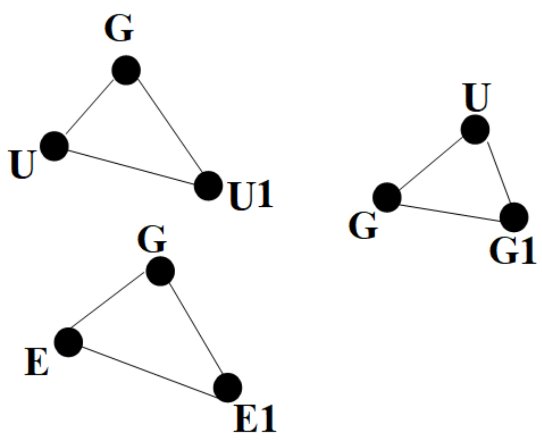
Fig.3 and 4, General graph with an algorithm with recurrent G, C, E and G, U, E for model1 and model2 respectively.





Therefore, in figure 5 and 6 presenting the sub-graph about fig 1 and 2.





Now, fig 3 and 4 = M and N for model1 and Q and R for model2.

$$If\ g\ = 0\ \rightarrow return \sum_{v \in v|c} P\ (v) \qquad (7a)$$

$$If\ g\ = 0\ \rightarrow return \sum_{v \in v|c} P\ (v) \qquad (7b)$$

$$If\ V\ \neq\ (\mathrm{c})_{\mathrm{M}}\ \rightarrow\ \mathrm{I\ D}\ (\mathrm{c}, \mathrm{g}\ \cap\ (\mathrm{c})_{\mathrm{M}}\ \mathrm{P(C)}_{\mathrm{M}}\ M\ [\mathrm{C}]_{\mathrm{M}} \qquad (8\mathrm{a})$$

$$If\ V\ \neq\ (\mathrm{u})_{\mathrm{Q}}\ \rightarrow\ \mathrm{I\ D}\ (\mathrm{u}, \mathrm{g}\ \cap\ (\mathrm{u})_{\mathrm{Q}}\ \mathrm{P(U)}_{\mathrm{Q}}\ Q\ [\mathrm{U}]_{\mathrm{Q}} \qquad (8\mathrm{b})$$

V = n vector for model 1 while r for model b:

$$If\ M\ [T]\ \in\ (M)$$

$$\rightarrow \sum_{v \in T|c} \prod vi\ \in T\ P(vi\ |v^{(i-1)}) \qquad (9a)$$

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$$If\ Q\,[T] \in (Q) \rightarrow \sum_{v \in T|c} \prod vi \in T\ P(vi\,|v^{(i-1)}) \qquad (9b)$$

$$If\ (\exists T^{'})\ TCT' \rightarrow M\,[T'] \in (M) \qquad (10a)$$

$$If\ (\exists T^{'})\ TUT' \rightarrow M\,[T'] \in (Q) \qquad (10b)$$

$$ID\ (C, g \cap t', \prod v \in t'\ P(Vi|V^{(i-1)} \cap T', v^{i-1}\, t'), M\,(T') \rightarrow do\,(G = g)\ on\ C \leftarrow Casuality\ effect \qquad (11a)$$

$$ID\ (U, g \cap t', \prod v \in t'\ P(Vi|V^{(i-1)} \cap T', v^{i-1}\, t'), Q\,(T') \rightarrow do\,(G = g)\ on\ U \leftarrow Casuality\ effect \qquad (11b)$$

If we use on M and N in model a and Q and R to n-time, the outcomes:

$$ID\ (e_n, g_n, \cap\ t'), \prod v \in t'\ P(v_i|V^{(i-1)} \cap T', V^{i-1)}\, t'), M\,(T')) \qquad (12a)$$

$$ID\ (e_r, g_r, \cap\ t'), \prod v \in t'\ P(v_i|V^{(i-1)} \cap T', V^{i-1)}\, t'), Q\,(T')) \qquad (12b)$$

$$ID\ (c_n, e_n, \cap\ t'), \prod v \in t'\ P(v_i|V^{(i-1)} \cap T', V^{i-1)}\, t'), M\,(T')) \qquad (13a)$$

$$ID\ (u_r, e_r, \cap\ t'), \prod v \in t'\ P(v_i|V^{(i-1)} \cap T', V^{i-1)}\, t'), Q\,(T')) \qquad (13b)$$

$$ID\ (c_n, g_n, \cap\ t'), \prod v \in t'\ P(v_i|V^{(i-1)} \cap T', V^{i-1)}\, t'), M\,(T')) \qquad (14a)$$

$$ID\ (u_r, g_r, \cap\ t'), \prod v \in t'\ P(v_i|V^{(i-1)} \cap T', V^{i-1)}\, t'), Q\,(T')) \qquad (14b)$$

Table 7 compares six scenarios to random noises when applied to various ITE scales. ε is positive for the whole time series under study (31 years). The baseline has six significant values and is denoted in the table with an asterisk. They match the user's choice that was made. The significant results shown in Table 7[5], with three different ITEs in four processes, we created six scenarios of each model. The algorithm (R) never yields a repetition count that is less than 500. The important instances (in Table 7) observed to the d-separation premise. In an unsupervised data sorting, the conditional distribution of each row of the algorithm is reliant on all the nodes that come before V (Eq. 8a and 8b). The d-separation factor is tracked in our case's selection procedures. On the other hand, the non-significant ITEs are the result nodes that can be divided by V and are thus disregarded by the algorithm. As a result, V separately conditions them. The results of the causal relationship between the variables are then obtained by ML training (16, 17, 18, 19, 20 and 21). The D2C algorithm produced some extremely intriguing results. The causal relationships that are substantially

[5] The single table use for both models 1 and 2.

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conditioned by the values of the substrates are shown in Tables 16, 17, 18, 19, 20, and 21. In fact, the study would not have needed the two primary predictors of causation if they had not been present (Causal Effect and Causal Effect with Local Centering). The noteworthy ITE results in the Selection analysis were re-elaborated for each estimating process for both the models (Table 7).

In actuality, the ML experiment required several times to fully understand how the variables behaved. According to Chen et al., (2017), R-learning has produced values between 14.2 and 20.2 s, are showing a causal relationship in sub-material layers. In specifically, by examining the potential pairings for model 1 is c1, ..., cn and e1, ..., en and u1, … u, and e1, … e2 for model 2 in our historical series, our experiment has attempted to explain the link between 'C' and 'E' (CO2 towards energy use in model 1). Therefore, in model 2, U and E (Urbanization towards energy use).

By contrasting the numbers for Causal Effect and Local Centering, we can see that the relationship does indeed exist in the sub-sedentary layer. In model1 the $g \rightarrow G$ is exceed from the other combinations of causality while in model2 the $U \rightarrow G$ value is higher than the other causality combinations.

Table 13 List of Data Generating Process (DGPs)

Selection without Random-noise							
Model1: $GDP_{pc} = \beta_0+\beta_1 ENGU_{pc}+\beta_2 CO2 + e$				**Model 2: $GDP_{pc}=\beta_0+\beta_1 URB+\beta_2 ENGU_{pc}+e$**			
	δ = in 31	**R**	**ε in 31**		**δ = in 31**	**R**	**ε in 31**
ITE0*	$\delta = 0$	2400	$\varepsilon = 0$	ITE0*	$\delta = 0$	2000	$\varepsilon = 0$
ITE1	$\delta = 2$	2400	$\varepsilon = 0$	ITE1	$\delta = 2$	2000	$\varepsilon = 0$
ITE2	$\delta = 4$	2400	$\varepsilon = 0$	ITE2	$\delta = 4$	2000	$\varepsilon = 0$
ITE0*	$\delta = 0$	600	$\varepsilon = 0$	ITE0*	$\delta = 0$	800	$\varepsilon = 0$
ITE1	$\delta = 2$	600	$\varepsilon = 0$	ITE1	$\delta = 2$	800	$\varepsilon = 0$
ITE2	$\delta = 4$	600	$\varepsilon = 0$	ITE2	$\delta = 4$	800	$\varepsilon = 0$
Selection-with random-noise							
ITE0	$\delta = 0$	2400	$\varepsilon \sim 1$	ITE0	$\delta = 0$	2000	$\varepsilon \sim 1$
ITE1*	$\delta = 2$	2400	$\varepsilon \sim 1$	ITE1*	$\delta = 2$	2000	$\varepsilon \sim 1$

ITE2	$\delta = 4$	2400	$\varepsilon \sim 1$	ITE2	$\delta = 4$	2000	$\varepsilon \sim 1$
ITE0	$\delta = 0$	600	$\varepsilon \sim 1$	ITE0	$\delta = 0$	800	$\varepsilon \sim 1$
ITE1*	$\delta = 2$	600	$\varepsilon \sim 1$	ITE1*	$\delta = 2$	800	$\varepsilon \sim 1$
ITE2	$\delta = 4$	600	$\varepsilon \sim 1$	ITE2	$\delta = 4$	800	$\varepsilon \sim 1$
Random assignment-without random-noise							
ITE0	$\delta = 0$	2400	$\varepsilon = 0$	ITE0	$\delta = 0$	2000	$\varepsilon = 0$
ITE1	$\delta = 2$	2400	$\varepsilon = 0$	ITE1	$\delta = 2$	2000	$\varepsilon = 0$
ITE2*	$\delta = 4$	2400	$\varepsilon = 0$	ITE2*	$\delta = 4$	2000	$\varepsilon = 0$
ITE0	$\delta = 0$	600	$\varepsilon = 0$	ITE0	$\delta = 0$	800	$\varepsilon = 0$
ITE1	$\delta = 2$	600	$\varepsilon = 0$	ITE1	$\delta = 2$	800	$\varepsilon = 0$
ITE2*	$\delta = 4$	600	$\varepsilon = 0$	ITE2*	$\delta = 4$	800	$\varepsilon = 0$
Random assignment and random-noise							
ITE0	$\delta = 0$	2400	$\varepsilon \sim 1$	ITE0	$\delta = 0$	2000	$\varepsilon \sim 1$
ITE1	$\delta = 2$	2400	$\varepsilon \sim 1$	ITE1	$\delta = 2$	2000	$\varepsilon \sim 1$
ITE2	$\delta = 4$	2400	$\varepsilon \sim 1$	ITE2	$\delta = 4$	2000	$\varepsilon \sim 1$
ITE0	$\delta = 0$	600	$\varepsilon \sim 1$	ITE0	$\delta = 0$	800	$\varepsilon \sim 1$
ITE1	$\delta = 2$	600	$\varepsilon \sim 1$	ITE1	$\delta = 2$	800	$\varepsilon \sim 1$
ITE2	$\delta = 4$	600	$\varepsilon \sim 1$	ITE2	$\delta = 4$	800	$\varepsilon \sim 1$
*GDPs' baseline							

Table 14 *Average Computation*

Average Computation $G \rightarrow C$				*Average Computation* $G \rightarrow U$			
Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$				**Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$**			
	ITE0	**ITE1**	**ITE2**		**ITE0**	**ITE1**	**ITE2**
CMR*	3.4	3.2	3.0	CMR*	3.3	3.4	3.4
CE**	3.9	3.9	3.1	CE**	4.9	5.0	5.1
ECwLC***	6.1	6.1	6.1	ECwLC***	4.4	4.4	4.5
Infeasible	2.3	4.3	4.1	Infeasible	1.7	1.7	1.9

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R-learning	17.3	17.3	17.3	R-learning	16.2	16.2	16.2

*, **, and *** represents conditional mean regression, causal effect and causal effect with local centering respectively.

Table 15 *Average Computation*

Average Computation $C \rightarrow G$				*Average Computation* $U \rightarrow G$			
Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$				**Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$**			
	ITE0	**ITE1**	**ITE2**		**ITE0**	**ITE1**	**ITE2**
CMR	3.4	3.4	3.6	CMR	3.5	3.5	3.6
CE	2.7	2.6	2.6	CE	2.8	2.9	2.9
ECwLC	3.4	3.4	3.4	ECwLC	6.4	6.4	6.5
Infeasible	2.1	2.1	2.1	Infeasible	2.1	2.1	2.2
R-learning	14.4	14.4	14.4	R-learning	20.2	20.2	20.2

Table16 *Average Computation*

Average Computation $G \rightarrow E$				*Average Computation* $G \rightarrow E$			
Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$				**Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$**			
	ITE0	**ITE1**	**ITE2**		**ITE0**	**ITE1**	**ITE2**
CMR	3.4	3.4	3.4	CMR	3.4	3.4	3.5
CE	4.9	4.8	5.2	CE	4.1	4.2	4.4
ECwLC	6.1	6.3	6.3	ECwLC	5.7	5.9	6.1
Infeasible	2.3	2.3	2.3	Infeasible	1.7	1.8	2.2
R-learning	19.2	19.2	19.2	R-learning	18.6	18.6	18.6

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Table 17 *Average Computation*

Average Computation $E \rightarrow G$				*Average Computation* $E \rightarrow G$			
Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$				**Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$**			
	ITE0	**ITE1**	**ITE2**		**ITE0**	**ITE1**	**ITE2**
CMR	3.8	3.8	3.8	CMR	3.1	3.2	3.5
CE	3.9	4.0	4.0	CE	4.1	4.3	4.3
ECwLC	4.6	4.7	4.7	ECwLC	5.2	5.2	5.2
Infeasible	1.9	2.0	2.0	Infeasible	1.9	2.2	2.2
R-learning	20.1	20.1	20.1	R-learning	20.4	20.4	20.4

Table 18 *Average Computation*

Average Computation $g \rightarrow G$				*Average Computation* $g \rightarrow G$			
Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$				**Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$**			
	ITE0	**ITE1**	**ITE2**		**ITE0**	**ITE1**	**ITE2**
CMR	3.2	3.2	3.2	CMR	3.3	3.5	3.8
CE	4.8	4.8	4.8	CE	4.1	4.4	4.5
ECwLC	6.4	6.4	6.5	ECwLC	6.3	6.3	6.2
Infeasible	1.7	2.1	2.1	Infeasible	1.9	1.9	1.9
R-learning	20.3	20.3	20.3	R-learning	18.3	18.3	18.3

Table 19 *Average Computation*

Average Computation $E \rightarrow C$				*Average Computation* $E \rightarrow U$			
Model1: $GDP_{pc} = \beta_0 + \beta_1 ENGU_{pc} + \beta_2 CO2 + e$				**Model 2: $GDP_{pc} = \beta_0 + \beta_1 URB + \beta_2 ENGU_{pc} + e$**			
	ITE0	**ITE1**	**ITE2**		**ITE0**	**ITE1**	**ITE2**
CMR	3.6	3.6	3.7	CMR	3.2	3.2	3.3

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CE	4.9	4.9	4.9	CE	3.6	3.8	3.9
ECwLC	5.2	5.8	5.9	ECwLC	4.4	4.5	4.9
Infeasible	2.1	2.2	2.2	Infeasible	1.5	1.6	2.1
R-learning	18.7	18.7	18.7	R-learning	16.8	16.8	16.8

The ML experiment required several times to fully understand how the variables behaved. R-learning has produced values between 14.2 and 20.2 s, showing a causal relationship in sub-material layers, according to Chen et al. (2017). In particular, by examining the potential pairings of c1, ..., cn and e1, ..., en in our historical series, our experiment has attempted to explain the link between C and E (CO2 towards energy use in model 1). Therefore, the u1, … un and e1, … en is our historical series for model 2 and U and E (Urbanization towards enemy use in aforementioned model) By contrasting the numbers for causal effect and local centering, we can see that the relationship does indeed exist in the sub-sedentary layer.

This value is greater in y K than the other causality combinations. Economists would attribute this process to a complex adaptive system with a propensity for self-organized growth and evolution. We may connect the second interpretation of our results from this point onward. Investments in education and training are needed if economic growth is to be more significant. Over time, a population with better levels of education will call for a more resilient economy. Additionally, as higher CO2 emissions are linked to health issues, the public will need policymakers to take action in favor of cleaner energy. Finally, we can state that, when compared to the results from the time-series experiment, the ML experiment produced similar values but with more specifics. Through self-learning, our programme was able to investigate the relational sub-layers that are hidden from conventional econometric analysis.

Conclusion

In conclusion, this study employed various statistical tests to explore the association between urbanization, energy use per capita, and CO2 with GDP per capita in four South Asian countries. Cointegration tests were used to identify long-run associations among the variables, and the results indicated that GDPPC, ENGUPC, and CO2 are cointegrated. In the long run, both urbanization and CO2 emissions have a statistically significant positive impact on GDP per capita in Sri Lanka and insignificantly positive impact in Pakistan. However, in Bangladesh and India, the relationship between urbanization growth and GDP per capita is significantly negative. Short-run outcomes were analyzed using the Vector Error Correction Model (VECM), and the results showed significant short-run associations between the regressor variables (GDPPC, ENGUPC, and CO2) and the response variable (GDP per capita). The error correction term (ECT) in the VECM suggests that there is a significant long-term association among the variables. However, in Eq.3, the ECT is neither negative nor significant, suggesting a divergence from equilibrium and no achievement of long-run equilibrium. Additionally, the study employed the Auto Regressive Distributed Lag (ARDL) approach to examine the cointegration relationship, and the results indicated the existence of cointegration among the variables. The F-statistics value was higher than both the lower and upper bound critical values, confirming the presence of cointegration. The overall explanatory variables jointly affect the targeted variable with a p-value of 0.0007, and the model explains 75% of the variation in GDP per capita. In the short run, the study found that urbanization and energy use per capita have a negative and statistically vital effect on GDP per capita in Pakistan. Specifically, a one-unit increase in urbanization and energy use per capita led to a decline of $28.79 and $33.23 in GDP per capita, respectively. In conclusion, this study highlights the complex and varied relationships between urbanization, energy use, CO2, and economic development in the selected South Asian countries. Policymakers need to consider these findings when formulating long-term urban planning policies to effectively mitigate environmental degradation and promote sustainable economic growth.

Recommendation

The finding of this study suggests, several recommendations can be made to policymakers in the Pakistan to address the complex association between urbanization, energy use, CO2, and economic development sustainable urban

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planning, promotion of green technologies, emission reduction strategies, climate education and awareness.

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