Chapter 4

DATA ANALYSIS & INTERPRETATION

India being an emerging economy is expected to be one of the fastest growing economies in the next decade. Post the adoption of globalization policies there has been an evident change in the structure of the economy. Consequently the utilization of resources in the economy has increased tremendously. A mix of coal, oil and gas is used to make necessary goods and services available in the economy. However, due to higher availability of coal, the use of coal as the major energy generating source is very high in India. India consumes **979,288,693 Tons** (short tons, "st") of Coal per year as of the year 2020.India ranks **2nd** in the world for Coal consumption, accounting for about **84.8%** of the world's total consumption of 1,139,471,430 tons (Statistical Review of World Energy, 2020). This has definitely led to an upward trend in emissions.

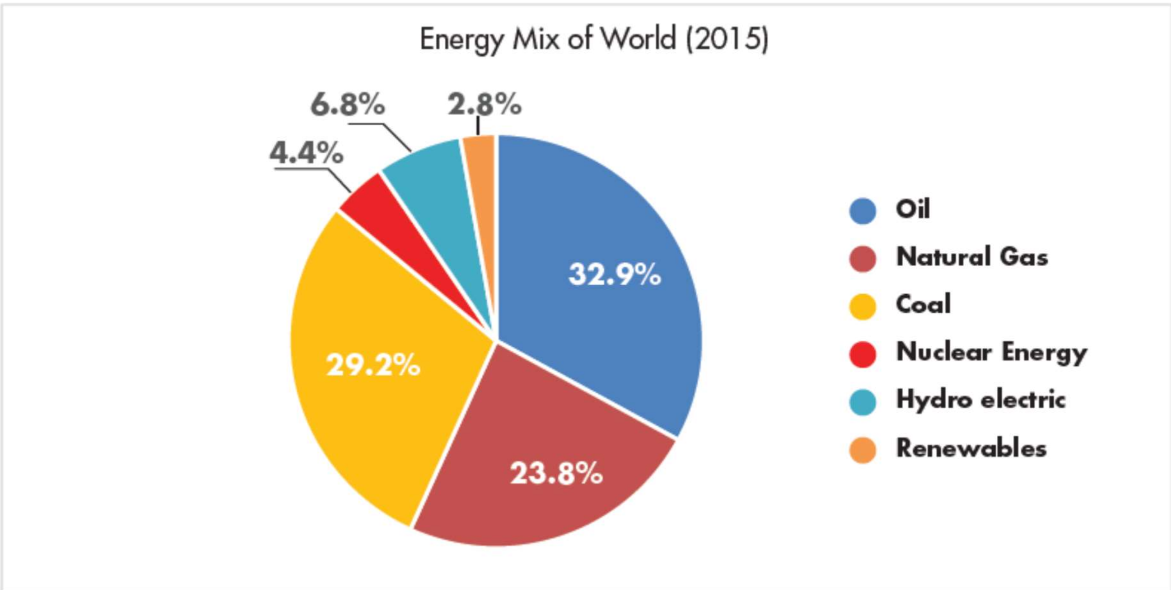


Figure 4.1: Energy Mix of the World

Source: NITI Aayog report, 2016

The environmental science researches have indicated varying trends in the atmospheric concentrations of environmental indicators. Thus, the emissions trend is likely to continue to rise over the next few decades.

The main greenhouse gases are carbon dioxide (CO_2), nitrous oxide (N_2O), chlorofluro carbons (CFC), perfluro carbons (PFC) and sulphuric floride. Several studies reveal that carbon dioxide is mainly emanated from fossil fuel and industrial activities in India. In the year 2018-19, total production of raw coal in India was 728.718 MT whereas it was 675.400 MT in 2017-18, showing a growth of 7.89% over the previous year. Also in the year 2018-19, total import of coal was 235.24 MT compared to 208.273 MT in 2017-18, thus increasing by 12.9%. (Coalcontroller.gov.in, 2018-19). This clearly shows that coal consumption has increased by 20% in India since 2017. India is the third highest emitter amongst the largest carbon dioxide emitters in the world. India has been upgraded by two positions on this list since 2005.

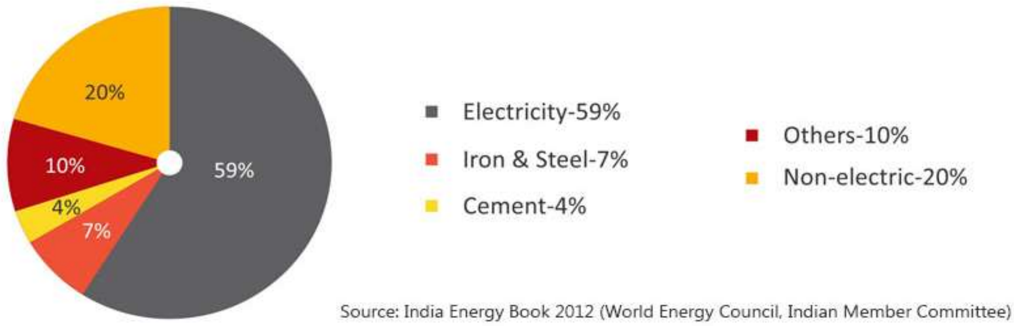


Figure 4.2: Sector-wise Coal consumption in India

Source: NITI Aayog report, 2016

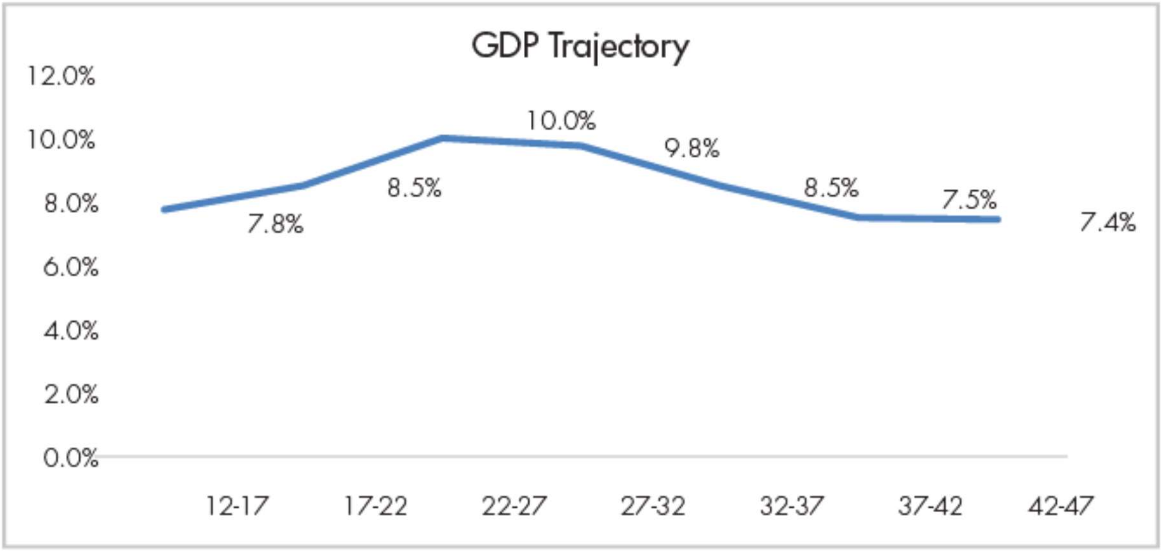


Figure 4.3: Expected GDP growth rate in future

Source: NITI Aayog report, 2016

4.1 The Growth-Environment Nexus

With of growth rates forecasted to be in double digits over the next few years, the demand for electricity consumption will also be high in India unless alternative energy be an available and affordable option for the masses. The major sectors that demand energy are transport, buildings (residential and commercials), agriculture, industry and cooking. With rising energy demands in these sectors the emissions are bound to be high. As per the report by India Energy Security Scenario (IESS), there is for potential for reducing energy demand by 25% through energy efficiency measures and technological interventions by 2047.

Achieving growth rates with manageable levels of pollution is easier said than done. Higher growth rates are implicit of higher share of manufacturing activities in the GDP. With India targeting around 34% to be contributed by industry and manufacturing sector to GDP by 2030 the reduction in "emissions intensity" up to 30-35% by 2030 as compared to 2005 levels seem unachievable. The alternative energy targets are also quite ambitious at 175 GW installed capacity of renewable energy by 2022.

An aggressive approach towards reducing emissions is the need of the hour. This is to be done not only to achieve various targets but also to make economic growth more sustainable. This study seeks to provide vital information needed to achieve these overambitious targets of India.

The data for the study has been extracted from World Development Indicators (latest editions), Our World Data and Handbook of Statistics (India).

4.2 PART A - Traditional EKC analysis over time.

The objective of this section is to examine carbon dioxide trend in India and to attempt to forecast the emissions based on the past data. The World Development Indicator carbon dioxide emissions (metric tons per capita) has increased to 1.73 in 2017 as compared to 0.2 in 1960 and 0.7 in 1990 as shown in figure 4.4 based on data in Table 4.1.

It is clearly evident from the figure above that the rate at which emissions have increased is comparatively higher after 1990. The structural and financial reforms implemented in 1991 have brought a shift in the growth trajectory of the Indian economy. Along with high growth rates and greater industrial and manufacturing opportunities, there has been an upsurge in pollution intensity too.

One of the main drawbacks of earlier EKC studies is the unavailability of longer term time series data. The absence of longer term time series data is the major reason why EKC studies use cross-country analysis. Few studies that used time series analysis could be divided into two categories: one that assumed the series to be stationary and the other that assumed the series to be non-stationary.

Table 4.1: CO_2 emissions per capita since 1960

Year	CO_2 emissions per capita	Year	CO_2 emissions per capita	Year	CO_2 emissions per capita
1960	0.268161	1981	0.474855	2001	0.971326
1961	0.284292	1982	0.478756	2002	0.967042
1962	0.306519	1983	0.506666	2003	0.992086
1963	0.322533	1984	0.507568	2004	1.02477
1964	0.3089	1985	0.545559	2005	1.068369
1965	0.333331	1986	0.572246	2006	1.121875
1966	0.337854	1987	0.597726	2007	1.193205
1967	0.331763	1988	0.631855	2008	1.310182
1968	0.353281	1989	0.679001	2009	1.431948
1969	0.351991	1990	0.71118	2010	1.397005
1970	0.35228	1991	0.740776	2011	1.480436
1971	0.363338	1992	0.771227	2012	1.597436
1972	0.375731	1993	0.782819	2013	1.590273
1973	0.378031	1994	0.811296	2014	1.61013
1974	0.381915	1995	0.844607	2015	1.670659
1975	0.405662	1996	0.900983	2016	1.7002
1976	0.414638	1997	0.919693	2017	1.73005
1977	0.428711	1998	0.921113		
1978	0.42511	1999	0.962115		
1979	0.435734	2000	0.97947		
1980	0.450377				

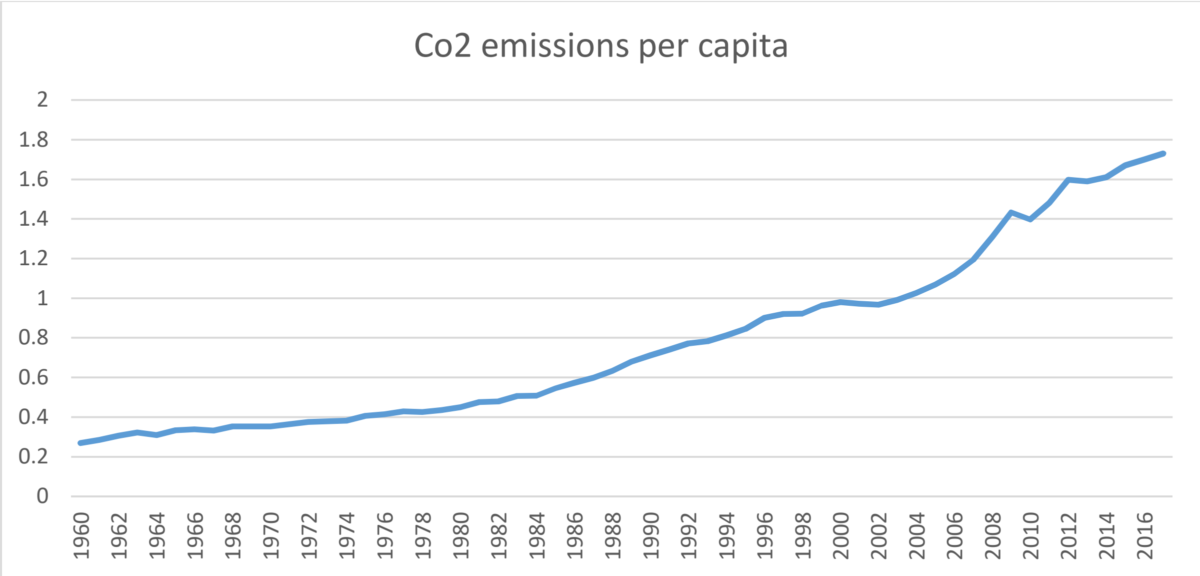


Figure 4.4: CO_2 emissions per capita since 1960

Created by researcher in Excel

The studies assuming the series to be stationary used curve estimation technique and fitted the quadratic or cubic equation to arrive at EKC relationship. New studies relaxed this assumption and adopted the unit root test to check for stationarity and later used cointegration test to check for existence of EKC. The figure 4.5 shows a simple scatter plot of CO_2 emissions against the Gross Domestic Product per capita based on data in Table 4.2. The figure shows an upward trend in CO_2 emissions in India since 1960.

This study adopted the traditional approach assuming the series to be stationary. The model was estimated using the curve estimation techniques in SPSS. The data was normalized.

Table 4.2: GDP per capita and CO_2 emissions per capita.

Year	GDP per capita	CO_2 emissions per capita	Year	GDP per capita	CO_2 emissions per capita	Year	GDP per capita	CO_2 emissions per capita
1960	15045	0.2681614	1981	19973	0.4748549	2001	38838	0.9713261
1961	15298	0.2842917	1982	20193	0.4787564	2002	39637	0.9670419
1962	15432	0.3065195	1983	21169	0.5066655	2003	42050	0.9920857
1963	16026	0.322533	1984	21481	0.5075678	2004	44651	1.0247696
1964	16868	0.3089004	1985	22106	0.5455593	2005	48030	1.0683693
1965	16086	0.3333306	1986	22654	0.5722459	2006	51673	1.1218747
1966	15747	0.337854	1987	23044	0.5977261	2007	55886	1.1932054
1967	16628	0.3317634	1988	24727	0.6318552	2008	57214	1.3101819
1968	16832	0.3532811	1989	25651	0.6790005	2009	61190	1.431948
1969	17551	0.3519907	1990	26515	0.7111801	2010	66552	1.3970046
1970	18053	0.3522799	1991	26254	0.7407761	2011	70046	1.4804356
1971	17940	0.3633376	1992	27145	0.7712274	2012	72942	1.5974362
1972	17435	0.3757311	1993	27879	0.782819	2013	76659	1.5902728
1973	17595	0.3780313	1994	29163	0.8112958	2014	81366	1.61013
1974	17393	0.3819147	1995	30775	0.8446074	2015	86980	1.670659
1975	18549	0.4056621	1996	32476	0.9009832	2016	92103	1.7002
1976	18428	0.4146381	1997	33164	0.9196925	2017	97103	1.73005
1977	19318	0.4287112	1998	34571	0.9211128			
1978	19961	0.4251097	1999	36954	0.962115			
1979	18487	0.4357343	2000	37699	0.9794703			
1980	19283	0.450377						

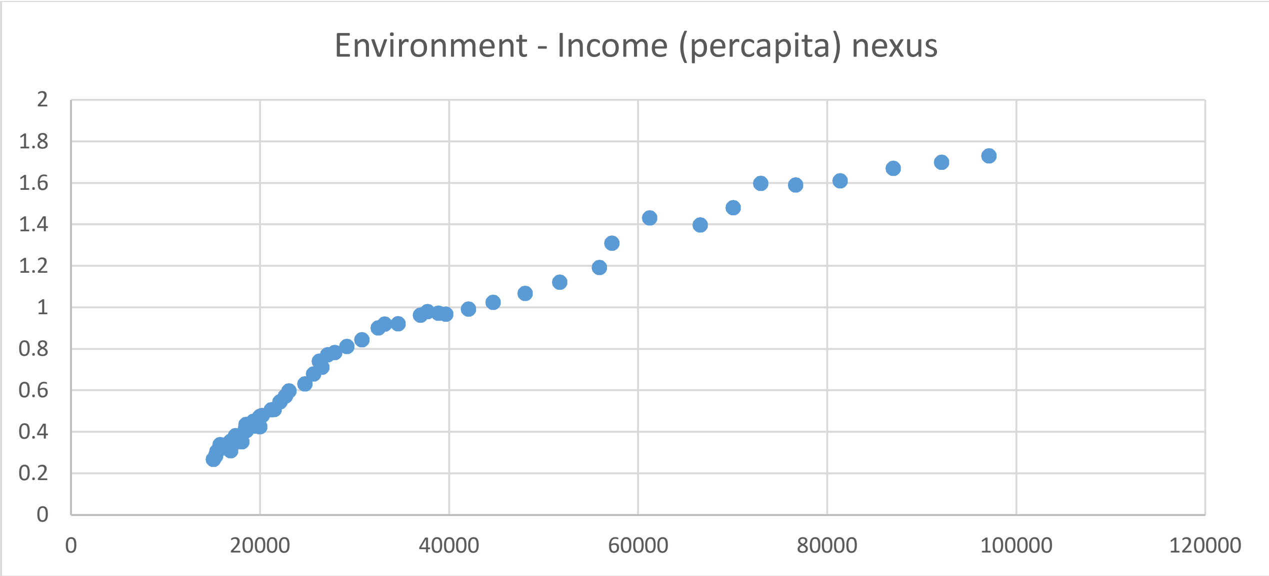


Figure 4.5: Growth – Income nexus (Created by researcher in Excel)

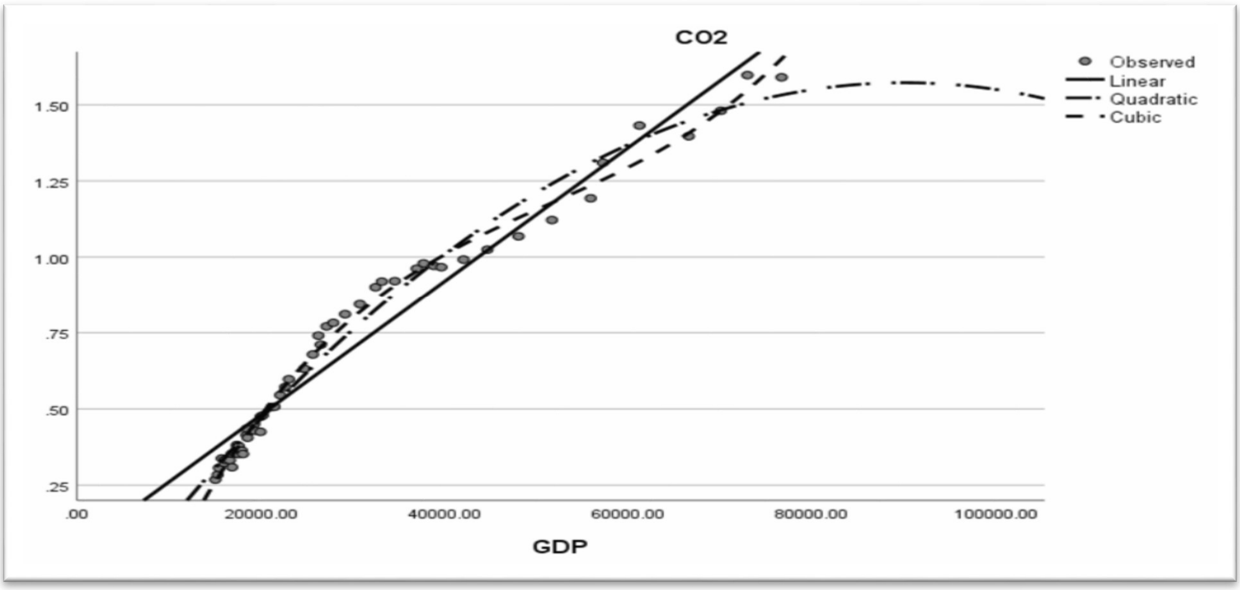


Figure 4.6: Curve-estimation (created by researcher in SPSS)

With the assumption of stationarity of the time series, CO_2 emissions show an upward trend depicting a non-linear relationship. In the figures above, an attempt has been made to examine the relationship between CO_2 emissions and GDP per capita. The figures depict that carbon dioxide emissions are growing with increasing GDP per capita. However, the rate of growth of carbon dioxide emissions is consistent as compared to GDP growth rates.

The Environmental Kuznets Curve hypothesises an inverted-U shape relationship between environmental indicators and income per capita in the economy. In the early stages of growth, environmental degradation increases and pollution intensifies. Later, as the rate of economic growth reaches a certain level, termed as turning points, the relationship reverses. With higher levels of income the environmental degradation reduces. However, in case of India the relationship clearly shows an upward trend. The carbon dioxide emissions increase with economic growth. The curve estimation produces the following results in SPSS.

Table 4.3: Regression estimates of curve estimation.

Model	R- square	F –statistics	Sig	Coefficients
Linear	.955	1111.278	0.00*	$\beta > 0$
Quadratic	.982	1388.25	0.00*	$\beta > 0$, $\beta_1 < 0$
Cubic	.991	1901.21	0.00*	$\beta > 0$, $\beta_1 < 0$ & $\beta_2 > 0$

* Significant at 95% confidence levels.

With carbon dioxide emissions as a dependent variable and gross domestic product (pc) as an independent variable, when the gdp per capita changes by one unit there is a change in carbon dioxide emissions by 8.29 units. With constant being negative at 0.71, these are minimum levels of emissions in the economy without any production activities. The carbon dioxide emissions are negatively correlated to GDP per capita as the quadratic coefficient is -1.34. This shows that after a certain income level the trend reverses and the emissions might decline in future. However, the estimation results are positive for the cubic estimation of the relationship, resulting into an N-shaped relationship. That is, the relationship after a certain level of income might again reverse and environmental degradation might increase.

$$CO_2 = -0.71 + 8.29\ (GDP\ pc) - 1.34\ (GDP\ pc)^2 + 8.71\ (GDP\ pc)^3 + \varepsilon \ \ldots\ldots\ldots\ldots\ldots \ (1)$$

The time series often have presence of unit roots making the statistical estimation more complex. With presence of stationarity the t-statistics are invalid and the relationship can be spurious. De-trending the time series can take care of the stationarity issues. But it is not necessary that all time series produce appropriate results post-detrending as in some cases de-trending might not be needed.

Using ARIMA (Autoregressive Integrated Moving Average) model for forecasting the values and relationship of economic growth and carbon dioxide emissions in the country, pure autoregressive models resemble a linear regression where the predictive variables are p number of previous periods. In an ARIMA the time series is transformed into stationary series using differencing. A time series is stationary when the mean and variance are constant overtime. Differencing is an important step in preparing data to be used in an ARIMA model, taking the first difference value, which is difference between current time period and previous time period.
Using the time series modeller in SPSS, the following model summary is estimated.

Table 4.4: Forecasting Model estimates

Model type	ARIMA (0,1,0)
R-square	.995
Stationary R-square	9.99
Ljung-Box Q statistics	10.058
Df	18
Sig.	.930

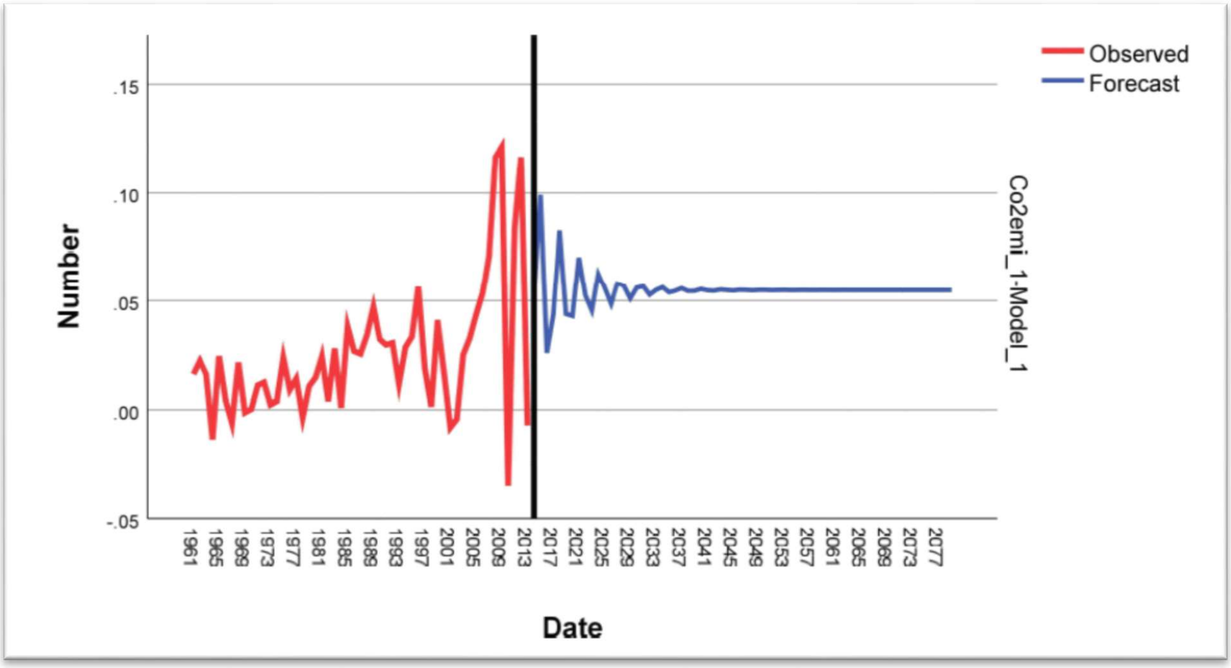


Figure 4.7: CO_2 emissions forecast for India till 2077

The forecast of carbon dioxide emissions in India become stagnant after 2050.
The Ljung Box test is used to determine whether the residuals are independent or not. The test determines whether or not the errors are white noise. The null hypothesis of this test is that the model does not show lack of fit. A significant p-value rejects the null hypothesis.

It can be inferred that carbon dioxide emissions in India has been consistently rising since 1960. India can be said to be on the upward rising portion of the EKC. With approx. 99,000 per capita income in India, carbon dioxide emissions doesn't seem to stagnate or decline. Environmental degradation can be expected to rise until a turning point is reached. The curve estimation concludes India to have an N-shaped EKC. The environmental degradation is rising as the economy is growing. The downturn of EKC can be expected at a certain future date and the curve will begin to rise again after reaching the lowest.

However, the forecasting estimates are consistent with the race to bottom concept of Dasgupta et al. 2002. Over time the curve will rise to a maximum environmental degradation level and stagnate.

4.3 PART – B Decomposition Analysis

Multiple regression technique, a linear modelling approach to analysis is very popular among researchers since more than five decades now. The reason being that it serves as an explanatory bridge between the correlation and analysis of variance. The multiple regression model is most commonly used as a prediction model for the interpretation of the relationship between the dependent and the independent variable. According to Draper & Smith (1981) a prediction model that uses least square method does not consider the relationship between the independent and dependent variable. This model is prone to multicollinearity between independent and dependent variables.

Use of factor analysis scores can be helpful in understanding the underlying structure between the investigated variables. Factor analysis is a set of methods explaining structure that is explained with *p* number of correlated variables with a smaller number of new variables (factors) that are related on their own but not related to each other (Kleinbaum et al., 1998). It helps in reducing the data to fewer number of variables (factors) instead of multiple variables that are complex to interpret. It also helps in eliminating the variables that have very less explanatory power. In a way multicollinearity serves as an advantage to factor analysis. The data with similar underlying characteristics are grouped under one factor.

Any macroeconomic data related to a particular country is not only highly correlated but also dependent on past values of itself with a given time lag. To overcome these drawbacks of multiple regression technique, this study first normalises the data and then transforms it into an index on the basis of its relation with dependent variable carbon dioxide emissions. Confirmatory factor analysis is used to extract the factors. The factor analysis scores are used to estimate the relationship among the dependent variable and the dependent variable. This technique along with elimination of multicollinearity and reducing the number of variables to a manageable extent, removes any kind of indirect effects variables have on the dependent variables. These effects are later captured by the study using structural equation modelling approach.

The previous chapter on research methodology provides a detailed explanation of the variables used such as source of data, method of calculation, the unit of measurement of data, time period for which the data has been collected and probable relation with the dependent variable.

The Principal component analysis is used to transform the data into smaller set of uncorrelated variables known as factors. The principal components are linear mathematical transformation of the raw data. The scores are obtained from combining the weights that are proportional to their component loading. These component scores are extracted from the variable on the basis of three decision rules; Kaiser’s criterion, Joliffe’s criterion and Cattell’s criterion. The most popularly used criterion is Kaiser’s criterion. If a principal component of a correlation matrix that is extracted has an Eigen value of less than one, it must be dropped. The variable used has the variance of one. Hence the component cannot contain the explanatory power of less than one. Joliffe’s criterion suggests that a value less than 0.7 can be discarded. Once the components are extracted, the percentage of total variance explained by that component can be found.

4.4 Economic factors - Principal Component extraction

The variables considered here for extracting the economic factor are: Industry (including construction); value added (% of GDP), Fossil fuel energy consumption (% of total), Electricity production from coal sources (% of total), Trade Openness (Ratio of exports and imports to GDP in %), Foreign direct investment, net outflows and inflows (% of GDP).

Table 4.5 (a): Model Summary of PCA of Economic factors

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.706
Bartlett's Test of Sphericity	Approx. Chi-square	382.015
	Df	15
	Sig.	.000

Table4.5 (b): Communalities of PCA of Economic factors

	Initial	Extraction
Industry	1.000	.738
Fossil	1.000	.843
Electricity	1.000	.205
Trade Openness	1.000	.893
FDI_outflows	1.000	.690
FDI_inflows	1.000	.830

Table 4.5 (c): Total Variance Explained of PCA of Economic factors

	Initial Eigenvalues			Extraction Sum of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.198	77.672	77.672	5.198	77.672	77.67
2	0.962	17.701	95.373			
3	0.432	3.535	98.908			
4	0.212	1.006	99.914			
5	0.060	0.053	99.967			
6	0.035	0.033	100.00			

Table 4.5 (d): Component Matrix of PCA of Economic factors

	Component 1
Trade Openness	.945
Fossil	.918
FDI_inflows	.911
Industry	.859
FDI_outflows	.830
Electricity	.453

To conduct factor analysis the minimum standard that should be met is the KMO-Bartlett's test. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy varies between 0 and 1. A minimum suggested standard is a value of 0.6. Values closer to one are considered better. The Bartlett's Test of Sphericity tests the null hypothesis. There should be enough variation to reject this null hypothesis and the correlation matrix should not be identity matrix. Table 4.5 (a) depicts sampling adequacy.

The proportion of each variable's variance is presented by communalities as presented in Table 4.5 (b). By the principal component method the initial value is 1. The extraction values indicate the proportion of each variable's variance that can be explained by the component extracted. Higher extraction values are better than lower values.

The Total variance table explains number of components extracted from the given data percentage of variance explained by the individual and the cumulative variance extracted by total components. Aforementioned initial eigenvalues are variance of components extracted. A component with an eigenvalue less than one is not considered for analysis. Table 4.5 (c) contains the information related to total variance.

This matrix presents the component loadings which are nothing but the correlations between the variable and component. The values range from -1 to +1. The positive and negative values (Table 4.5 (d)) suggest the direction of the correlation between the component and the variable. The component loadings can be suppressed below 0.3, which makes the interpretation simpler.

The economic factor is an independent variable and carbon dioxide emissions per capita is dependent variable. The model summary is presented in Table 4.5 (e).

Table 4.5 (e): Model summary of Regression estimates of Economic factors

Model	R- square	F –statistics	Sig	Coefficients
Linear	0.816	248.276	0.00*	$\beta > 0$
Quadratic	0.852	158.149	0.00*	$\beta > 0$, $\beta_1 <0$
Cubic	0.892	148.181	0.00*	$\beta > 0$, $\beta_1 >0$ & $\beta_2<0$.

Based on coefficient values the quadratic estimation is considered significant where the coefficient of squared economic factor is negative depicting an inverted-U shape relationship. The following equation is estimated:

$CO_2 = 0.395 + 0.432(\text{Ecofact}) + 1.035\ (\text{Ecofact})^2 - 0.231\ (\text{Ecofact})^3 + \varepsilon$ ………….. (2)

The graphical presentation of carbon dioxide emissions and economic factor extracted is shown in figure 4.8.

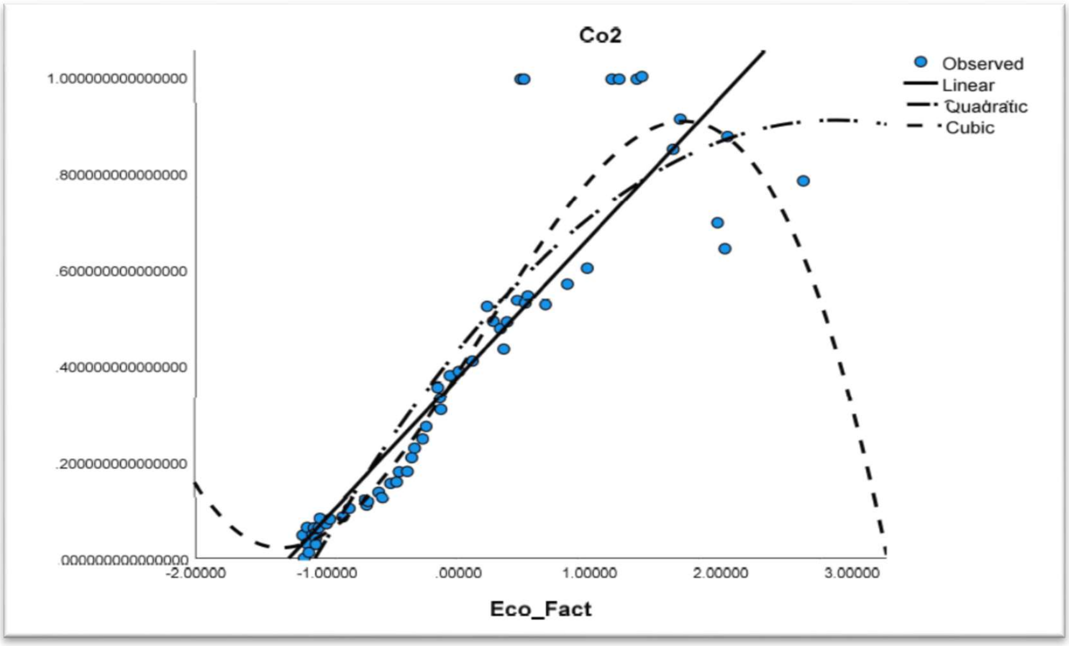


Figure 4.8: Scatter plot of Economic factors as independent variable and carbon dioxide as dependent variable (created by researcher in SPSS)

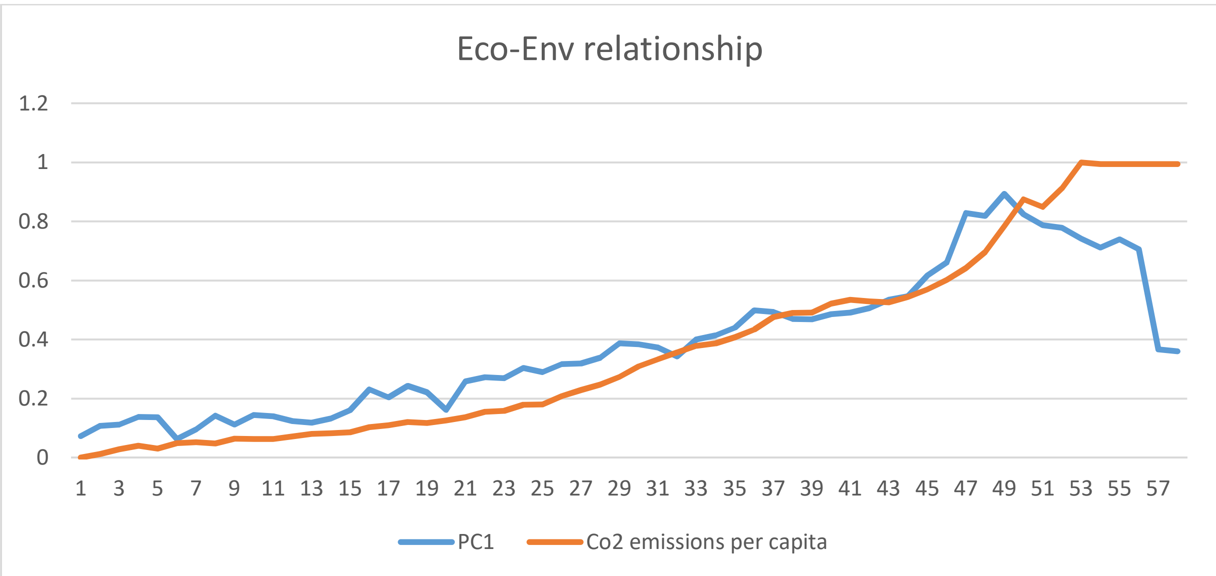


Figure 4.9: Line chart of Economic factors as independent variable and carbon dioxide as dependent variable (created by researcher in Excel)

Above analysis infers that the variables used for extracting the principal component "Economic factors" are highly correlated with the component. The KMO test results as shown in Table 4.5(a) infers good sample adequacy and evaluates correlation to determine that data amalgamates on extracted component. Bartlett's test evaluates that correlation matric is not an identity matrix. The communalities shown in Table 4.5 (b) infers extracted component (Economic) accounts for 73.8 % variance in industrial share, 84.3 % variance in fossil fuel consumption, 89.3% variance in trade openness, 69% variance in foreign direct investment inflows outflows and 83 % variance in foreign direct investment inflows. Though Economic factors accounts for only 20.5% variance in electricity production from coal sources, it is an important variable for analysis.

It can also be inferred from Table 4.5 (c) that 77.67% of variance in items is explained by the one component extracted. The above variables used for extraction are capable of explaining 77.67% of changes in economic factors in Indian economy. Table 4.5 (d) depicts high positive correlation between the variables and Economic factor.

Economic factor successfully extracted is then used for curve estimation to investigate its impact on carbon dioxide emissions in India. Model summary presented in Table 4.5 (e) infers Economic factor to have an N-shaped functional relationship with carbon dioxide emissions in India. This results is consistent with results of analysis in PART A of this chapter.

Null hypothesis that there is no relation between economic factors and the Environmental Kuznets Curve is rejected and alternate hypotheses is accepted.

H1a: Degree of globalization in the economy influences the environmental quality depicting an EKC relationship.

H1b: A higher level of fossil fuel consumption influences the environmental quality depicting an EKC relationship

H1c: A higher share of manufacturing in GDP degrades the environmental quality depicting an EKC relationship in the long run.

H1d: A higher share of electricity generation from non-renewable resources reflects the EKC relationship.

Overall economic factor impacts the EKC curve in a way that India is on the upward rising portion on the curve.

4.5 Demographic factor - Principal Component extraction

The variables considered here for extracting the demographic factor are; Population density (people per sq. km of land area), Population ages 15-64 (% of total), Urban population (% of total), Literacy rate, Poverty rate Rural (%) and Poverty rate Urban (%). The poverty rates are transformed using intrapolations.

Table 4.6 (a): Model Summary of PCA of Demographic Factors

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.791
Bartlett's Test of Sphericity	Approx. Chi-square	954.707
	Df	15
	Sig.	.000

Table 4.6 (b): Communalities of PCA of Demographic Factors

	Initial	Extraction
Popu_density	1.000	.974
Popu_ages	1.000	.919
Urban	1.000	.986
Literacy rate	1.000	.958
Poverty rate Rural (%)	1.000	.875
Poverty rate Urban (%)	1.000	.986

Table 4.6 (c): Total Variance Explained of PCA of Demographic Factors

	Initial Eigenvalues			Extraction Sum of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.698	94.958	94.958	5.698	94.958	94.958
2	.169	2.821	97.779			
3	.104	1.737	99.516			
4	.017	.286	99.802			
5	.011	.178	99.980			
6	.001	.020	100.00			

Table 4.6 (d): Component Matrix of PCA of Demographic Factors

	Component 1
Poverty rate Urban (%)	-.993
Urban	.993
Popu_density	.987
Literacy rate	.979
Popu_ages	.958
Poverty rate Rural (%)	-.936

The variance shared by the common factor extracted is high in all the variables. Urban population and urban poverty rate have high common variance as can be seen from Table 4.6(d). The error variance is extremely low indicating high explanatory power of the component.

As can be seen from table 4.6 (c) total variance in the variables is explained to the tune of 95 percent by the component extracted. The factor loadings of the variables are very high. The factor loading of poverty rate in urban and rural areas are high but negative. The poverty rates are negatively correlated to the component extracted.

The demographic factor is an independent variable and carbon dioxide emissions per capita is dependent variable. The model summary of curve estimation is presented in Table 4.6 (e).

Table 4.6 (e): Model summary of Regressions estimates of Demographic Factors

Model	R- square	F –statistics	Sig	Coefficients
Linear	.932	773.353	0.00*	$\beta > 0$
Quadratic	.975	1058.540	0.00*	$\beta > 0$, $\beta_1 > 0$
Cubic	.980	867.045	0.00*	$\beta > 0$, $\beta_1 > 0$ & $\beta_2 < 0$.

Based on coefficient values the cubic estimation is considered significant where the coefficient betas of the cubic term are negative depicting N-shape relationship. The following equation is estimated

$CO_2 = 0.313 + 0.346\ (\text{Demofact}) + 0.066\ (\text{Demofact})^2 - 0.022\ (\text{Demofact})^3 + \varepsilon$ ………..(3)

The graphical presentation of carbon dioxide emissions and demographic factor extracted is shown in Figure 4.10.

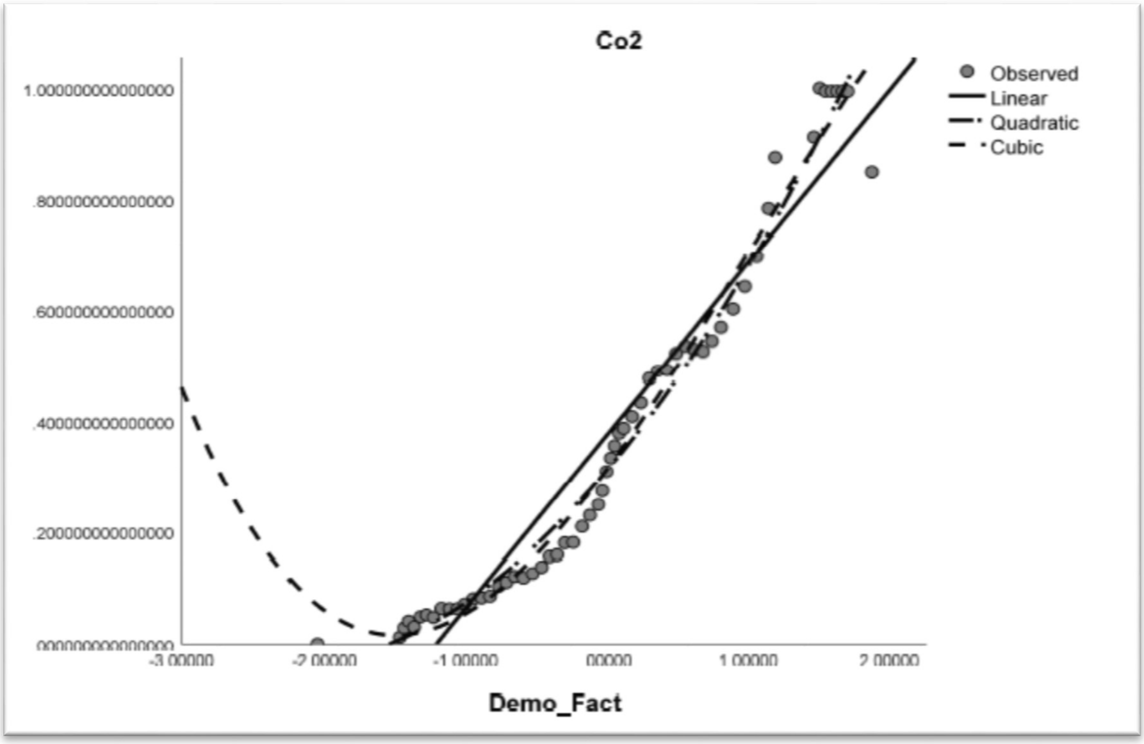


Figure 4.10: Scatter plot of Demographic factors as independent variable and carbon dioxide as dependent variable (created by researcher in SPSS)

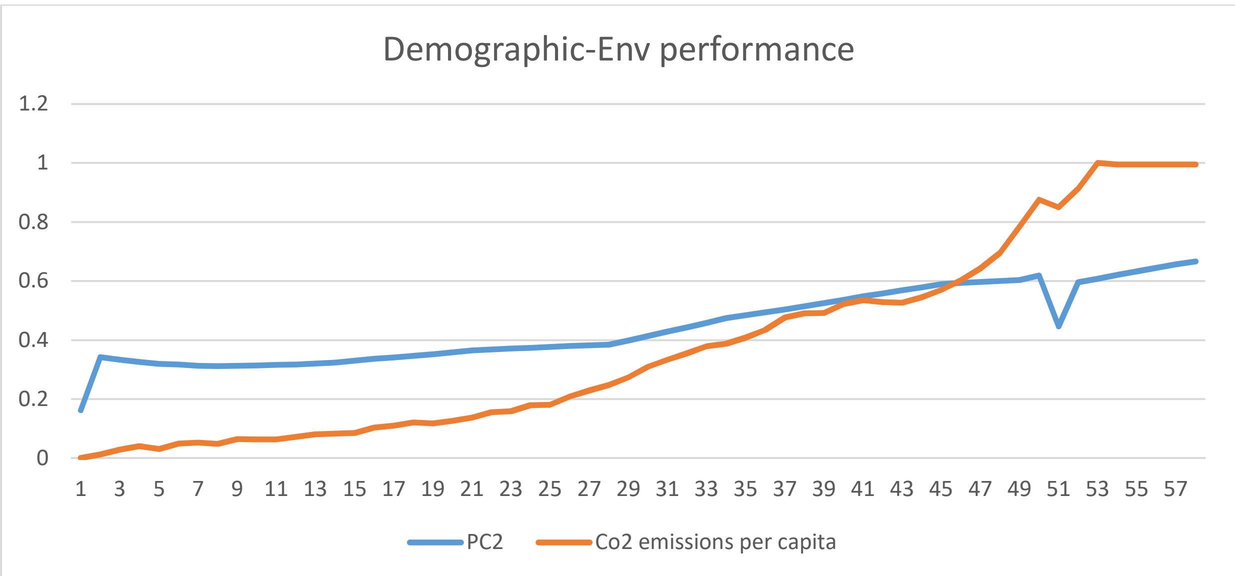


Figure 4.11: Line chart of Demographic factors as independent variable and carbon dioxide as dependent variable (created by researcher in Excel)

It can be inferred from the above analysis that variables used for extracting the principal component, "Demographic factor", is highly correlated with it. The KMO test results as shown in Table 4.6 (a) infers a good sample adequacy and evaluates correlation to determine that data combine well on extracted component. Bartlett's test evaluates that correlation matrix is not an identity matrix. The communalities shown in Table 4.6 (b) infers that Demographic factor accounts for 97.4 % variance in population density, 91.9 % variance in population ages between 15-64 age, 98.6 % variance in urban population, 98.8% variance in literacy rates, 87.5 % variance in rural poverty rates and 98.6% variance in urban poverty rates.

Table 4.6(c) provides a strong evidence that 94.9 % variance in the items is explained by the demographic factor. Variables used in extracting demographic factor are capable of explaining 94.9% of changes in demographic factor in Indian economy. It has the highest explanatory power among the components extracted. Results on high positive correlation between variables and demographic factor is presented in Table 4.6(d).

Demographic factor is then utilized for curve estimation to investigate its impact on carbon dioxide emissions in India.

The relationship between demographic factor and carbon dioxide is expected to be an inverted-U shaped. As can be seen from Table 4.6 (e) the coefficient of the cubic term is approaching zero. Initially the carbon dioxide emissions rise with increase in the demographic factor, reached a turning point and has started declining.

On the basis of above results null hypotheses stands rejected. That is, there is some relationship between demographic factor and economic growth in the economy. The alternative hypotheses are:

H1e: A higher share of urban population in total population negatively influences the environmental quality depicting an EKC relationship.

H1f: Higher population density negatively influences the environmental quality causing an EKC relationship.

H1g: Age composition of the population indirectly exerts pressure on the environmental quality in the economy.

H1h: Higher literacy indirectly influences the environmental quality causing an EKC relationship.
H1i: Poverty rates negatively influence environmental quality degrading the environment.

It can be inferred that the demographic factor has a larger impact on the EKC. It can be helpful in reducing carbon emissions in the economy. If the trend continues there can be an inverted U relationship the between demographic factor and the EKC.

4.6 Environment factor - Principal Component extraction

The variables considered here for extracting the environment factor are; Alternative and nuclear energy (% of total energy use), access to clean fuels and technologies for cooking (% of population), access to electricity (% of population) and people practicing open defecation (% of population).

Table 4.7 (a): Model Summary of PCA of Environmental Factors

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.628
Bartlett's Test of Sphericity	Approx. Chi-square	277.162
	Df	6
	Sig.	.000

Table 4.7 (b): Communalities of PCA of Environmental Factors

	Initial	Extraction
Alternative	1.000	.191
Access_clean_fuel	1.000	.972
Access to electricity	1.000	.957
Open_defec	1.000	.679

Table 4.7 (c): Total Variance Explained of PCA of Environmental Factors

	Initial Eigenvalues			Extraction Sum of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.800	69.992	69.992	2.800	69.992	69.992
2	0.982	25.356	95.347			
3	0.173	4.328	99.676			
4	0.013	0.324	100.00			

Table 4.7 (d): Component Matrix of Environmental Factors

	Component 1
Access_clean_fuel	.986
Access to electricity	.978
Open_defec	-.824
Alternative	.437

The communality extraction values indicate the proportion of each variable's variance that can be explained by the component extracted. Higher extraction values are better. The values for alternative and nuclear fuel used as percentage of total energy used are very low. This indicates high error variance and least contribution in the explanatory power of the component.

The component extracted explains approximately 70 percent variance. The factor loadings of the components extracted are significantly high. The negative factor loading of open defecation specifies negative correlation. The other variables used for analysis are positively correlated with the component extracted.

The Environment factor is an independent variable and carbon dioxide emissions per capita is dependent variable. The model summary is presented in Table 4.10.

Table 4.7 (e): Model summary of Regression estimates of Environmental Factors

Model	R- square	F –statistics	Sig	Coefficients
Linear	.852	321.493	0.00*	$\beta > 0$
Quadratic	.859	167.970	0.00*	$\beta > 0$, $\beta_1 > 0$
Cubic	.862	112.893	0.00*	$\beta > 0$, $\beta_1 > 0$ & $\beta_2 > 0$.

Based on coefficient values no clear shape can be estimated as all the betas are greater than zero, depicting an upward trend. The following equation can be estimated:

$CO_2 = 0.350 + 0.750\ (\text{Envfact}) + 0.039\ (\text{Envfact})^2 + 0.172\ (\text{Envfact})^3 + \varepsilon$ …………(4)

The graphical presentation of carbon dioxide emissions and environment factor extracted is shown in Figure 4.12.

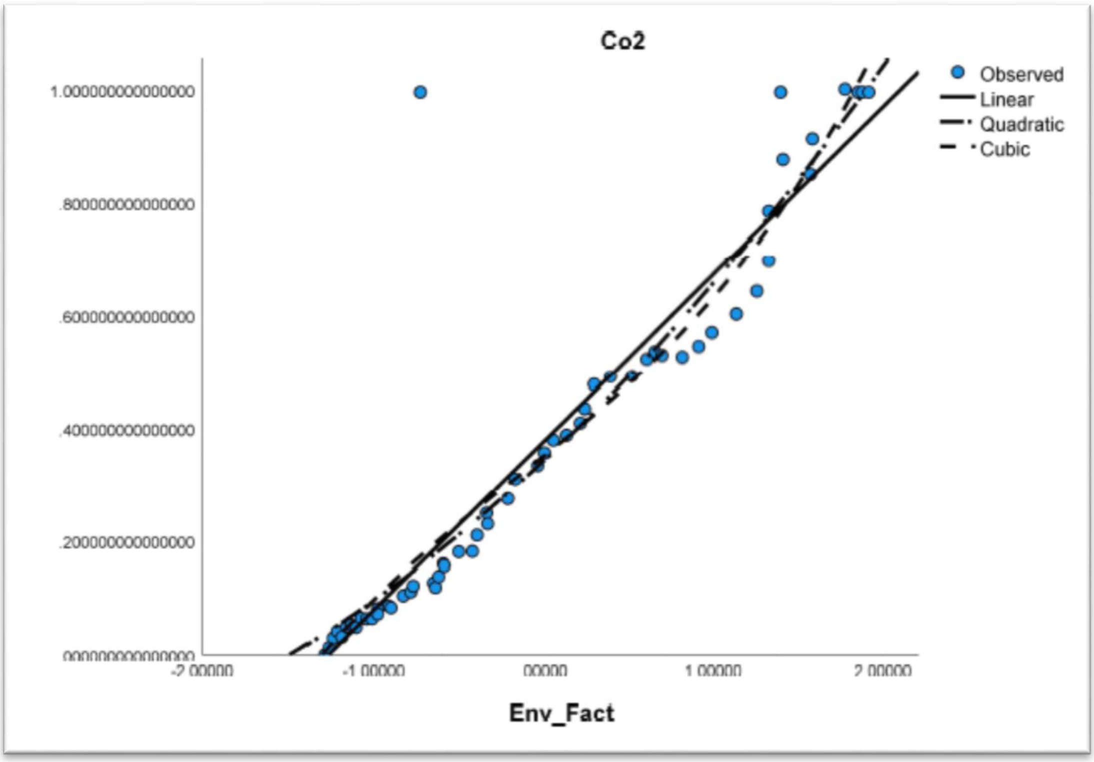


Figure 4.12: Scatter plot of Environmental factor as independent variable and carbon dioxide as dependent variable (created by researcher in SPSS)

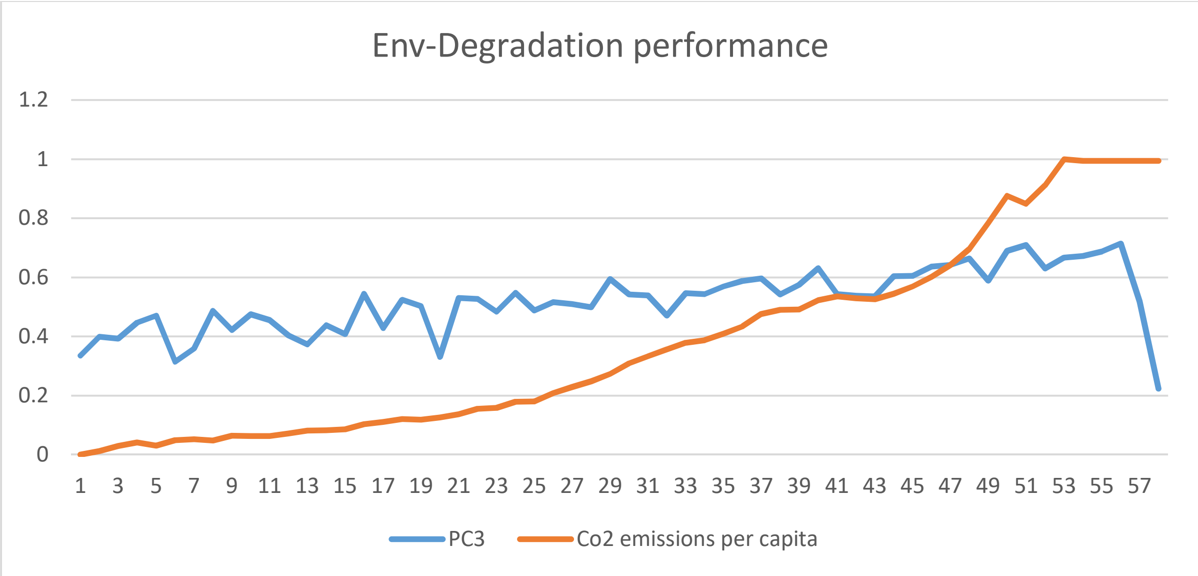


Figure 4.13: Line chart of Environmental factor as independent variable and carbon dioxide as dependent variable (created by researcher in Excel)

The results presented above depict the principal component extraction for Environmental factor. The results of KMO-Bartlett's test shown in Table 4.7 (a) show good sample adequacy and significant presence of identity correlation matrix to be non-zero. The communalities extracted in Table 4.7 (b) that Environmental factor accounts for 97.2 % variance in access to clean fuel, 95.7 % variance in access to electricity, 67.9 % variance in open defecation and only 19.1% variance in use of alternative energy sources. Total of 69.99% variance in these variables is explained by factor extracted (Environmental). Component matrix of Environmental factor presents positive as well as negative correlation with its variables.

The curve is then estimated using scores of factor analysis and data on carbon dioxide emissions. The model summary in Table 4.7 (e) depicts all positive coefficients illustrates a monotonically increasing function.

The analysis reject the null hypotheses and accepts the following alternate hypotheses, implying that there is an increasingly monotonic relationship that environmental factor and economic growth follows in India.

H1j: Higher share of alternative fuel in total fuel consumption reduces environmental damage.

H1k: Higher access to clean fuel technologies improves environmental quality.

H1l: Access to electricity indirectly impacts environmental quality depicting an EKC relationship.
H1m: Open defecation directly damages the environment depicting an EKC relationship

4.7 Governance factor – Principal component extraction

The variables considered here for extracting the governance factor are; Voice and accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of corruption. This is an index which ranges from -2.5 to 2.5. The negative value indicates a weaker governance performance and positive value indicates stronger governance performance.

Factor analysis scores to extract Governance factor had a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) of 0.523. It can be considered for further analysis only if researcher is sure about it (Stephanie Glen, 2016). This study did not consider the results of factor analysis to be significant in extraction of Governance factor. Results related to component matrix were utilized to create an index and under the relationship between environmental degradation and governance performance.

Lack of data points on Governance indicators can be considered as a limitation of the study. New index is formed using control of corruption, political stability and absence of violence/terrorism, regulatory quality and rule of law. These variables were amalgamated to form a Governance factor. Due to lower correlation values with the component, voice and accountability and government effectiveness were dropped from further analysis. The graphical presentation is given in Figure 4.14. Comparing the data points it can be observed that though not directly, but ineffectiveness and instability in implementing the rule of law by government have influenced environmental degradation in the economy.

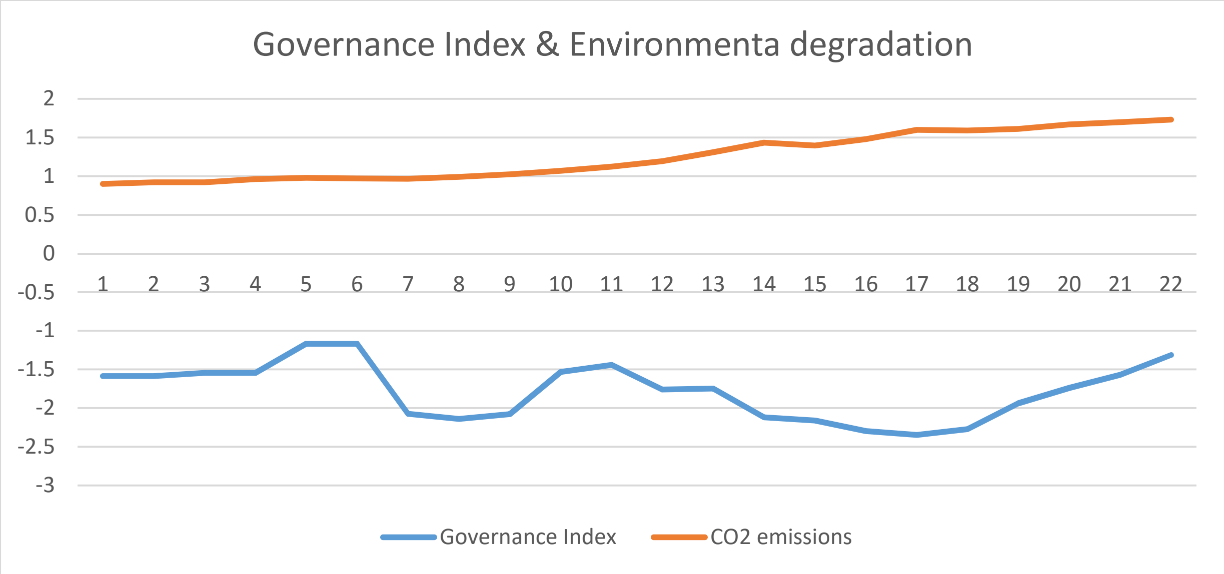


Figure 4.14: Line chart of governance factor against carbon dioxide emissions in India.

Mixed results are extracted from the above analysis.

H1n: Corruption reduces the enforcement of rules and regulations indirectly influencing environmental quality.

H1o: Political stability and absence of violence indirectly enhances environmental quality.

H1p: The effectiveness of government directly impacts environmental quality.

H1q: Better quality of public institutions leads to less environmental pressure.

The factors are extracted individually from the given data set on the Indian economy. These factors can now be used as new variables in the regression analysis. The dependent variable is carbon dioxide emissions per capita and independent variables are the components extracted from the factor analysis. The basic objective using factor analysis and extract components is to identify the influence of each factor on carbon dioxide emissions in India depicting the decomposition analysis of EKC. Higher economic activities are associated with increased use of fossil fuel consumption and electricity generation in the economy. This is synonymous with scale effect discussed in most of the earlier studies on EKC hypothesis.

Similarly, access to electricity and use of clean fuel influences carbon dioxide emissions and help in reducing the environmental degradation in the economy. The environment factor tries to capture the accessibility of alternative and clean fuel in India since 1960. The regularity framework in the economic system does impact emissions in the form of implementation of the environmental pollution benchmarks devised to control environmental degradation. With higher corruption levels, these regulations serve no purpose in the economy. This factor is used to understand the impact of governance factor on environmental quality in the economy.

In a nutshell, decomposition analysis of EKC with respect to Indian economy can be said to have been successful with the help of economic, demographic, environmental and governance factors. Each factor share its individual impact on carbon dioxide emissions in India.

4.8 PART – C Structural Equation Model

The empirical estimation of EKC has been prone to lot of criticism, especially the use of reduced form approaches, in which the underlying process of economic growth and environmental relationship remains unexplained. The variation in the results, with regard to existence of EKC, varied from pollutant to pollutant. The use of cross country analysis has its own set of criticism. Of these, one of the important criticism is the possibility of causal mechanism amongst the variables.

In earlier studies, three hypothesis have been tested; EKC hypothesis, the pollution haven hypothesis and trade-environment hypothesis for developed countries. The results for developing countries are still unclear owing to data problems.

An attempt to overcome these criticisms, is made by adopting structural equation modelling to EKC hypothesis. One of the biggest advantage is the possibility of combination of many structural relationships into one model along with causal mechanism between variables.

The model is built in AMOS and the diagram is shown in Figure 4.14.

The squares represent the observed variables. GDP per capita and carbon dioxide are observed endogenous variables and economic, demographic, environmental and governance factors are observed exogenous variables. There are unobserved exogenous variables known as errors.

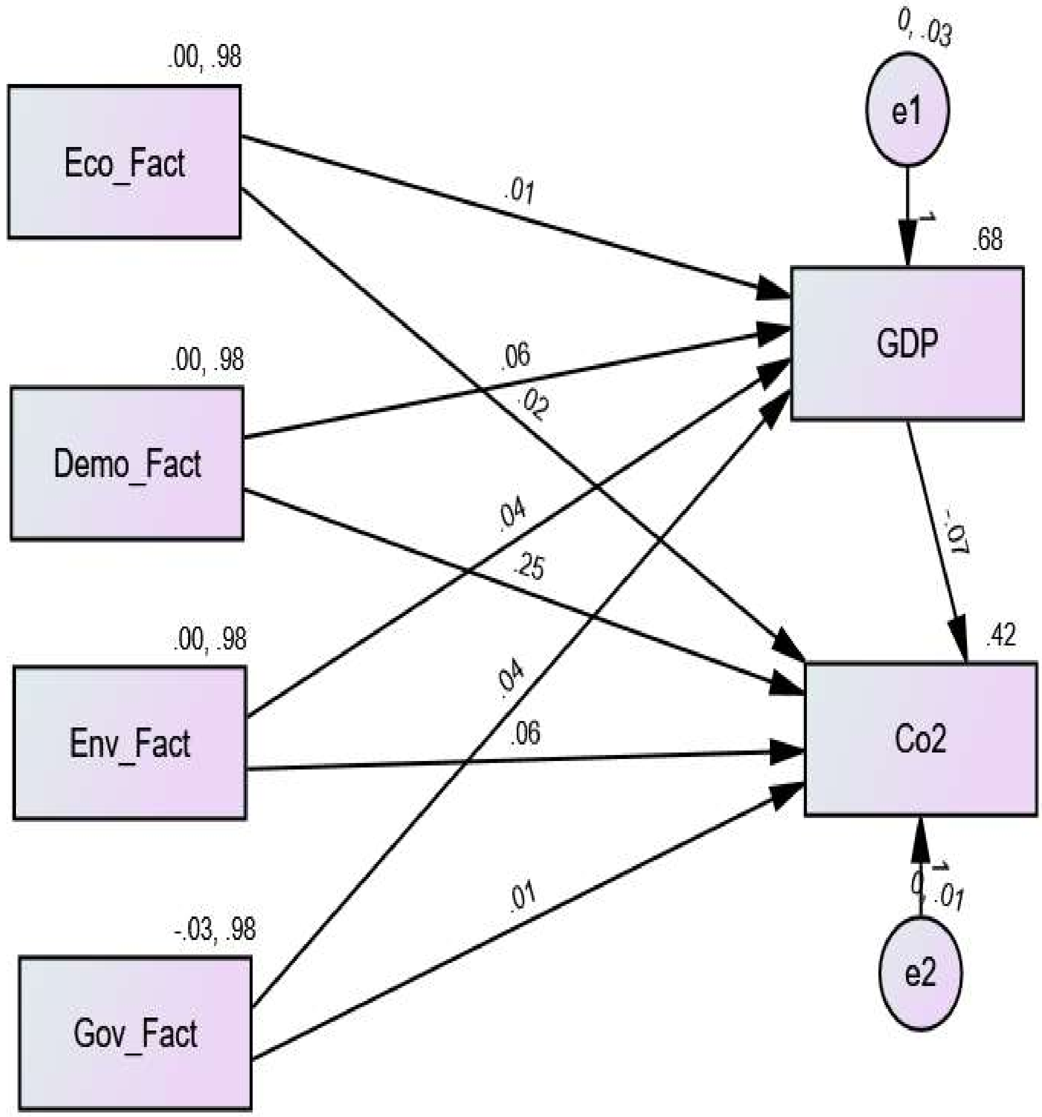


Figure 4.15: Path diagram – Model A (Overall)

Created by researcher in AMOS

Result (Default model)

Minimum was achieved

Chi-square = 241.539

Degrees of freedom = 6

Probability level = .000

Table 4.8 - Regression Weights of all Factors

	Estimates	P value	T values
GDP<---Eco_Fact	.005	.003	.236
GDP<---Demo_Fact	.060	.009	2.608
GDP<---Env_Fact	.043	.061	1.876
GDP<---Gov_Fact	.041	.272	1.098
Co2<---Eco_Fact	.020	.062	1.864
Co2<---Demo_Fact	.248	***	22.097
Co2<---Env_Fact	0.56	***	5.118
Co2<---GDP	-.069	.297	-1.042
Co2<---Gov_Fact	.009	.616	.501

Table 4.8 on regression weights estimates the structural equations of the model. The structural equation of the model is:

$$GDPpc = 0.680 + 0.029\ (Ecofact) + 0.315\ (Demofact) + 0.227\ (Envfact) + 0.218\ (Govfact) \text{ with Errorvar} = 0.028\ (4.835)^{*} \qquad \ldots\ldots\ldots\ldots(5)$$

$$CO_2 = 0.422 - 0.049\ (GDPpc) + 0.075\ (Ecofact) + 0.944\ (Demofact) + 0.212\ (Envfact) + 0.036\ (Govfact) \text{ with Errorvar} = 0.006\ (5.206)^{*} \qquad \ldots\ldots\ldots\ldots(6)$$

*tvalue

The estimated structural equation shows positive and significant impact of economic, demographic, environmental and governance factors on carbon dioxide emissions. Though the magnitude varies, it definitely collectively impacts carbon dioxide emissions in the country. The most significant impact is that of demographic factors. That is, higher the population density and poverty ratios in the country, higher will be the emissions. The impact of governance factor is less but is significant with squared multiple correlations (R^2) at 90.9. The predictors of carbon dioxide emissions can explain 90.9 percent of its variance.

However, as can been seen in the path diagram, there are both direct and indirect effects, through structural changes, on the observed endogenous variables of the model. These effects are presented in Table 4.9.

Table 4.9: Standardized Regression Coefficients of all Factors

			Estimate
GDP	<---	Eco_Fact	.029
GDP	<---	Demo_Fact	.315
GDP	<---	Env_Fact	.227
GDP	<---	Gov_Fact	.218
Co2	<---	Eco_Fact	.075
Co2	<---	Demo_Fact	.944
Co2	<---	Env_Fact	.212
Co2	<---	GDP	-.049
Co2	<---	Gov_Fact	.036

Table 4.10: Indirect Effects of all Factors

	Govfact	Envfact	Demofact	Ecofact	GDP
CO_2	-.011	-.011	-.016	-.001	.000

Table 4.11: Direct effects of all Factors

	Govfact	Envfact	Demofact	Ecofact	GDP
Co2	.036	.212	.944	.075	-.049
GDP	.218	.227	.315	.029	.000

Table 4.12: Total effects of all Factors

	Govfact	Envfact	Demofact	Ecofact	GDP
CO_2	.025	.201	.928	.073	-.049
GDP	.218	.227	.315	.029	.000

The mediated effect of governance factor on carbon dioxide is -0.011, which implies that due to the mediated effect when the governance factors increase, the carbon dioxide emissions reduces by .011. Though low, there is significant impact of political stability, control of corruption and regulatory quality on carbon dioxide emissions in the country. Similarly when the population gets access to clean fuel and electricity carbon emissions reduce by .011. Higher population density and poverty ratios, both rural and urban, directly impact carbon dioxide emissions, and indirectly through growth and structural changes.

The unmediated effect of governance factors on the GDP is 0.218. Implying that due to unmediated effect when the governance factors improve to the tune 1 unit the GDP rises by 0.218. An improvement in regulatory quality, control of corruption and a stable government have a direct impact on the GDP of the economy. Of all the unmediated effects on the GDP, demographic factors have the greatest direct impact. It can be implied that the burden of poverty actually diminishes growth opportunities.

The unmediated effect of demographic factors on carbon dioxide emissions is the highest of all the factors. The direct effect of change in GDP per capita of the country decreases carbon dioxide emissions by 0.049.

The mediated and unmediated effects of all the factors on carbon dioxide emissions and GDP per capita is presented above. Clearly demographic factors have significant and greatest impact on both the observed endogenous variables of our model.

The goodness of fit statistics after the model was identified is as presented in Table 4.15. The number of parameters in the model are 21 with 6 degrees of freedom. The chi-square is 241.5 at p =0.000. The ratio of CMIN/df is 40.25, which is way higher than the fit ratios suggested by various researchers. Byrne, B., (1989) suggested a ratio less than 2. Several other researchers have suggested the ratio to be closer to one. The ratio can be greater than one, but how far the researcher can go is unclear. RMSEA is an absolute fit index which assesses how far a hypothesised model is from the perfect model. Values less than 0.05 are considered satisfactory models. The incremental fit statistics should be closer to 1 for better fitting model.

Table 4.13: CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default Model	21	241.539	6	0.000	40.256
Saturated Model	27	.000	0		
Independence Model	6	418.48	21	0.000	19.928

Table 4.14: RMSEA

Model	RMSEA	LO90	HI90	PCLOSE
Default Model	0.796	.712	.883	.000
Independence Model	.553	.507	.599	.000

Table 4.15: Incremental Fit Index

Model	NFI	RFI	IFI	TLI	CFI
Default Model	.423	.401	.429	.829	.407
Saturated Model	1.000		1.000		1.000
Independence Model	.000	.000	.000	.000	.000

4.9 SEM WITHOUT ANY DIRECT EFFECT OF GOVERNANCE FACTORS ON CARBON DIOXIDE EMISSIONS.

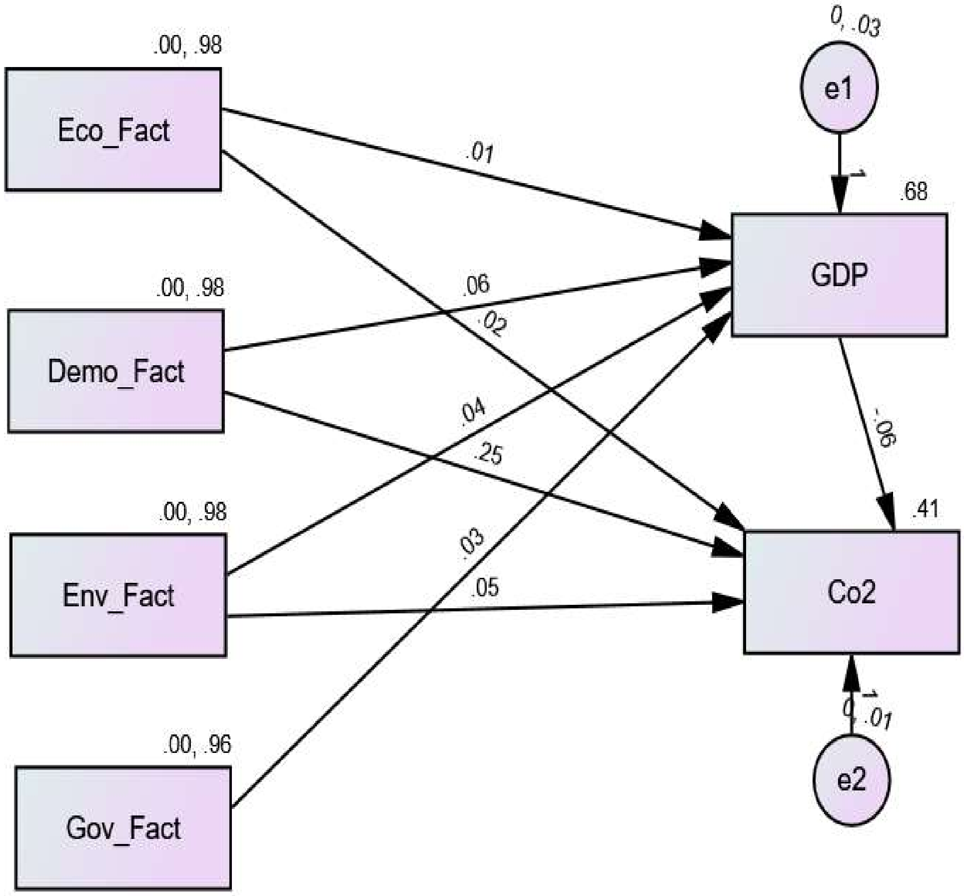


Figure 4.16: Path diagram – Model B

Created by researcher in AMOS

Result (Default model)

Minimum was achieved

Chi-square = 241.790

Degrees of freedom = 7

Probability level = .000

Table 4.16: Regression Weights of Model B

	Estimates	P value	T values
GDP<---Eco_Fact	.008	.004	.342
GDP<---Demo_Fact	.063	.006	2.746
GDP<---Env_Fact	.036	.118	1.564
GDP<---Gov_Fact	.029	.463	.734
Co2<---Eco_Fact	.021	.051	1.954
Co2<---Demo_Fact	.252	***	22.472
Co2<---Env_Fact	0.49	***	4.568
Co2<---GDP	-.057	.349	-.937

GDP = 0.678 + 0.042 (Ecofact) + .334 (Demofact) + 0.190 (Envfact) + 0.152 (Govfact) with an Errorvar 0.029 (5.071)* ………….(7)

CO_2 = 0.413 – 0.040 (GDPpc) + 0.078 (Ecofact) + 0.947 (Demofact) + 0.185 (Envfact) With an Errorvar 0.006 (5.342)* ………..…(8)

*tvalue

Table 4.17: Standardized Regression Weights of Model B

	Estimate
GDP <--- Eco_Fact	.042
GDP <--- Demo_Fact	.334
GDP <--- Env_Fact	.190
GDP <--- Gov_Fact	.152
Co2 <--- Eco_Fact	.078
Co2 <--- Demo_Fact	.947
Co2 <--- Env_Fact	.185
Co2 <--- GDP	-.040

Table 4.18: Total Effects of Model B

	Govfact	Envfact	Demofact	Ecofact	GDP
GDP	.029	.036	.063	.008	.000
CO_2	-.002	.047	.248	.020	-.057

Table 4.19: Direct Effects of Model B

	Govfact	Envfact	Demofact	Ecofact	GDP
GDP	.029	.036	.063	.008	.000
CO_2	.000	.049	.252	.021	-.057

Table 4.20: Indirect Effects of Model B

	Govfact	Envfact	Demofact	Ecofact	GDP
GDP	.000	.000	.000	.000	.000
CO_2	-.002	-.002	-.004	.000	.000

- The total, in this case only the unmediated, effect of governance factors changes the GDP per capita of the country by 0.029 and CO_2 emissions by -.002 with an improvement of 1 unit in these factors. Implying governance factor indirectly through control of corruption, political stability and high regulatory quality impact the environmental quality in the economy and reduces carbon dioxide emissions by 0.002.
- The total (direct and indirect) effect of environmental factors on GDP is .036 and on CO_2 is .047. This implies that environmental factor improves GDP per capita by 0.036, when there is improvement in accessibility to clean fuel and electricity and reduces the carbon emissions in the economy by 0.047 units.
- Influence of demographic factor on GDP is .063 and on CO_2 is .248 implying that when there is an improvement in population density, urban and rural poverty rates and literacy rates, GDP is affected to the tune of 0.063 and environmental quality improves by 0.248.

- The total (direct and indirect) effect of Eco_Fact on GDP is .008and on CO_2 is .020, implying that when fossil fuel consumption takes place in the economy along with trade and foreign investment the GDP improves by 0.008 and emissions increase by 0.020

It can be inferred that demographic factor has a significant impact on GDP per capita and CO_2 emissions in India. This model –B, tries to capture the indirect effect of governance factor on CO_2 emissions and finds that though very low it does have an impact on CO_2 emissions.

Model Fit Summary: Table 4.21: CMIN of Model B

Model	NPAR	CMIN	DF	P	CMIN/DF
Default Model	20	241.790	7	.000	34.541
Saturated Model	27	.000	0		
Independence Model	6	418.483	21	.000	19.28

Table 4.22: RMSEA of Model B

Model	RMSEA	LO90	HI90	PCLOSE
Default Model	.736	.658	.817	.000
Independence Model	.553	.507	.599	.000

Table 4.23: Incremental Fit Index of Model B

Model	NFI	RFI	IFI	TLI	CFI
Default Model	.422	-.733	.429	-.772	.409
Saturated Model	1.000		1.000		1.000
Independence Model	.000	.000	.000	.000	.000

The goodness of fit statistics after the model was identified is as presented in Table 4.21, 4.22 and 4.23. The number of parameters in the model are 20 with 7 degrees of freedom. The chi-square is 241.790 at p =0.000. The ratio of CMIN/df is 34.54, which is higher than the fit ratios suggested by various researchers

4.10 SEM FOR PRE-LIBERALIZATION PERIOD

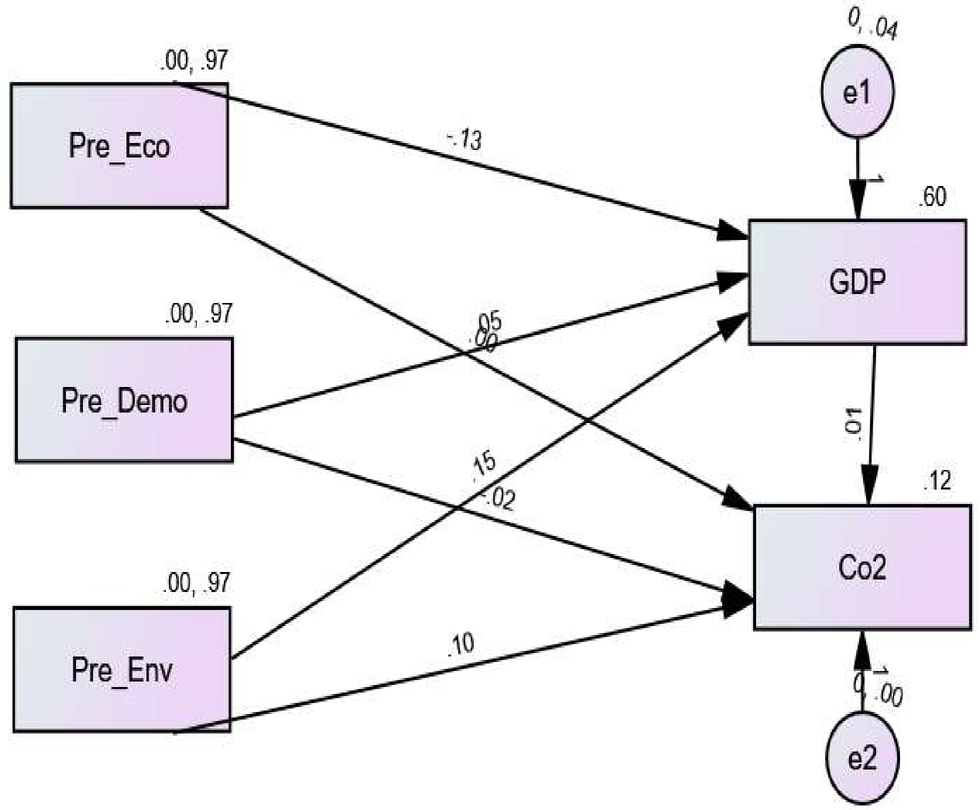


Figure 4.17: Path diagram – Model C (pre-liberalization)

Created by researcher in AMOS

Result

Minimum was achieved

Chi-square = 179.352

Degrees of freedom = 3

Probability level = .000

Table 4.24: Regression Weights of Model C

	Estimates	P value	T values
GDP<--- Pre_Eco	-.134	***	-3.597
GDP<--- Pre_Demo	.047	.211	1.251
GDP<--- Pre_Env	.152	***	4.065
Co2<--- Pre_Eco	.003	.277	1.087
Co2<--- Pre_Demo	-.021	***	-8.946
Co2<--- Pre_Env	.104	***	36.060
Co2<---GDP	.006	.589	.540

Table 4.25: Standardized Regression Weights of Model C

			Estimate
GDP	<---	Pre_Eco	-.459
GDP	<---	Pre_Demo	.160
GDP	<---	Pre_Env	.518
Co2	<---	Pre_Eco	.028
Co2	<---	Pre_Demo	-.198
Co2	<---	Pre_Env	.965
Co2	<---	GDP	.017

Structural Equations

CO_2 = 0.118 + 0.017 (GDPpc) + 0.028 (Ecofact) + 0.198 (Demofact) + 0.965 (Envfact) with Errorvar = 0.001 (3.903)* $p < 0.05$ ………………(9)
GDP = 0.602 – 0.459 (Ecofact) + 0.162 (Demofact) + 0.518 (Envfact) with Errorvar =0.041 (3.903)* $p<0.05$ ………………(10)

*tvalue

Table 4.26: Total Effects of Model C

	Pre_Env	Pre_Demo	Pre_Eco	GDP
GDP	.518	.160	-.459	.000
CO_2	.973	-.195	.020	.017

Table 4.27: Direct Effects of Model C

	Pre_Env	Pre_Demo	Pre_Eco	GDP
GDP	.518	.160	-.459	.000
CO_2	.965	-.198	.028	.017

Table 4.28: Indirect Effects of Model C

	Pre_Env	Pre_Demo	Pre_Eco	GDP
GDP	.000	.000	.000	.000
CO_2	.009	.003	-.008	.000

- The total (direct and indirect) effect of pre-liberalization environmental factors (which includes alternative energy consumption, access to clean fuel, access to electricity and open defecation) on CO_2 is .973 and on GDP is 0.518.
- It implies that during pre-liberalization period because of non-accessibility to clean fuel, open defecation and lesser alternatives for energy CO_2 emissions rose by 0.972 and
- The total (direct and indirect) effect of pre-liberalization economic factors (which include industry value added, trade openness and fossil fuel from coal sources) on GDP is -.459 on CO_2 is .0.028. This implies that during pre-liberalization industrial value added and trade openness did not affect the economic growth positively. These variables also contributed in increasing the CO_2 emissions.
- The pre-liberalization demographic factors though significant does not impact the carbon dioxide and GDP much.

Model Fit Summary

Table 4.29: CMIN of Model C

Model	NPAR	CMIN	DF	P	CMIN/DF
Default Model	17	179.352	3	.000	59.784
Saturated Model	20	.000	0		
Independence Model	5	300.143	15	.000	20.010

Table 4.30: RMSEA of Model C

Model	RMSEA	LO90	HI90	PCLOSE
Default Model	1.000	.892	1.00	.000
Independence Model	.577	.522	.635	.000

Table 4.31: Incremental Fit Index of Model C

Model	NFI	RFI	IFI	TLI	CFI
Default Model	.402	-1.988	.407	-2.092	.382
Saturated Model	1.000		1.000		1.000
Independence Model	.000	.000	.000	.000	.000

Goodness of fit indices for the pre-liberalization model is presented in Table 4.29, 4.30 and 4.31. The number of parameters in this Model –B are 20 with 3 degrees of freedom. Chi-square is significant and suggests a good fit ratio.

It evident from the direct, indirect and total effects that pre-liberalization values are high for environmental factors, i.e. during pre-liberalization sources of carbon dioxide emissions were mainly related to access to fuel and electricity. Due to weaker regulations for environmental quality the economic factor influenced the carbon dioxide through higher consumption of fossil fuel in industries. Due to the absence of governance factor and foreign investment flow during this period, the emissions are mainly influenced by environment factors.

4.11 SEM FOR POST LIBERALIZATION PERIOD

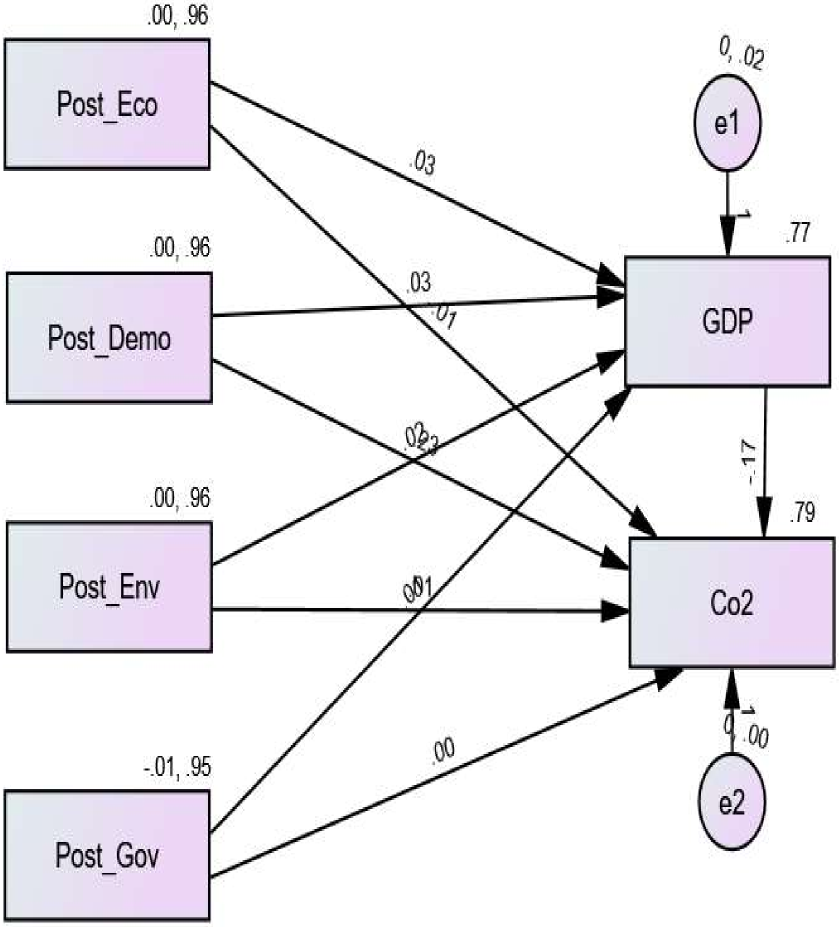


Figure 4.18: Path diagram – Model D (post-liberalization)

Created by researcher in AMOS

Result (Default model) Model D

Minimum was achieved

Chi-square = 47.863

Degrees of freedom = 6

Probability level = .000

Table 4.32: Regression Weights of Model D

	Estimates	P value	T values
GDP<--- Post_Eco	.027	.280	1.080
GDP<--- Post_Demo	.025	.304	1.028
GDP<--- Post_Env	.020	.412	.821
GDP<--- Post_Gov	.012	.688	.402
Co2<--- Post_Eco	-.007	.536	-.619
Co2<--- Post_Demo	.234	***	21.697
Co2<--- Post_Env	.007	.540	.613
Co2<--- Post_Gov	-.003	.795	-.260
Co2<---GDP	-.167	.048	-1.979

Table 4.33: Standardized Regression Weights of Model D

	Estimate
GDP <--- Post_Eco	.200
GDP <--- Post_Demo	.191
GDP <--- Post_Env	.152
GDP <--- Post_Gov	.088
Co2 <--- Post_Eco	-.028
Co2 <--- Post_Demo	.986
Co2 <--- Post_Env	.028
Co2 <--- Post_Gov	-.014
Co2 <--- GDP	-.094

Structural equations

CO_2 =0.793 – 0.028 (Ecofact) +.986 (Demofact) +0.028 (Envfact) – 0.014 (Govfact) – 0.094 (GDPpc) with Errorvar = 0.003 (3.600)* p value 0.000 …………...(11)	
GDP = 0.766 +0.20 (Ecofact) + 0.191 (Demofact) + 0.152 (Envfact) +0.088 (Gov) with Errorvar = 0.015 (3.593) p value 0.000 ……………..(12)	

*tvalue

Table 4.34: Total Effects of Model D

	Post_Gov	Post_Env	Post_Demo	Post_Eco	GDP
GDP	.088	.152	.191	.200	.000
CO_2	-.022	.013	.968	-.047	-.094

Table 4.35: Direct Effects of Model D

	Post_Gov	Post_Env	Post_Demo	Post_Eco	GDP
GDP	.088	.152	.191	.200	.000
CO_2	-.014	.028	.986	-.028	-.094

Table 4.36: Indirect Effects of Model D

	Post_Gov	Post_Env	Post_Demo	Post_Eco	GDP
GDP	.000	.000	.000	.000	.000
CO_2	-.008	-.014	-.018	-.019	.000

- The total (direct and indirect) effect of post-liberalization demographic factor on CO_2 emissions is .968 and on GDP is .200. Both these values are higher as compared to pre-liberalization period. It implies that structural change in the economy has affected economic growth and demographic profile to a great extent.
- On the other hand, the total (direct and indirect) effect of post-liberalization environmental factor on GDP is 0.088 and on CO_2 emissions is 0.152. There is

an improvement in both these values. It implies that with better economic growth post liberalization accessibility to better resources has helped reduce the emissions through environmental factor.

- Model Fit Summary

Table 4.37: CMIN of Model D

Model	NPAR	CMIN	DF	P	CMIN/DF
Default Model	21	47.863	6	.000	7.977
Saturated Model	27	.000	0		
Independence Model	6	129.395	21	.000	6.162

Table 4.38: RMSEA of Model D

Model	RMSEA	LO90	PCLOSE
Default Model	.518	.388	.000
Independence Model	.446	.374	.000

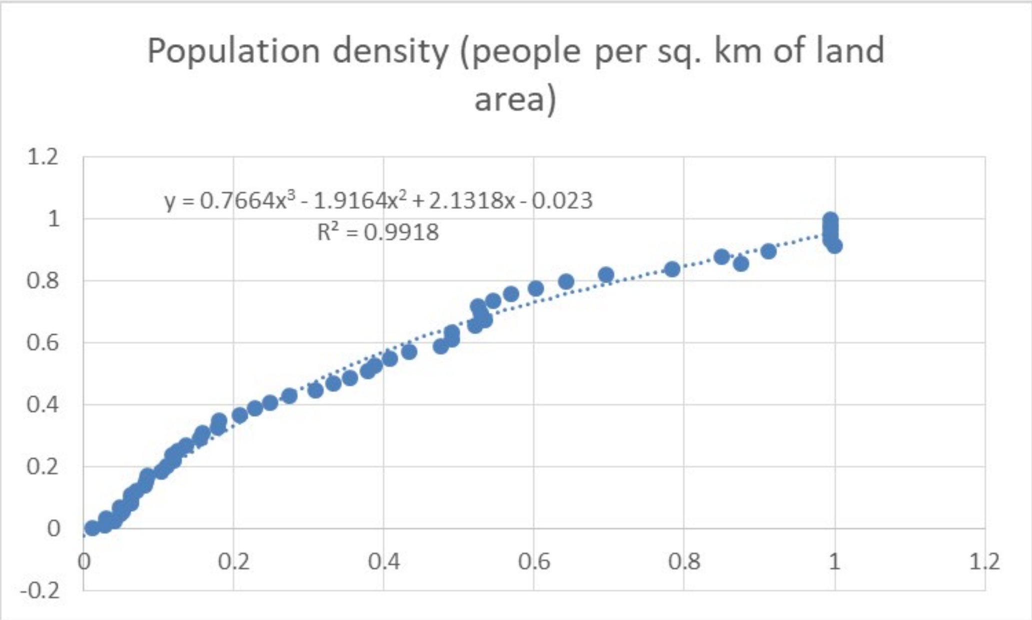
Table 4.39: Incremental Fit Index of Model D

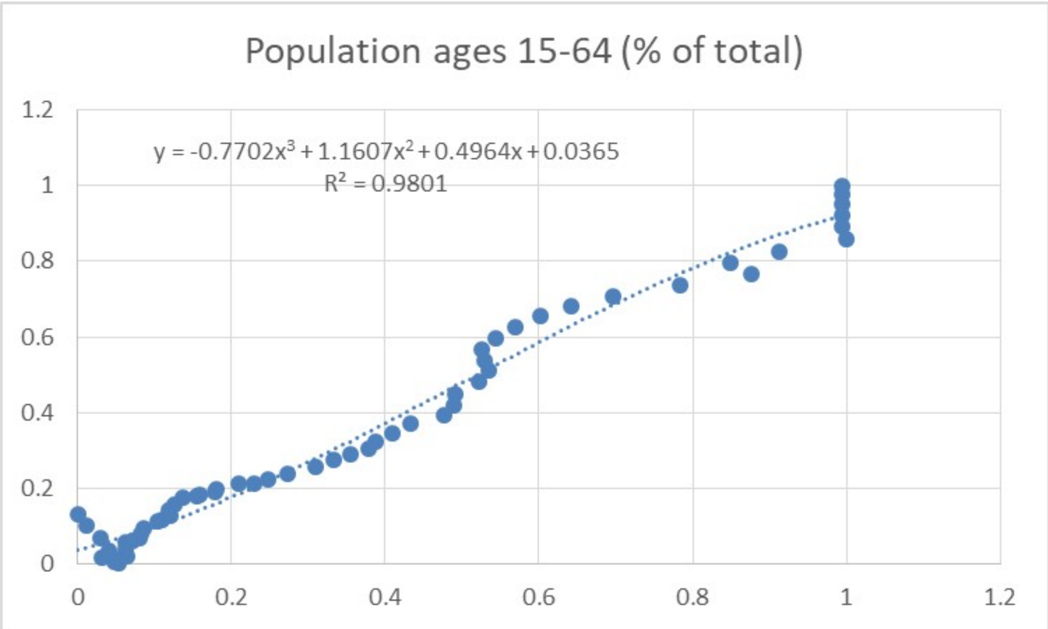
Model	NFI	RFI	IFI	TLI	CFI
Default Model	.630	-.295	.661	-.352	.614
Saturated Model	1.000		1.000		1.000
Independence Model	.000	.000	.000	.000	.000

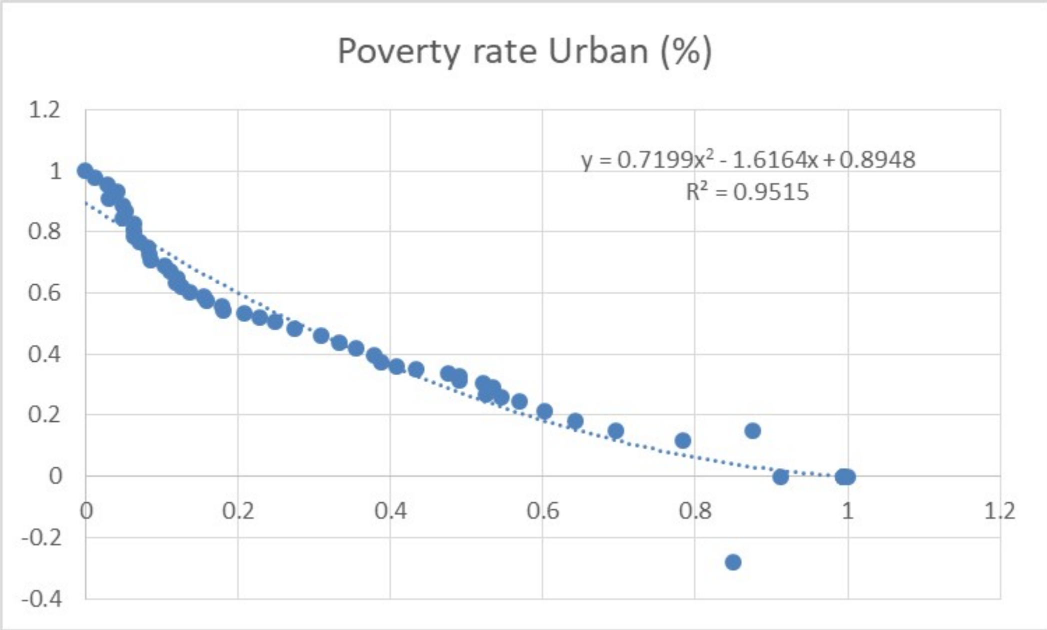
The incremental model fit ratios are comparatively significant during the post-liberalization period than pre-liberalization period. Demographic factors have greater influence on GDP per capita and carbon dioxide emissions in the country as compared to other factors during post-liberalization period. All indirect effects during post-liberalization period are inversely related to carbon dioxide emissions.

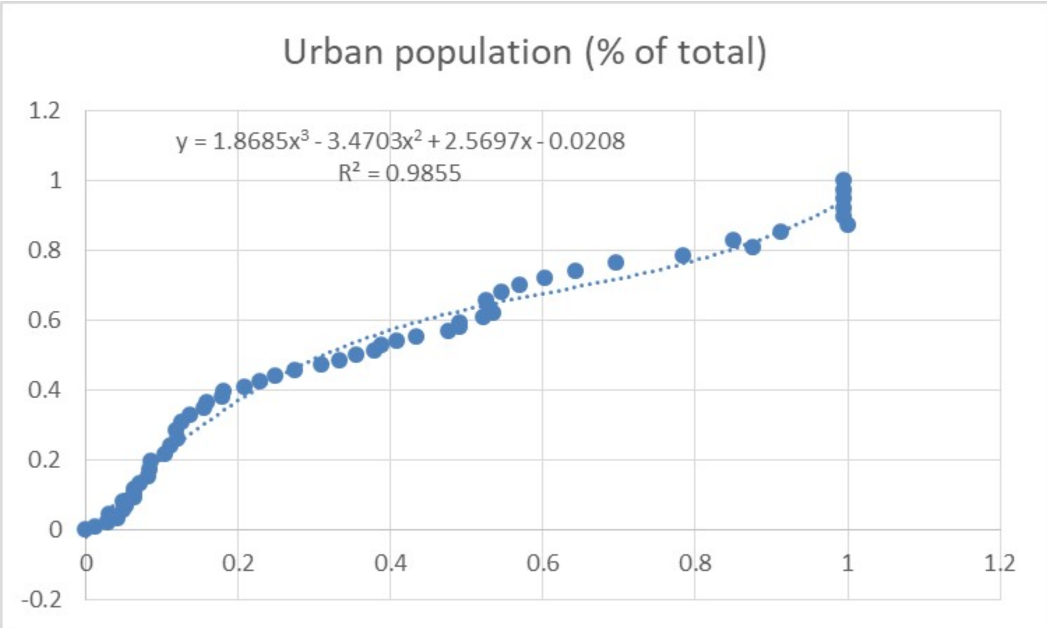
It can be inferred from the information presented in the above tables that during post-liberalization on one hand, there has been an improvement in the environment factor and so its impact on GDP per capita and CO_2 emissions. Structural shift in the economy has brought about improvement in the standard of living, and accessibility to basic amenities which has not only affected economic growth positively but also CO_2 emissions. On the other hand, there is a deterioration in the demographic factor and its impact on GDP and CO_2 emissions. That is, increase in the rate of urbanization, population density and larger population in age group of 15-64 years, has increased the pressure on environmental quality. This has caused higher CO_2 emissions in the economy. Liberalization has opened up foreign investment avenues impacting the economic growth in the economy.

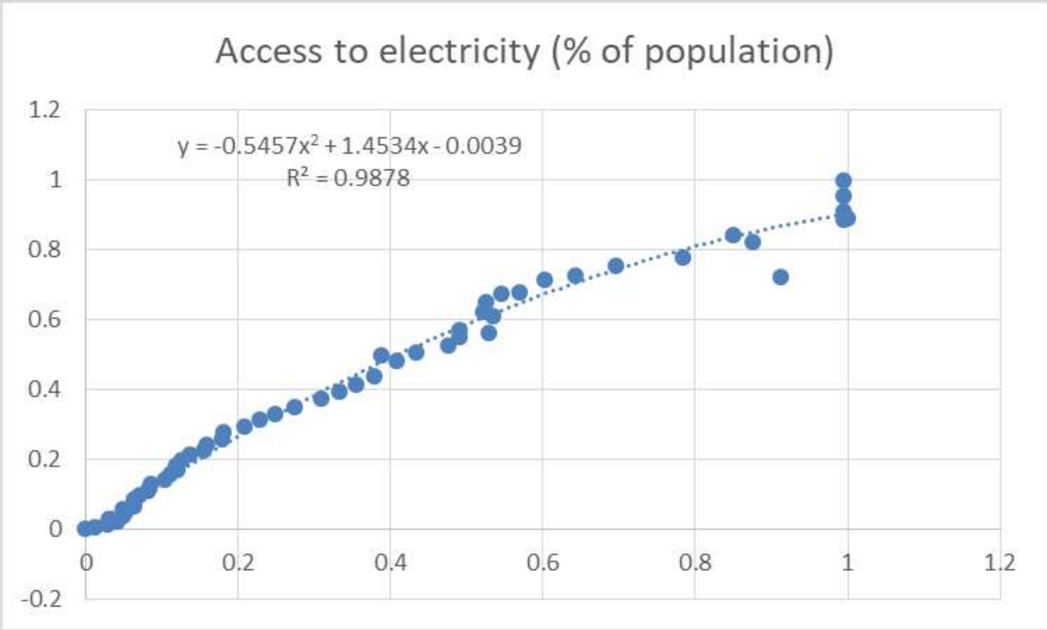
Annexure

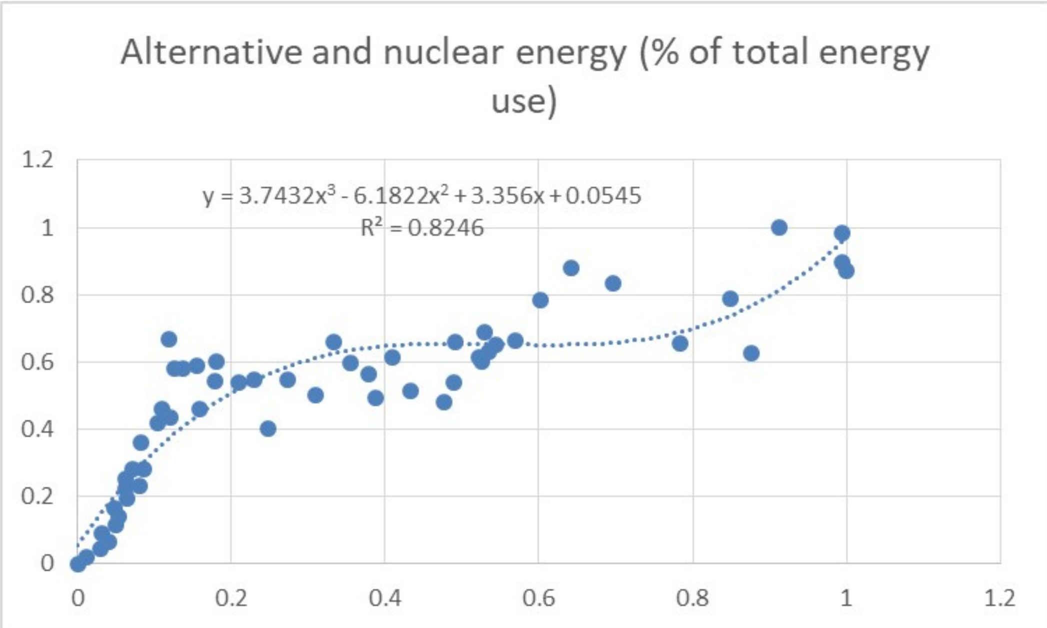

Population density (people per sq. km of land area)
y = 0.7664x³ - 1.9164x² + 2.1318x - 0.023
R² = 0.9918
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0
0.2
0.4
0.6
0.8
1
1.2

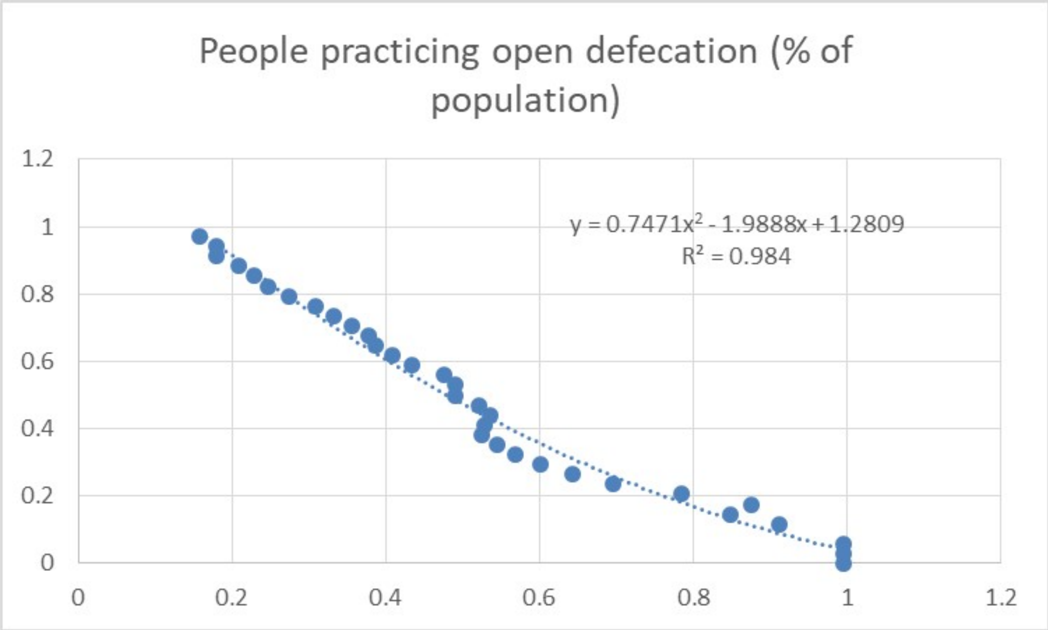

Population ages 15-64 (% of total)
y = -0.7702x³ + 1.1607x² + 0.4964x + 0.0365
R² = 0.9801
1.2
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8
1
1.2


Poverty rate Urban (%)
y = 0.7199x² - 1.6164x + 0.8948
R² = 0.9515
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
0.2
0.4
0.6
0.8
1
1.2


Urban population (% of total)
y = 1.8685x³ - 3.4703x² + 2.5697x - 0.0208
R² = 0.9855
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0
0.2
0.4
0.6
0.8
1
1.2


Access to electricity (% of population)
y = -0.5457x² + 1.4534x - 0.0039
R² = 0.9878
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0
0.2
0.4
0.6
0.8
1
1.2


Alternative and nuclear energy (% of total energy use)
y = 3.7432x³ - 6.1822x² + 3.356x + 0.0545
R² = 0.8246
1.2
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8
1
1.2



People practicing open defecation (% of population)
y = 0.7471x² - 1.9888x + 1.2809
R² = 0.984
1.2
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8
1
1.2

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