CHAPTER - 4

RESULTS AND DISCUSSION

The speedy economic growth and expansion of the process of industrialization in India and China propels severe use of natural resources. All the remaining deposits out of this use are released in to the atmosphere thus bringing down the environment quality. The present study shows how burgeoning rise of greenhouse gas emissions is a major menace to the environment of the globe.

The Emissions Gap report of 2019 revealed that the last decade witnessed 1.5 percent annual increase in GHG emissions and was constant only for a short period between 2014 and 2016. The report also showed that in 2018, total GHG emissions reached a record high of 55.3 gtCO_2e. An important component of GHG emissions namely the Fossil CO_2 emissions from energy use and industry grew 2.0 per cent in 2018, touching37.5 gtCO_2e per year as per the same report. The amount of greenhouse gas emissions of India and China is 34 percent of total world emissions and is rising at a greater speed over a period of time. Without proper policy action in place, these emission trends are likely to continue drastically as supply of energy from fossil fuels will be the maximum as a country grows with resultant implications on GHG emissions. Regardless of continuous improvements in energy intensities, the demand and supply of energy in the world are predicted to continue to grow because of the industrialization of developing economies. GHG emission projections for 2030 show a 25–90 percent rise more than the rise in 2000 and are also predicted to be even higher. Therefore the research of this aspect is becoming more important for all the societies from developing countries to developed countries. (Hossain, 2011).

The results and discussion pertaining to the study Relationship between Greenhouse Gas Emissions per capita, Trade openness and Gross Domestic Product per capita-A Comparative Study of India and China are summarised under the following headings:

4.1 Growth and Trend Analysis

4.1.1 Growth and trend of Macro Economic Variables used in the study for India and China

4.1.2 Descriptive Statistics

4.11 Long run relationship between GHG Emissions per capita and its determinants using cointegration analysis

4.11.1 The ADF Unit Root Test of Stationarity

4.11.2 Johansen Cointegration Test for LGHGpc, LGDP pc, LEN pc and TO

4.11.3 Estimation of long run greenhouse gas emissions per capita function using the Normalised Cointegrating Coefficient

4.11.4 Estimation of short run greenhouse gas emissions per capita function using Vector Error Correction Model(VECM)

4.12 Variance decomposition Analysis

4.13Impulse Response Function Analysis

4.14Test of Stability

4.15 Granger Causality Test for analyzing the direction of relationship among the variables

4.1 Growth and Trend Analysis

4.1.1(a)Growth of Gross Domestic Product per capita at constant Prices in India and China

The table 4.1.1 (a) shows the gross domestic product per capita annual growth rate of India and China for the period 1970 to 2018. From the reform period of 1978, average annual growth rate of GDP per capita in China was 10 percent. This faster impressive growth overtaking India has been due to the improved efficiency of labour and capital, more than average female labour force participation due to one child policy, the non-democratic and authoritarian political regime in China making it possible to adopt western-style free market economics, export led growth, encouraging private enterprise and many other reasons.

Table 4.1.1(a):Growth of Gross Domestic Product per capita at constant prices in India and China

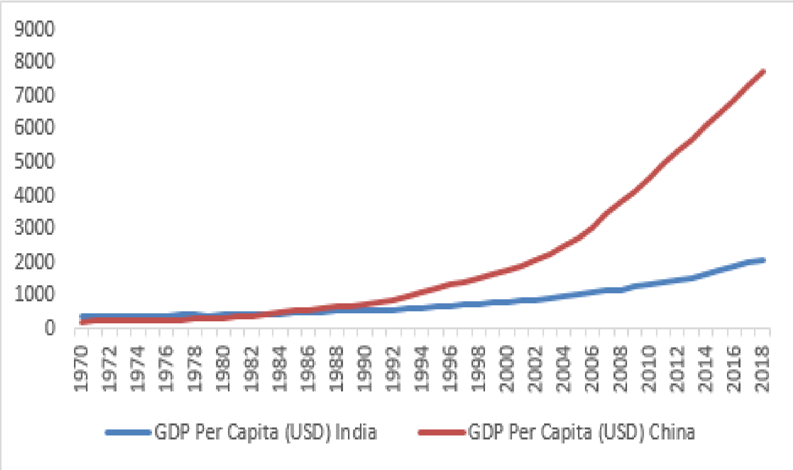
Year	GDP Per Capita (USD)				Year	GDP Per Capita (USD)				Year	GDP Per Capita (USD)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
1970	396.01	-	228.91	-	1980	422.90	4%	347.12	6%	1990	581.2	3%	729.1606	2%
1971	393.53	-1%	238.43	4%	1981	438.01	4%	360.43	4%	1991	575.5	-1%	786.1297	8%
1972	382.45	-3%	241.50	1%	1982	442.80	1%	386.89	7%	1992	595.0	3%	886.9504	13%
1973	385.97	1%	254.37	5%	1983	464.18	5%	422.66	9%	1993	611.1	3%	998.4048	13%
1974	381.54	-1%	254.92	0%	1984	470.97	1%	480.30	14%	1994	639.3	5%	1116.033	12%
1975	406.89	7%	272.30	7%	1985	484.64	3%	537.50	12%	1995	674.6	6%	1224.849	10%
1976	404.24	-1%	263.91	-3%	1986	496.64	2%	576.91	7%	1996	711.9	6%	1332.417	9%
1977	423.74	5%	280.04	6%	1987	505.18	2%	634.09	10%	1997	727.0	2%	1440.59	8%
1978	437.82	3%	307.09	10%	1988	542.05	7%	694.06	9%	1998	757.9	4%	1538.663	7%
1979	405.47	-7%	326.05	6%	1989	562.30	4%	712.12	3%	1999	810.2	7%	1642.357	7%
Average AGR		**0.3%**		**4.1%**			**3.3%**		**8.2%**			**3.7%**		**8.8%**

Year	GDP Per Capita (USD)				Year	GDP Per Capita (USD)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
2000	826.5924	2%	1767.834	8%	2010	1357.56	7%	4550.45	10%
2001	851.6165	3%	1901.408	8%	2011	1410.43	4%	4961.24	9%
2002	869.2013	2%	2061.162	8%	2012	1469.18	4%	5325.16	7%
2003	922.1679	6%	2253.93	9%	2013	1544.62	5%	5710.59	7%
2004	979.2838	6%	2467.133	9%	2014	1640.18	6%	6096.49	7%
2005	1040.312	6%	2732.166	11%	2015	1751.66	7%	6484.44	6%
2006	1106.926	6%	3062.535	12%	2016	1874.23	7%	6883.90	6%
2007	1173.875	6%	3480.153	14%	2017	1987.34	6%	7308.07	6%
2008	1192.512	2%	3796.633	9%	2018	2104.16	6%	7754.96	6%
2009	1268.249	6%	4132.902	9%					
Average AGR		**4.6%**		**9.7%**			**5.8%**		**7.3%**
CAGR of India - 3.39 % **CAGR of China-7.29 %**									

Source: Computed based on World Bank data, 2018

For India, GDP per capita grew at an average of 0.3 percent in 1970s and improved to 3.3 percent in the 1980s. It accelerated to 3.7 percent during the 1990s and to 4.6 percent in the decade of 2000, and further to 6.8 percent in the past one decade. This increase can be attributed to the liberalisation of Industry and trade and borrowings from abroad. China's average gross domestic product per capita was 4.1 percent in 1970s, 8.2 percent in 1980s, 8.8 percent in 1990s and increased to 9.7 percent in the decade of 2000. But the last decade showed a decline in the gross domestic product per capita to 7.3 percent. The global slowdown of 2008 had an impact on Indian Economy and Chinese economy reflecting in the annual growth rate which stood at 2 percent for India and dropped down from 14 percent to 9 percent for China. After this period, the real GDP of

China has slowed down significantly reflecting in the per capita gross domestic product making China's economy matured. Its growth has slowed significantly and dropped to 6 percent in 2018. International Monetary Fund (IMF) has projected a further fall to 5.5 percent by 2024. For India, the average pace of per capita growth was 5.8 percent a year in the last decade which is stable and steady compared to China.



Source: World Bank data,2018

Figure 4.1: Growth of GDP of India and China (1970 – 2018)

To conclude

- **Though China outperformed India during the 1990s in GDP per capita growth rate, the impact of 2008 crisis slowed down China's growth. International Monetary Fund has projected a further fall in growth rate to 5.5 percent in 2024.**
- **Comparatively India had a steady and stable average growth rate of 5.8 percent in the last decade.**

4.1.1(b): Greenhouse gas emissions per capita for India and China

The growth of greenhouse gas emissions in Indian and China is given in table 4.1.1(b).Greenhouse gas emissions have been growing at much faster rate in China than in India. The reasons are obvious as China grows faster, consumption of energy, increased production at the manufacturing sectors; trade and transport have soared up the emissions. Chinese government often disregards its own environmental laws in order to promote rapid economic growth. In comparison to India, Chinese emissions rate is higher.

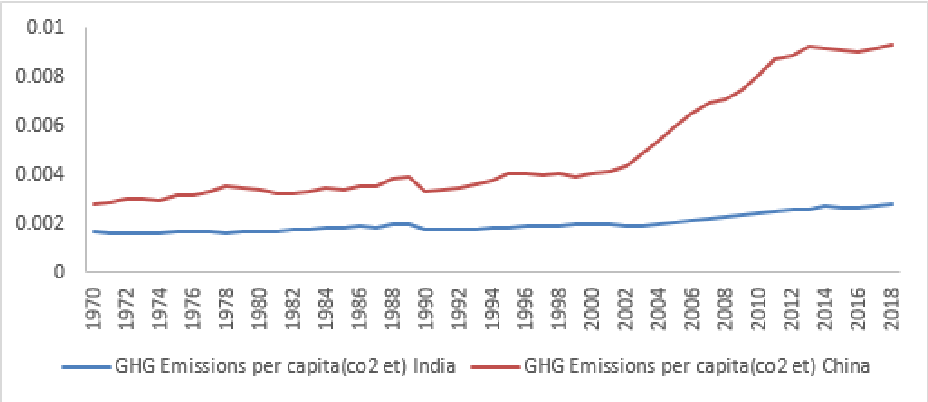
Table 4.1.1(b): Greenhouse gas emissions per capita for India and China

Year	GHG Emissions per capita(co_2 et)				Year	GHG Emissions per capita(co_2 et)				Year	GHG Emissions per capita(co_2 et)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
1970	0.002	-	0.003	-	1980	0.002	0%	0.003	-3%	1990	0.002	-12.2%	0.003	-16%
1971	0.002	-1%	0.003	3%	1981	0.002	3%	0.003	-4%	1991	0.002	2%	0.003	3%
1972	0.002	0%	0.003	4%	1982	0.002	1%	0.003	1%	1992	0.002	0%	0.003	2%
1973	0.002	-1%	0.003	0%	1983	0.002	2%	0.003	2%	1993	0.002	0%	0.004	5%
1974	0.002	1%	0.003	-1%	1984	0.002	3%	0.003	4%	1994	0.002	1%	0.004	3%
1975	0.002	2%	0.003	7%	1985	0.002	0%	0.003	-2%	1995	0.002	2%	0.004	9%
1976	0.002	1%	0.003	0%	1986	0.002	3%	0.004	3%	1996	0.002	1%	0.004	-1%
1977	0.002	0%	0.003	5%	1987	0.002	-2%	0.004	1%	1997	0.002	2%	0.004	-1%
1978	0.002	-2%	0.004	6%	1988	0.002	6%	0.004	8%	1998	0.002	0%	0.004	2%
1979	0.002	1%	0.003	-1%	1989	0.002	2%	0.004	2%	1999	0.002	3%	0.004	-3%
Average AGR		**0.1%**		**2.5%**			**1.9%**		**1.2%**			**-0.1%**		**0.2%**

Year	GHG Emissions per capita(co_2 et)				Year	GHG Emissions per capita(co_2 et)			
Country	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
2000	0.002	12.1%	0.004	2.9%	2010	0.002	3%	0.008	8%
2001	0.002	-1%	0.004	3%	2011	0.002	2%	0.009	8%
2002	0.002	-1%	0.004	5%	2012	0.003	4%	0.009	2%
2003	0.002	1%	0.005	11%	2013	0.003	1%	0.009	3%
2004	0.002	3%	0.005	12%	2014	0.003	4%	0.009	-0.5%
2005	0.002	2%	0.006	10%	2015	0.003	-1%	0.009	-1%
2006	0.002	3%	0.006	8%	2016	0.003	0%	0.009	-1%
2007	0.002	5%	0.007	7%	2017	0.003	3%	0.009	1%
2008	0.002	3%	0.007	2%	2018	0.003	3%	0.009	2%
2009	0.002	4%	0.007	6%					
Average AGR		**3.1%**		**6.7%**			**2%**		**2.5%**
CAGR of India -3.35 % **CAGR of China -4.41 %**									

Source: Computed based on World Bank data,2018

From the table 4.1.1(b), it can be seen that the decade from 2000 to 2009 showed peak emissions to 6.7 percent. A 2018 report by ExxonMobil estimated that China contributed about 60 percent of the growth in global CO2 emissions from 2000 to 2016. The compound annual growth rate of India in GHG emissions per capita is 3.35 percent and China is 4.41 percent. Though comparatively India emits low still it is not far behind in emissions, the country being the third largest emitter in the world. India too faces the big challenge of curbing greenhouse gas as the economy grows and population increases.



Source: World resources Institute,2018

Figure 4.2: GHG emissions per capita of India and China (1970-2018)

To conclude

- **Greenhouse gas emissions have been growing at much faster rate in China than in India.**
- **Though comparatively India emits lower than China, it is not far behind in emissions, the country being the third largest emitter in the world.**

4.1.1(c) Gross Fixed Capital Formation per capita in India and China

Gross Fixed capital formation in other words the investment in China has had a growth rate twice than the growth rate of India. The decade wise annual average growth rate comparison showed that China had almost double the growth rate of India. It can be seen from table 4.1.1(c) that during 1970s, investment average annual growth rate of China was 7.6 percent, while India's investment growth rate was 2.7 percent only. Similarly in the decades of 90s, 2000 and 2010, China showed higher growth rate of 6 percent, 15.3 percent and 7 percent respectively in comparison to India.

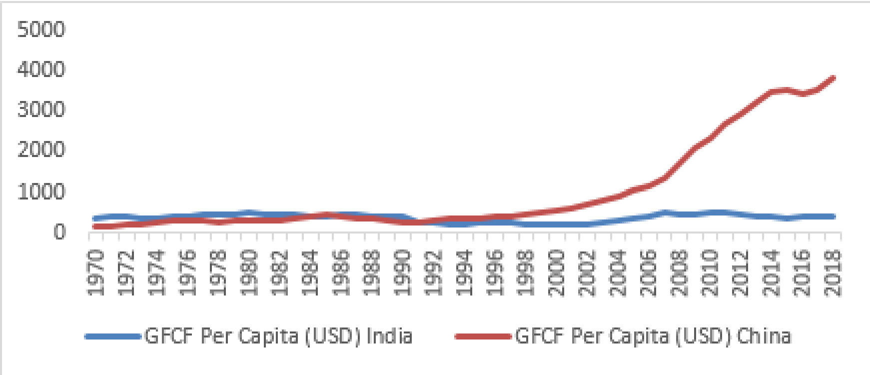
Table 4.1.1(c): Gross Fixed Capital Formation per capita in India and China

Year	GFCF per capita (USD)				Year	GFCF per capita (USD)				Year	GFCF per capita (USD)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
1970	380.98	-	171.78	-	1980	508.66	7%	327.35	3%	1990	408.73	1%	264.22	-10%
1971	410.86	8%	183.38	7%	1981	482.62	-5%	308.94	-6%	1991	281.34	-31%	278.24	5%
1972	395.37	-4%	202.24	10%	1982	482.03	0%	330.46	7%	1992	274.18	-3%	334.22	20%
1973	367.73	-7%	237.82	18%	1983	458.2	-5%	361.59	9%	1993	221.72	-19%	365.4	9%
1974	379.04	3%	265.30	12%	1984	412.67	-10%	398.58	10%	1994	235.66	6%	353.04	-3%
1975	399.20	5%	327.15	23%	1985	432.2	5%	440.89	11%	1995	256.89	9%	375.56	6%
1976	398.70	0%	303.58	-7%	1986	441.31	2%	410.26	-7%	1996	245.56	-4%	401.49	7%
1977	441.76	11%	326.02	7%	1987	455.13	3%	344.29	-16%	1997	245.5	0%	426.57	6%
1978	486.15	10%	290.24	-11%	1988	434.14	-5%	351.43	2%	1998	226.07	-8%	483.88	13%
1979	477.33	-2%	318.49	10%	1989	406.03	-6%	292.51	-17%	1999	237.29	5%	511.1	6%
Average AGR		**2.7%**		**7.6%**			**-1.5%**		**-0.3%**			**-4.4%**		**6%**

Year	GFCF per capita (USD)				Year	GFCF per capita (USD)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
2000	217.99	-8%	550.83	8%	2010	490.51	9%	2338.15	11%
2001	237	9%	608.5	10%	2011	500.32	2%	2666.87	14%
2002	225.46	-5%	691.3	14%	2012	447.29	-11%	2955.92	11%
2003	260.96	16%	825	19%	2013	395.82	-12%	3248.95	10%
2004	331.57	27%	933.14	13%	2014	399.75	1%	3462.9	7%
2005	381.3	15%	1041.06	12%	2015	380.86	-5%	3530.78	2%
2006	407.02	7%	1177.87	13%	2016	390.64	3%	3435.47	-3%
2007	517.3	27%	1372.74	17%	2017	437.6	12%	3550.94	3%
2008	445.95	-14%	1690.16	23%	2018	430.67	-2%	3826.86	8%
2009	449.62	1%	2099.06	24%					
Average AGR		**7.4%**		**15.3%**			**-0.2%**		**7%**
CAGR of India -6.4 **CAGR of China- 13.04**									

Source: Computed based on World Bank data,2018

Economic performance of China no doubt has been propelled by investment. Investment is about 50 percent of its GDP in China, compared with about 30 percent in India. The compound annual growth rate of GFCF per capita in India is 6.4 percent and that of China is 13.04 percent, more than double of India's. India has to learn from the tried and true path to growth of China to increase investment, improve infrastructure and grow economic output.



Source: World Bank,2018

Figure 4.3: Gross Fixed Capital Formation per capita of India and China

To conclude

- **Gross Fixed Capital Formation in other words the investment in China has had a growth rate twice than the growth rate of India.**

4.1.1(d). Trade openness in India and China

Trade openness in India and China is given in the table 4.1.1(d). The table shows that the trade openness growth rate in the last five decades has been fluctuating. India had higher growth rate of 5.1 percent and 6.9 percent in 1990s and in the decade of 2000. The reason must be the good effects of economic reforms. During 70s and 80s, China showed tremendous increase in the trade openness with10.5 percent and 9.5 percent respectively.

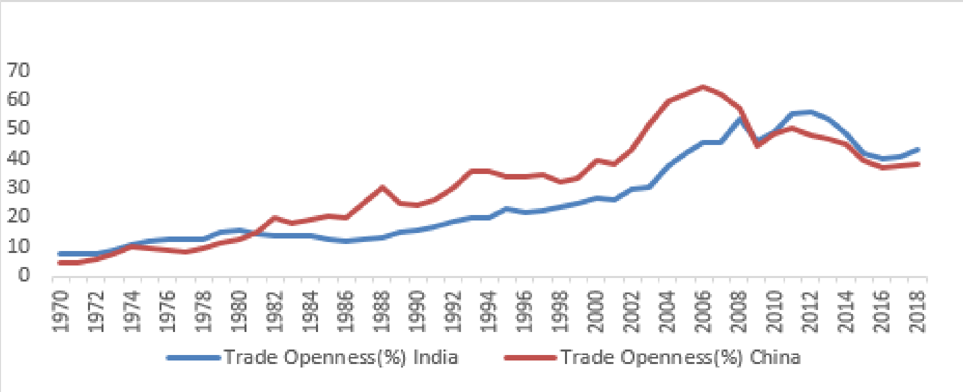
Table 4.1.1(d):Trade openness in India and China

Year	Tradeopenness(%)				Year	Tradeopenness(%)				Year	Tradeopenness(%)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
1970	7.66	-	4.95	-	1980	15.4	3%	12.42	12%	1990	15.51	2%	24.27	-3%
1971	7.67	0%	4.92	-1%	1981	14.51	-6%	14.9	20%	1991	16.99	10%	25.95	7%
1972	7.74	1%	5.76	17%	1982	14.13	-3%	19.69	32%	1992	18.43	8%	30.15	16%
1973	8.93	15%	8.00	39%	1983	13.69	-3%	17.92	-9%	1993	19.65	7%	36.06	20%
1974	10.85	22%	10.33	29%	1984	14.01	2%	19.03	6%	1994	20.08	2%	35.77	-1%
1975	12.29	13%	9.55	-8%	1985	12.9	-8%	20.71	9%	1995	22.87	14%	34.27	-4%
1976	12.80	4%	8.84	-7%	1986	12.22	-5%	19.88	-4%	1996	21.93	-4%	33.81	-1%
1977	12.65	-1%	8.38	-5%	1987	12.58	3%	24.86	25%	1997	22.62	3%	34.53	2%
1978	12.90	2%	9.65	15%	1988	13.49	7%	30.06	21%	1998	23.7	5%	32.42	-6%
1979	14.92	16%	11.09	15%	1989	15.17	12%	25.11	-16%	1999	24.82	5%	33.52	3%
Average AGR		**8%**		**10.5%**			**0.3%**		**9.5%**			**5.1%**		**3.3%**

Year	Tradeopenness(%)				Year	Tradeopenness(%)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
2000	26.9	8%	39.41	18%	2010	49.26	6%	48.89	10%
2001	25.99	-3%	38.53	-2%	2011	55.62	13%	50.6	3%
2002	29.51	14%	43	12%	2012	55.76	0%	48	-5%
2003	30.59	4%	52	21%	2013	53.84	-3%	46.57	-3%
2004	37.5	23%	59.51	14%	2014	48.92	-9%	45	-3%
2005	42	12%	62.21	5%	2015	41.92	-14%	39.45	-12%
2006	45.72	9%	64.48	4%	2016	40.16	-4%	37.03	-6%
2007	45.69	0%	62.1	-4%	2017	40.77	2%	37.8	2%
2008	53.37	17%	57.45	-7%	2018	43.12	6%	38.24	1%
2009	46.27	-13%	44.61	-22%					
Average AGR		**6.9%**		**3.7%**			**-0.5%**		**-1.5%**
CAGR of India- 3.52 CAGR of China-4.17									

Source: Computed based on World Bank data, 2018

The compound annual growth rate of trade openness during 1970-2018 was 3.52 percent for India and 4.17 percent for China. The institutional change and reform policies that occurred in China and India though gradual and different in the last three decades resulted in a significant increase in the openness to international relations in trade and foreign direct investment of the two economies (Marelli &Signorelli, 2011).



Source: World Bank, 2018

Figure 4.4: Trade openness of India and China

To conclude

- **Growth rate in trade openness has been tremendous in China in 70s and 80s but after 2010 it has been declining**
- **For India, trade openness in the decades of 1970, 1990 and 2000 had been good. After 2010, it has been fluctuating.**

4.1.1(e) Energy consumption per capita in India and China

Energy consumption per capita in India and China is shown in table 4.1.1(e). China and India together are the largest contributors to the global incremental energy demand for last several years and because of their growth targets they are expected to demand more in the coming years. But the energy demand between China and India has significantly widened after 2002. India´s energy demand is expected to double by 2040 as India is working to improve the share of manufacturing sector to total GDP and also has called upon ‘Make in India.

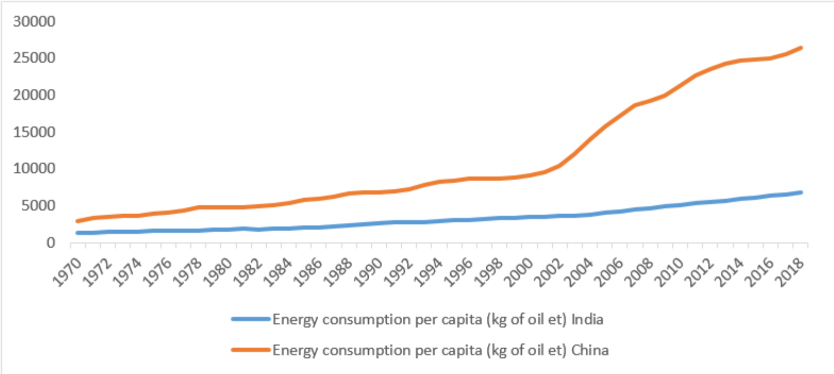
Table 4.1.1(e): Energy consumption per capita in India and China

Year	Energy Cons per capita (kg of oil$_2$et)				Year	Energy Cons per capita (kg of oil et)				Year	Energy Cons per capita (kg of oil et)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
1970	1365.67	-	2848.46	-	1980	1729.04	1%	4855.86	1%	1990	2619.87	5%	6774.27	0%
1971	1388.25	2%	3292.94	16%	1981	1871.09	8%	4724.73	-3%	1991	2707.06	3%	7021.38	4%
1972	1428.35	3%	3465.18	5%	1982	1812.23	-3%	4866.68	3%	1992	2790.48	3%	7309.31	4%
1973	1424.12	-0.3%	3575.43	3%	1983	1863.09	3%	5107.31	5%	1993	2804.24	0%	7792.12	7%
1974	1474.91	4%	3609.71	1%	1984	1944.43	4%	5398.45	6%	1994	2896.63	3%	8195.95	5%
1975	1548.33	5%	3965.09	10%	1985	2007.63	3%	5744.27	6%	1995	3055.45	5%	8373.59	2%
1976	1586.90	2%	4102.01	3%	1986	2102.14	5%	5913.45	3%	1996	3119.74	2%	8734.28	4%
1977	1640.22	3%	4402.26	7%	1987	2188.36	4%	6256.76	6%	1997	3232.3	4%	8712.99	0%
1978	1664.07	1%	4756.49	8%	1988	2331.01	7%	6592.81	5%	1998	3364.63	4%	8656.42	-1%
1979	1717.60	3%	4830.11	2%	1989	2492.37	7%	6794.68	3%	1999	3393.38	1%	8893.21	3%
Average AGR		**2.6%**		**6.1%**			**3.8%**		**3.5%**			**3.1%**		**2.8%**

Year	Energy Cons per capita (kg of oil et)				Year	Energy Cons per capita (kg of oil et)			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
2000	3507.54	3%	9137.61	3%	2010	5075.99	3%	21162.75	6%
2001	3465.36	-1%	9588.04	5%	2011	5305.54	5%	22710.79	7%
2002	3564.22	3%	10378.2	8%	2012	5511.19	4%	23488.29	3%
2003	3640.65	2%	12011.43	16%	2013	5655.34	3%	24222.73	3%
2004	3843.38	6%	13971.09	16%	2014	5973.56	6%	24652.08	2%
2005	4009.03	4%	15780.64	13%	2015	6099.98	2%	24755.3	0%
2006	4149.48	4%	17201.31	9%	2016	6305.74	3%	24938.4	1%
2007	4443.92	7%	18591.77	8%	2017	6501.97	3%	25574.68	3%
2008	4628.16	4%	19176.68	3%	2018	6838.84	5%	26416.96	3%
2009	4909.96	6%	19901.85	4%					
Average AGR		**3.8%**		**8.5%**			**3.8%**		**3.2%**
CAGR for India -2.07 CAGR for China-3.79									

Source: Computed based on World Bank data,2018

The table 4.1.1(e) shows that the annual growth rate of energy consumption per capita has been the highest in the 1970s and 2000 to 2009 for China with 6.1 percent and 8.5 percent respectively. The compound annual growth rate for India in energy consumption per capita was 2.07 percent and for China it was 3.79 percent during the study period. But energy consumption per capita has slowed down in China after 2010 showing signs of maturing economy that moves away from heavy industry to less energy-intensive service.



Source: World Bank, 2018

Figure 4.5: Energy consumption per capita of India and China

To conclude

- **Energy consumption per capita has slowed down in China after 2010 showing signs of maturing economy that moves away from heavy industry to less energy-intensive service.**
- **India's per capita consumption of energy has been stable throughout the study period.**

4.1.1(f). Population of India and China

Table 4.1.1(f) shows the population of India and China. Both China and India had begun to see a slower growth rate in population as the gap between births and deaths is narrowing. The table 4.1.1(f) shows that there has been decline in population growth in the periods 1970s to 2018 in both India and China. The compound annual growth rate in population is negative with -1.49 percent for India and -3.53 percent for China. But still population of India is 17.99 percent of the world´s total population meaning that one person in every 6 people on the planet is a resident of India.

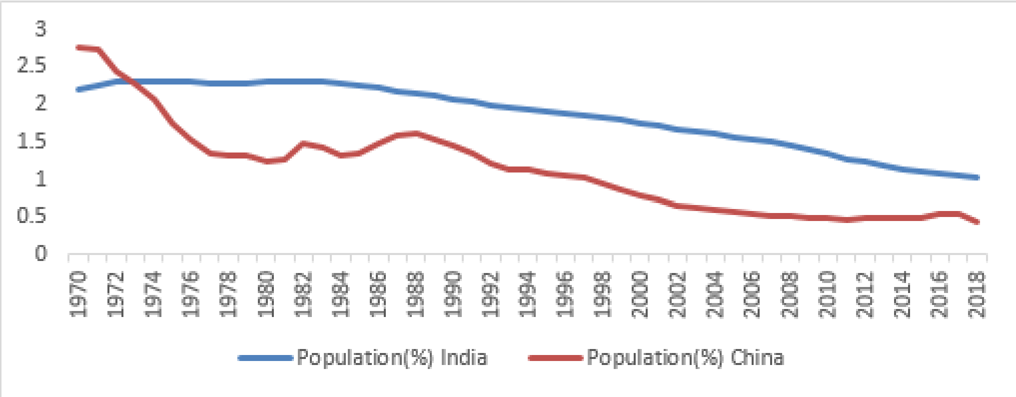
Table 4.1.1(f): Population of India and China

Year	Population (%)		Year	Population (%)		Year	Population (%)	
	India	China		India	China		India	China
1970	2.20	2.76	1980	2.3	1.25	1990	2.07	1.46
1971	2.25	2.74	1981	2.32	1.28	1991	2.03	1.36
1972	2.30	2.45	1982	2.32	1.47	1992	2	1.22
1973	2.32	2.28	1983	2.32	1.44	1993	1.97	1.14
1974	2.30	2.06	1984	2.29	1.31	1994	1.94	1.13
1975	2.32	1.76	1985	2.25	1.36	1995	1.91	1.08
1976	2.30	1.54	1986	2.22	1.48	1996	1.89	1.04
1977	2.29	1.36	1987	2.18	1.6	1997	1.86	1.02
1978	2.28	1.33	1988	2.14	1.61	1998	1.83	0.95
1979	2.29	1.33	1989	2.11	1.53	1999	1.8	0.86
Average GR	**2.29**	**1.96**		**2.24**	**1.43**		**1.93**	**1.13**

Year	Population(%)		Year	Population(%)	
	India	China		India	China
2000	1.76	0.78	2010	1.35	0.48
2001	1.72	0.72	2011	1.28	0.47
2002	1.68	0.66	2012	1.23	0.48
2003	1.65	0.62	2013	1.18	0.49
2004	1.61	0.59	2014	1.14	0.5
2005	1.57	0.58	2015	1.11	0.5
2006	1.54	0.55	2016	1.08	0.54
2007	1.5	0.52	2017	1.06	0.55
2008	1.46	0.51	2018	1.03	0.45
2009	1.41	0.49			
Average DR	**1.59**	**0.6**		**1.05**	**0.45**
CAGR for India- -1.49 **CAGR for China- -3.53**					

Source: Computed based on World Bank data,2018

China's population growth rates are expected to be lower in future compared to India. India's population growth rate also has been declining since 2000 and is also expected to be so in the future.



Source: World Bank,2018

Figure 4.6: Population growth of India and China

To conclude

- **Both China and India had begun to see a slower growth rate in population.**

4.1.1(g). Exchange rate in India and China

The table 4.1.1(g) shows the exchange rate of India and China in terms of US dollars. The exchange rate of India in the first year of the study period 1970 was Rs.7.50 which increased to Rs.68.38 in 2018 bringing down the value of Indian Rupee against US Dollars. In India the noteworthy changes are, moving to the Liberalized Exchange Rate Management System (LERMS) in 1992 and the market determined exchange rate regime in 1993, depreciation of rupee during the Post-Lehman global financial crisis period in 2009 and the sovereign debt crisis across the advanced world in 2011.

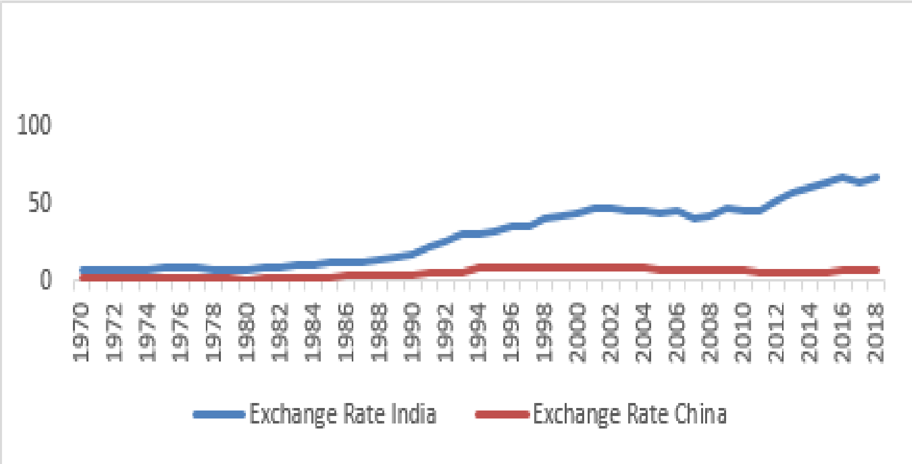
Table 4.1.1(g): Exchange rate in India and China

Year	Exchange Rate				Year	Exchange Rate				Year	Exchange Rate			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
1970	7.50	-	2.46	-	1980	7.86	-3%	1.49	-4%	1990	17.5	8%	4.78	27%
1971	7.49	0%	2.46	0%	1981	8.65	10%	1.7	14%	1991	22.74	30%	5.32	11%
1972	7.59	1%	2.24	-9%	1982	9.45	9%	1.89	11%	1992	25.91	14%	5.51	4%
1973	7.74	2%	1.98	-12%	1983	10.09	7%	1.97	4%	1993	30.49	18%	5.76	5%
1974	8.10	5%	1.96	-1%	1984	11.36	13%	2.32	18%	1994	31.37	3%	8.61	49%
1975	8.37	3%	1.85	-6%	1985	12.36	9%	2.93	26%	1995	32.42	3%	8.35	-3%
1976	8.96	7%	1.94	5%	1986	12.61	2%	3.45	18%	1996	35.43	9%	8.314	0%
1977	8.73	-3%	1.85	-5%	1987	12.96	3%	3.72	8%	1997	36.31	2%	8.28	0%
1978	8.19	-6%	1.68	-9%	1988	13.91	7%	3.72	0%	1998	41.25	14%	8.27	0%
1979	8.12	-1%	1.55	-8%	1989	16.22	17%	3.76	1%	1999	43.05	4%	8.27	0%
Average AGR		**1%**		**-4.9%**			**7.3%**		**9.6%**			**10.5%**		**9.2%**

Year	Exchange Rate				Year	Exchange Rate			
	India	Annual GR	China	Annual GR	Country	India	Annual GR	China	Annual GR
2000	44.94	4%	8.27	0%	2010	45.72	-6%	6.77	-1%
2001	47.18	5%	8.27	0%	2011	46.67	2%	6.46	-5%
2002	48.6	3%	8.27	0%	2012	53.43	14%	6.31	-2%
2003	46.58	-4%	8.27	0%	2013	58.59	10%	6.19	-2%
2004	45.31	-3%	8.27	0%	2014	61.02	4%	6.14	-1%
2005	44.09	-3%	8.19	-1%	2015	64.15	5%	6.22	1%
2006	45.3	3%	7.97	-3%	2016	67.19	5%	6.64	7%
2007	41.34	-9%	7.6	-5%	2017	65.12	-3%	6.75	2%
2008	43.5	5%	6.94	-9%	2018	68.38	5%	6.61	-2%
2009	48.4	11%	6.83	-2%					
Average AGR		**1.3%**		**-1.9%**			**4.1%**		**-0.3%**
CAGR of India—8.82 **CAGR of China-1.99**									

Source: Computed based on World Bank data,2018

China’s Yuan was valued at 2.46 in terms of US dollars in 1970 which increased to 6.61 Yuan in 2018. Some of the significant events related to exchange rate in China are the foreign exchange retention system, permission to sell unused foreign exchanges to other companies, ‘internal settlement rate’ of RMB2.8 per US dollar, foreign exchange swap centres, devaluation of the official exchange rate of the renminbi against the dollar, abolishing the internal settlement rate and all international transactions were settled at the official exchange rate, RMB exchange rate was on the rise, the East Asian Financial Crisis. ‘no devaluation’ policy and shifting from managed floating to a very hard de facto peg to the US dollar. India’s exchange rate had been fluctuating compared to the stable exchange rate of China..



Source: World Bank,2018

Figure 4.7: Exchange rate of India and China

To conclude

- **India’s exchange rate had been fluctuating compared to China which is stable.**

4.1.1(h): Inflation rate in India and China

The table 4.1.1(h) shows the trends of inflation in India and China. The inflation rate in India increased steadily to 8.47percent in the 1970s and 8.7 percent in the 1980s. India had usually not gone through runaway inflation. The lift up in inflation rate from 1970s onwards mirrors the impact of a sharp rise in growth of money supply and also partly supply shocks from crude oil prices and crop failures. Widening of fiscal balances created demand pressures and became the reason for inflationary pressures in the 1980s. After the structural adjustment policies of 1991, inflation rate had increased drastically. The second half of the 1990s was marked by a significant spin in the inflation effect reflecting the improved monetary-fiscal interface. Inflation in India has declined steadily from an average of 8.7 percent in the 1990s to 5.7 percent during the decade of 2000. From 2010 to 2018, inflation fell to 5 percent.

Table 4.1.1(h): Inflation rate in India and China

Year	Inflation rate		Year	Inflation rate		Year	Inflation rate	
	India	China	Country	India	China	Country	India	China
1970	1.56	-2.61	1980	11.5	3.77	1990	10.66	5.72
1971	5.32	0.67	1981	10.82	2.29	1991	13.75	6.7
1972	10.83	0.07	1982	8.095	-0.06	1992	8.96	8.2
1973	17.82	0.21	1983	8.55	1.09	1993	9.86	15
1974	16.66	0.28	1984	7.92	1.9	1994	9.98	21
1975	2.71	-1.13	1985	7.19	10.19	1995	9.06	13.6
1976	5.98	-0.11	1986	6.78	1.7	1996	7.57	6.5
1977	5.63	0.09	1987	9.32	5.05	1997	6.47	1.62
1978	2.46	1.85	1988	8.23	12.09	1998	8.01	-0.89
1979	15.72	3.59	1989	8.43	8.62	1999	3.06	-1.27
Average Inflation rate	**8.47**	**1.06**		**8.7**	**4.7**		**8.7**	**8.05**

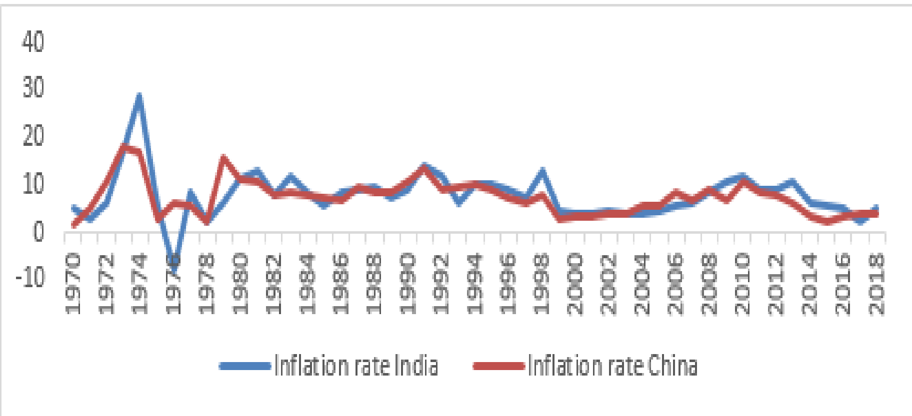
Year	Inflation rate		Year	Inflation rate	
	India	China		India	China
2000	3.64	2.06	2010	10.52	6.9
2001	3.21	2.04	2011	8.73	8.07
2002	3.71	-0.60	2012	7.93	2.33
2003	3.86	2.60	2013	6.18	2.16
2004	5.72	6.95	2014	3.33	0.79
2005	5.62	3.9	2015	2.27	0.06
2006	8.4	3.9	2016	3.12	1.07
2007	6.94	7.7	2017	3.83	3.9
2008	9.19	7.8	2018	4.18	2.9
2009	7.04	-0.21			
Average Inflation Rate	**5.7**	**3.5**		**5**	**2.8**

Source: World Development Indicators, 2018

On the other hand, inflation in China has been comparatively low with 1.06 percent in 1970s, 4.7 percent in 1980s, 3.5 percent in the decade of 2000 and 2.8 percent in the last decade. This has been accomplished despite the fact that

China has been recording fiscal surplus for the past many years and ideally should be reeling with inflation. To the contrary, China has established sovereign wealth funds, which invested the additional cash in foreign assets keeping the inflation rate low. Given the fact that Indian economy is severely marred by inflation, it seems unlikely that they will be able to compete against China in the long run.

China's inflationary crisis during 1988-1989 had devastating effect on its political and economic system. But later years witnessed a significant improvement in both these aspects. Soft landing was the target of the policy makers in China and was achieved by bringing down the inflation rate to very low. Negative inflation rates were seen during the periods of 1998, 1999, 2002 and 2009.But in 1994, inflation rate was double digit 21 per cent. In 1998 to 2002, inflation fell into deflation due to the decline in consumer price continuously for 2 years. Since 2003, Chinese economy had shown high growth and low inflation. In 2004 again inflation showed an increase. Again in 2007 inflation rose to 7 percent due to rising CPI index. Even in 2009 when world was facing crisis, China had a negative inflation rate. From 2010 to 2018, the average inflation rate was only 2.8 percent. Compared to India, the inflation rates are lower in China.



Source: World Bank,2018

Figure 4.8: Inflation Rate of India and China

To conclude

- **Inflation rate has been low in China for many years compared to India which is severely marred by it.**

4.1.2 Descriptive statistics

The table 4.1.2(a) gives the descriptive statistics for selected macro economic variables for India. The mean shows the average value for each of the variables. The median shows the middle values of each of these variables. The maximum and minimum values give the highest and lowest values. The standard deviation shows the deviation from the sample mean with respect to each variable.

Table 4.1.2(a): Descriptive Statistics of Selected Macro-Economic Variables -India

VARIABLE/ STATISTICAL INDICATORS	GDP PC	GFCF PC	GHG PC	ENERGY PC	TRADE OPENNESS	INFLATION	POPULATIO N	EXCHANGE RATE
Mean	834.7203	380.2229	0.001654	4.27E-07	25.83673	7.480913	9.49E+08	30.58139
Median	639.2687	399.7517	0.001579	4.08E-07	20.08000	7.575018	9.46E+08	31.37374
Maximum	2104.163	517.3069	0.002603	5.35E-07	55.76000	17.82972	1.35E+09	68.38947
Minimum	381.5396	217.9967	0.001209	3.83E-07	7.660000	1.562243	5.55E+08	7.491935
Std. Dev.	480.1859	91.71807	0.000412	3.98E-08	15.24355	3.698354	2.48E+08	20.11560
Skewness	1.101935	-0.550770	0.834814	1.100949	0.652883	0.736173	0.026240	0.263029
Kurtosis	3.147503	2.003317	2.613165	3.197725	1.976722	3.524073	1.711444	1.694147
Probability	0.006871	0.105111	0.049862	0.006811	0.060238	0.082634	0.183089	0.132221
Sum	40901.30	18630.92	0.081070	2.09E-05	1266.000	366.5647	4.65E+10	1498.488
Sum Sq. Dev.	11067766	403785.9	8.16E-06	7.61E-14	11153.55	656.5354	2.94E+18	19422.60
Observations	49	49	49	49	49	49	49	49

Source: Computed based on World bank data, 2018

For normal skewness the value is zero so the variables GFCF per capita, GHG emissions per capita, trade openness, inflation, population and exchange rate mirrors a normal distribution. Variables like GDP per capita and energy consumption per capita have skewness values more than 1 implying positive skewness. Kurtosis measures the peakness or flatness of the distribution of the series. In the above table GFCF per capita, GHG emissions per capita, trade openness, population and Exchange rate are platykurtic as their values are lower than 3. Platykurtic implies that these series will have values lower than sample mean. Remaining variables like GDP Per capita, energy consumption and inflation have values more than 3 implying leptokurtic nature. The table 4.1.2(b) shows the descriptive statistics of selected macro-economic variables for China. The variables GHG emissions per capita, trade openness, population and exchange rate shows normal distribution of the series.

Table 4.1.2(b):Descriptive Statistics of Selected Macro Economic Variables- China

VARIABLES/ STATISTICAL INDICATORS	GDP PC	GCFC PC	GHG EMISSIONS PC	ENERGY PC	TRADE OPENNESS	INFLATION	POPULATION	EXCHANGE RATE
Mean	2086.659	1020.260	0.004760	9.04E-07	31.05469	7.833049	1.16E+09	5.216182
Median	1116.033	401.4927	0.003727	6.85E-07	33.52000	7.164252	1.19E+09	6.143434
Maximum	7754.962	3826.860	0.010492	1.95E-06	64.48000	28.59873	1.39E+09	8.618743
Minimum	228.9056	171.7827	0.002067	5.14E-07	4.920000	-7.633948	8.18E+08	1.498386
Std. Dev.	2207.133	1138.469	0.002612	4.30E-07	17.00866	4.962607	1.73E+08	2.597915
Skewness	1.198170	1.414181	0.946027	1.197985	0.157151	1.027125	-0.367761	-0.164877
Kurtosis	3.173819	3.422992	2.446048	2.943830	2.068296	9.050240	1.818826	1.425498
Probability	0.002759	0.000237	0.018917	0.002841	0.372693	0.000000	0.138553	0.071240
Sum	102246.3	49992.75	0.233229	4.43E-05	1521.680	383.8194	5.67E+10	255.5929
Sum Sq. Dev.	2.34E+08	62213378	0.000327	8.87E-12	13886.13	1182.119	1.44E+18	323.9599
Observations	49	49	49	49	49	49	49	49

Source: Computed based on World bank data,2018

The other variables GDP per capita, GFCF per capita, energy consumption per capita and inflation have values more than 1 and so implies positive skewness. The variables GDP per capita, GFCF per capita and Inflation have kurtosis values more than 3 and are leptokurtic. The remaining variables GHG emissions per capita, energy consumption per capita, trade openness, population and exchange rate are platykurtic.

4.2 Decoupling Analysis

Decoupling refers to breaking the link between environmental bads and economic goods (OECD). Decoupling happens when the growth rate of an environmental pressure is less than that of its economic driving force over a period. Generally decoupling can take two forms, either absolute or relative. Absolute decoupling is when an important environment variable is constant or declining while economic variable is growing. It is relative when the environment variable is increasing at a lower rate compared to the economic variable. The decoupling analysis was performed for India and China for the period 1970 to 2018 for three sets of variables as follows. Greenhouse gas emissions per capita and gross domestic product per capita, greenhouse gas emissions per capita and energy consumption per capita, greenhouse gas emissions per capita and trade openness.

Strong decoupling is the ideal state in which the economy grows, while the environmental pressure decreases. During weak decoupling, energy efficiency would improve as the energy consumption or pollutant emissions growth rate is slower than the economic growth. Strong negative coupling is a situation where economic growth is falling but emissions are on a rise. In periods of weak negative decoupling, the economic growth decreases and emissions too decrease but at a rate less than economic growth. During expansive negative decoupling, economic growth increases and emissions increase more than economic growth. Recessive decoupling is when pollutant reduction rate is faster than economic recession. Expansive coupling happens when economic growth occurs at the cost of accelerated environmental destruction.

4.2.1 Decoupling between GHG Emissions per capita and GDP per capita for India and China

The table 4.2.1(a) shows the decoupling status of GHG emissions per capita and GDP per capita in India. In India during the period 1970-2018, majority of the years had weak decoupling status which means that as GDP per capita increases, greenhouse gas emissions per capita increase but less than GDP per capita. Second most seen status was that of strong decoupling (1973, 1978,1987,1990,2001 and 2002). During these periods gross domestic product per capita has increased whereas greenhouse gas emissions per capita have decreased. Recessive decoupling and weak negative decoupling were seen in 1971 and 1972 respectively. Weak negative decoupling implies that as GDP per capita falls, greenhouse gas emissions per capita falls less than GDP per capita.

Table 4.2.1(a): Decoupling Status between GHG emissions per capita and GDP per capita in India

Year	Change in GHG emissions per capita / GHG pc(ΔC/C)	Change in GDP per capita /GDP pc (ΔY/Y)	Elasticity Coefficient	Status	Year	Change in GHG emissions per capita /GHG pc(ΔC/C)	Change in GDP per capita /GDP pc (ΔY/Y)	Elasticity Coefficient	Status
1971	-0.0100	-0.0062	1.5981	RD	1995	0.0231	0.0552	0.4194	WD
1972	-0.0029	-0.0281	0.1043	WND	1996	0.0125	0.0553	0.2269	WD
1973	-0.0124	0.0091	-1.3523	SD	1997	0.0161	0.0212	0.7616	WD
1974	0.0089	-0.0114	-0.7792	SND	1998	0.00004	0.0424	0.0019	WD
1975	0.0165	0.0664	0.2485	WD	1999	0.0251	0.0689	0.3647	WD
1976	0.0092	-0.0065	-1.4156	SND	2000	0.0023	0.02021	0.1173	WD
1977	0.0012	0.0482	0.0253	WD	2001	-0.0066	0.0302	-0.2206	SD
1978	-0.0172	0.0332	-0.52	SD	2002	-0.0071	0.0206	-0.3462	SD
1979	0.0123	-0.0738	-0.1678	SND	2003	0.0054	0.0609	0.0894	WD
1980	0.0040	0.0429	0.0945	WD	2004	0.0265	0.0619	0.4292	WD
1981	0.0297	0.0357	0.8316	EC	2005	0.0193	0.0623	0.3111	WD
1982	0.0086	0.0109	0.7918	WD	2006	0.0281	0.0640	0.4400	WD
1983	0.0228	0.0482	0.4726	WD	2007	0.0473	0.0604	0.7835	WD
1984	0.0299	0.01464	2.0448	END	2008	0.0255	0.0158	1.6114	END
1985	-0.0032	0.0290	-0.1103	WD	2009	0.0412	0.0635	0.6499	WD
1986	0.0271	0.0247	1.0965	EC	2010	0.0264	0.0704	0.3750	WD
1987	-0.021	0.0171	-1.2213	SD	2011	0.0233	0.0389	0.5995	WD
1988	0.0577	0.0729	0.7912	WD	2012	0.0345	0.0416	0.8299	EC
1989	0.0218	0.0373	0.5852	WD	2013	0.0052	0.0513	0.1023	WD
1990	-0.1393	0.0336	-4.1398	SD	2014	0.0413	0.0618	0.6678	WD
1991	0.0204	-0.0098	-2.0791	SND	2015	-0.0109	0.0679	-0.1617	SD
1992	0.0015	0.0339	0.0457	WD	2016	-0.0026	0.0699	-0.0380	SD
1993	0.0006	0.0270	0.0244	WD	2017	0.0246	0.0603	0.4084	WD
1994	0.0108	0.0460	0.2354	WD	2018	0.0288	0.0587	0.4909	WD

Source: Computed based on World bank data,2018

Strong negative decoupling was observed in the following years, 1974, 1976, 1979 and 1991. In these four years, there has been fall in GDP per capita and a rise in greenhouse gas emissions per capita. Expansive negative decoupling was seen during 1984 and 2008 which shows that as GDP per capita increased, greenhouse gas emissions per capita increased more than the increase in GDP per capita. Expansive coupling was found during 1981, 1986 and 2012.

During the study period in China, it can be seen from table 4.2.1 (b) that weak decoupling was mostly found in about 27 years spread out. Strong decoupling can be seen in 12 years in the country. Expansive coupling was observed in 7years over the period. Expansive negative decoupling was found in 1975 and weak negative decoupling in 1976.

Table 4.2.1(b): Decoupling Status between GHG emissions per capita and GDP per capita in China

Year	Change in GHG emissions per capita (ΔC/C)	Change in GDP per capita (ΔY/Y)	Elasticity Coefficient	Status	Year	Change in GHG emissions per capita ΔC/C)	Change in GDP per capita (ΔY/Y)	Elasticity Coefficient	Status
1971	0.031	0.04	0.7	WD	1995	0.079	0.098	0.81	WD
1972	0.035	0.01	2.7	END	1996	-0.01	0.088	-0.1	SD
1973	0.004	0.05	0.1	WD	1997	-0.01	0.081	-0.2	SD
1974	-0.015	0	-7	SD	1998	0.016	0.068	0.23	WD
1975	0.062	0.07	0.9	EC	1999	-0.03	0.067	-0.4	SD
1976	-3E-04	-0	0	WND	2000	0.029	0.076	0.37	WD
1977	0.051	0.06	0.8	EC	2001	0.027	0.076	0.36	WD
1978	0.053	0.1	0.5	WD	2002	0.049	0.084	0.58	WD
1979	-0.01	0.06	-0	SD	2003	0.098	0.094	1.04	EC
1980	-0.034	0.06	-1	SD	2004	0.106	0.095	1.12	EC
1981	-0.04	0.04	-1	SD	2005	0.091	0.107	0.85	EC
1982	0.008	0.07	0.1	WD	2006	0.077	0.121	0.64	EC
1983	0.024	0.09	0.3	WD	2007	0.063	0.136	0.46	WD
1984	0.039	0.14	0.3	WD	2008	0.024	0.091	0.26	WD
1985	-0.016	0.12	-0	SD	2009	0.055	0.089	0.62	WD
1986	0.028	0.07	0.4	WD	2010	0.074	0.101	0.73	WD
1987	0.006	0.1	0.1	WD	2011	0.072	0.09	0.8	WD
1988	0.078	0.09	0.8	EC	2012	0.022	0.073	0.3	WD
1989	0.019	0.03	0.7	WD	2013	0.032	0.072	0.45	WD
1990	-0.194	0.02	-8	SD	2014	-0.01	0.068	-0.1	SD
1991	0.032	0.08	0.4	WD	2015	-0.01	0.064	-0.1	SD
1992	0.023	0.13	0.2	WD	2016	-0.01	0.062	-0.1	SD
1993	0.046	0.13	0.4	WD	2017	0.012	0.062	0.19	WD
1994	0.026	0.12	0.2	WD	2018	0.019	0.061	0.31	WD

Source: Computed based on World bank data,2018

From the computed results of decoupling status for India and China, it can be seen that weak decoupling status has been prevalent for majority of the years in the 49 year period. It can be inferred that there has been a mild breakage of link between greenhouse gas emissions per capita and gross domestic product per capita in both the countries. This decoupling though weak has been due to the promises made by India to ensure that 40 percent of its electricity-generation capacity will come from non-fossil fuel sources by 2030 and that it will bring down its emissions intensity by at least one-third compared with 2005 levels. India has improved its solar-energy capacity more than twelvefold since 2014 and launched initiatives to save electricity (The Washington Post, 2020).China in Copenhagen Accord has also vowed to reduce Carbon intensity to 45 percent below 2005 levels and increase the non-fossil fuel share of energy supply to 15 percent by 2020. It has also signed in the Paris Agreement, to reduce Carbon intensity to 65 percent below 2005 levels and increase the non-fossil fuel share of energy supply to 20 percent by 2030 (The Climate Action Tracker,2020).

To conclude

- **Weak decoupling status has been prevalent for majority of the years in the 49 year period in both India and China**

4.2.2 Decoupling between GHG emissions per capita and energy consumption per capita for India and China

Energy consumption per capita and greenhouse gas emissions per capita are interlinked as emissions happen as a result of production where energy in different forms are consumed whether be it manufacturing , agricultural sector or service sectors. When extracting a resource, cheaper options are generally used first, which means that most readily available energy and materials resources mobilised by the economy have already been exploited. The extraction of remaining stock is more complex, more technology demand, more socially disruptive, more expensive, more energy intensive resulting in total environment degradation(Parrique et al., 2019). The decoupling status between GHG emissions per capita and energy consumption per capita in India is given in table 4.2.2(a).

Table 4.2.2(a): Decoupling Status between GHG emissions per capita and energy consumption per capita in India

Year	Change in GHG emissions per capita (ΔC/C)	Change in Energy consumption per capita (ΔE/E)	Elasticity Coefficient	Status	Year	Change in GHG emissions per capita ΔC/C)	Change in Energy consumption per capita (ΔE/E)	Elasticity Coefficient	Status
1971	-0.01001	0.016266	-0.61538	SD	1995	0.023192	0.051979	0.446184	WD
1972	-0.00294	0.028072	-0.10465	SD	1996	0.01255	0.020608	0.609018	WD
1973	-0.01243	-0.00297	4.181982	RD	1997	0.016171	0.034821	0.464388	WD
1974	0.008937	0.034437	0.25953	WD	1998	8.16E-05	0.03933	0.002074	WD
1975	0.016515	0.047424	0.348235	WD	1999	0.025161	0.008472	2.969815	END
1976	0.009246	0.024304	0.380426	WD	2000	0.002371	0.032549	0.072855	WD
1977	0.001222	0.032505	0.037596	WD	2001	-0.00668	-0.01217	0.548864	WND
1978	-0.01728	0.014335	-1.20527	SD	2002	-0.00715	0.027736	-0.2578	SD
1979	0.012399	0.031162	0.397892	WD	2003	0.005453	0.020995	0.259731	WD
1980	0.004067	0.006616	0.614654	WD	2004	0.026586	0.052747	0.504035	WD
1981	0.029701	0.075918	0.391224	WD	2005	0.019389	0.04132	0.469235	WD
1982	0.008663	-0.03248	-0.26671	SND	2006	0.028178	0.033846	0.832539	EC
1983	0.02282	0.027301	0.835859	EC	2007	0.047391	0.066257	0.715254	WD
1984	0.029945	0.041833	0.715819	WD	2008	0.025584	0.039809	0.642671	WD
1985	-0.0032	0.03148	-0.10175	SD	2009	0.04128	0.057393	0.719241	WD
1986	0.027142	0.04496	0.6037	WD	2010	0.02641	0.032709	0.807423	EC
1987	-0.021	0.039397	-0.53304	SD	2011	0.023344	0.043267	0.539531	WD
1988	0.057757	0.061197	0.943782	EC	2012	0.034572	0.037313	0.926521	EC
1989	0.021855	0.064743	0.337561	WD	2013	0.005258	0.02549	0.206283	WD
1990	-0.13931	0.048665	-2.86256	SD	2014	0.04132	0.053272	0.775646	WD
1991	0.02045	0.032207	0.634961	WD	2015	-0.01099	0.020723	-0.53056	SD
1992	0.001552	0.029897	0.051904	WD	2016	-0.00266	0.032632	-0.0816	SD
1993	0.000662	0.004905	0.134918	WD	2017	0.024652	0.03018	0.81682	EC
1994	0.010845	0.031897	0.339998	WD	2018	0.028861	0.049257	0.585928	WD

Source: Computed based on World bank data, 2018

In India, it can be observed from the table 4.2.2(a) that among the 49 years of the study period, 29 years showed weak decoupling implying that as the energy consumption increases as result of economic growth of the country, there is an accompanied emission which also increases at a rate lesser than GDP. Strong decoupling was found in 9 years spread out in the study period. Expansive coupling was also found in six years (1983, 1988, 2006, 2010,2012 and 2017). Recessive decoupling, strong negative decoupling, expansive negative decoupling and weak negative decoupling could be observed in 1973, 1982, 1999 and 2001 respectively.

Decoupling status between GHG emissions per capita and energy consumption per capita in China is given in table 4.2.2(b). The table shows that weak decoupling was the status for about 32 years in China spread over the period 1970 to 2018. Strong decoupling was observed in 6 years. Weak negative decoupling was evident in 5 years. Recessive decoupling was seen in 1981 and 1990. Expansive negative decoupling, expansive coupling and strong negative coupling happened to occur in 1988, 1998 and 1999 respectively.

Table 4.2.2(b):Decoupling Status between GHG emissions per capita and energy consumption per capita in China

Year	Change in GHG emissions per capita ΔC/C)	Change in Energy consumption per capita (ΔE/E)	Elasticity Coefficient	Status	Year	Change in GHG emissions per capita ΔC/C)	Change in Energy consumption per capita (ΔE/E)	Elasticity Coefficient	Status
1971	0.030974	0.134978	0.229473	WD	1995	0.07882	3.715586	0.021213	WD
1972	0.034799	0.049708	0.700054	WD	1996	-0.00649	-0.15707	0.041296	WND
1973	0.00391	0.030834	0.126806	WD	1997	-0.0141	5.769146	-0.00244	SD
1974	-0.0154	0.009497	-1.62173	SD	1998	0.015594	-2.3863	-0.00653	SND
1975	0.062086	0.089626	0.692727	WD	1999	-0.0269	-1.01136	0.026626	WND
1976	-0.00027	0.03338	-0.00821	SD	2000	0.028512	1.06602	0.026746	WD
1977	0.05077	0.068203	0.744397	WD	2001	0.027309	0.58132	0.046978	WD
1978	0.052703	0.074474	0.707672	WD	2002	0.049077	0.644602	0.076136	WD
1979	-0.01021	0.015241	-0.67018	SD	2003	0.097561	0.717502	0.135973	WD
1980	-0.03411	0.005302	-6.43211	SD	2004	0.10583	0.754501	0.140265	WD
1981	-0.04035	-0.02775	1.45379	RD	2005	0.091288	0.796102	0.114669	WD
1982	0.008161	0.029167	0.279795	WD	2006	0.077297	0.935896	0.082591	WD
1983	0.023897	0.047116	0.507194	WD	2007	0.063158	0.844479	0.074789	WD
1984	0.039418	0.05393	0.73091	WD	2008	0.023578	0.773011	0.030501	WD
1985	-0.01552	0.060202	-0.25776	WD	2009	0.054932	1.50757	0.036438	WD
1986	0.027682	0.02861	0.967568	SD	2010	0.073696	1.236901	0.059581	WD
1987	0.006397	0.054869	0.11658	WD	2011	0.071907	1.054925	0.068163	WD
1988	0.077785	0.050972	1.526046	END	2012	0.022003	0.66472	0.033101	WD
1989	0.018573	0.02971	0.625131	WD	2013	0.032348	1.066874	0.030321	WD
1990	-0.19439	-0.00301	64.5208	RD	2014	-0.00504	-0.28956	0.017416	WND
1991	0.032067	0.035194	0.911147	EC	2015	-0.00641	-1.53717	0.004169	WND
1992	0.023161	0.039392	0.587956	WD	2016	-0.00578	-0.78701	0.007342	WND
1993	0.046229	0.061962	0.746085	WD	2017	0.011509	0.462613	0.024879	WD
1994	0.026256	0.049272	0.532888	WD	2018	0.01904	0.597176	0.031884	WD

Source: Computed based on World bank data,2018

For both India and China, weak decoupling in majority of the years shows that pollution emissions growth is slower than the economic growth. This may be a welcome sign showing the shift to energy efficient and low polluting fuels used in the various spheres for the country's development. This energy efficiency shift has been due to the policy action of both the countries. India has a Perform Achieve and Trade (PAT) scheme which is a market based mechanism to facilitate energy efficiency improvements in large energy intensive industries and facilities, by issuing energy saving certificates that can be traded. There are other similar schemes for ensuring energy efficiency such as Market Transformation for Energy Efficiency (MTEE), Energy Efficiency Financing Platform (EEFP), Framework for Energy Efficient Economic Development (FEEED), Promotion of Electricity efficient LED bulbs, Promotion of electric vehicles etc. The Government of India created the National Clean Energy Fund (NCEF) for the purpose of financing and promoting clean energy initiatives and funding research in the area of clean energy in the country. Similarly China has number of plans such as The Energy Conservation Target Responsibility Plan, The One Hundred Energy Efficiency Standard Promotion Programme, Clean Coal Action Plan, Top Thousand Enterprise Energy Efficiency Programme etc. According to the World Bank between the years 1980 and 2010, China's GDP increased by 18 times, while Chinese energy consumption increased by only five times. It must be the result of such stringent energy conservation measures.

To conclude

- **Among the 49 years, weak decoupling was seen for 29 years and 32 years in India and China respectively implying that as the energy consumption increases as result of economic growth of the country, there is an accompanied emission which also increases at a rate lesser than GDP.**

4.2.3 Decoupling between GHG emissions per capita and trade openness in India and China

. Trade openness has three effects on the environment pollution like scale effect, composition effect and technological effect. An increase in trade causes more usage of energy which results in high emissions and resultant environmental damage. This is scale effect. Composition effect states that the comparative advantage possessed by the country decides whether the country would be more capital intensive or labour intensive. Technology effect happens when best practices pass on to a country through its trading partner resulting in energy efficient methods of production (Karedla, 2021).

Table 4.2.3(a): Decoupling Status between GHG Emissions and Trade openness in India

Year	Change in GHG emissions per capita (ΔC/C)	Change in trade openness (ΔT/T)	Elasticity Coefficient	Status	Year	Change in GHG emissions per capita ΔC/C)	Change in Trade openness (ΔT/T)	Elasticity Coefficient	Status
1971	-0.01001	0.001304	-7.67773	SD	1995	0.023192	0.121994	0.190111	WD
1972	-0.00294	0.009044	-0.32482	SD	1996	0.01255	-0.04286	-0.2928	SND
1973	-0.01243	0.133259	-0.09328	SD	1997	0.016171	0.030504	0.530114	WD
1974	0.008937	0.176959	0.050505	WD	1998	8.16E-05	0.04557	0.00179	WD
1975	0.016515	0.117168	0.140948	WD	1999	0.025161	0.045125	0.557594	WD
1976	0.009246	0.039844	0.232052	WD	2000	0.002371	0.077323	0.030668	WD
1977	0.001222	-0.01186	-0.10306	SND	2001	-0.00668	-0.03501	0.190813	WND
1978	-0.01728	0.01938	-0.8915	SD	2002	-0.00715	0.119282	-0.05995	SD
1979	0.012399	0.135389	0.09158	WD	2003	0.005453	0.035306	0.154449	WD
1980	0.004067	0.029909	0.135972	WD	2004	0.026586	0.184267	0.144281	WD
1981	0.029701	-0.05996	-0.49536	SND	2005	0.019389	0.107143	0.180962	WD
1982	0.008663	-0.02689	-0.32211	SND	2006	0.028178	0.081365	0.34632	WD
1983	0.02282	-0.03214	-0.71	SND	2007	0.047391	-0.00066	-72.1759	SND
1984	0.029945	0.022841	1.311014	END	2008	0.025584	0.143901	0.177789	WD
1985	-0.0032	-0.08605	0.037225	WND	2009	0.04128	-0.15345	-0.26902	SND
1986	0.027142	-0.05565	-0.48777	SND	2010	0.02641	0.060698	0.435098	WD
1987	-0.021	0.028617	-0.73385	SD	2011	0.023344	0.114347	0.20415	WD
1988	0.057757	0.067457	0.856193	EC	2012	0.034572	0.002511	13.76937	END
1989	0.021855	0.110745	0.197342	WD	2013	0.005258	-0.03566	-0.14745	SND
1990	-0.13931	0.021921	-6.35487	SD	2014	0.04132	-0.10057	-0.41085	SND
1991	0.02045	0.08711	0.234764	WD	2015	-0.01099	-0.16698	0.065844	WND
1992	0.001552	0.078133	0.01986	WD	2016	-0.00266	-0.04382	0.060763	WND
1993	0.000662	0.062087	0.010658	WD	2017	0.024652	0.014962	1.64762	END
1994	0.010845	0.021414	0.506427	WD	2018	0.028861	0.054499	0.529575	WD

Source: Computed based on World bank data,2018

The above table 4.2.3 (a)shows the decoupling status of greenhouse gas emissions per capita and trade openness in India. It can be observed that for 23 years, the country had weak decoupling status. Strong negative decoupling can be seen for 10 years in the study period. Expansive negative decoupling and weak negative decoupling can be seen in 3 years and 4 years respectively. Expansive coupling was evident in the year 1988.

The table 4.2.3(b) shows the decoupling status between GHG emissions per capita and trade openness in China. The relationship between trade openness and greenhouse gas emissions per capita was found to be strong negative decoupling in China for 13 years and weak decoupling for 15 years. Strong decoupling was observed for 8 years and weak negative decoupling for 5 years. Expansive negative decoupling was evident for 4 years. Recessive decoupling was seen in 1990 and expansive coupling status was seen in 2004 and 2010.

Table 4.2.3(b): Decoupling Status between GHG emissions per capita and Trade openness in China

Year	Change in GHG emissions per capita (ΔC/C)	Change in Trade openness (ΔT/T)	Elasticity Coefficient	Status	Year	Change in GHG emissions per capita ΔC/C)	Change in Trade openness (ΔT/T)	Elasticity Coefficient	Status
1971	0.0309	-0.0061	-5.0797	SND	1995	0.0788	-0.0437	-1.8007	SND
1972	0.0347	0.1458	0.2386	WD	1996	-0.0064	-0.0136	0.4767	WND
1973	0.0039	0.28	0.0139	WD	1997	-0.0141	0.0208	-0.6760	SD
1974	-0.0154	0.2255	-0.0682	SD	1998	0.0155	-0.0650	-0.2396	WD
1975	0.0620	-0.0816	-0.7601	SND	1999	-0.0269	0.0328	-0.8205	SD
1976	-0.0002	-0.0803	0.0034	WND	2000	0.0285	0.1494	0.1907	WD
1977	0.0507	-0.0548	-0.9248	SND	2001	0.0273	-0.0228	-1.1957	SD
1978	0.0527	0.1316	0.4004	WD	2002	0.0490	0.1039	0.4721	WD
1979	-0.0102	0.1298	-0.0786	SD	2003	0.0975	0.1730	0.5636	WD
1980	-0.0341	0.1070	-0.3184	SD	2004	0.1058	0.1261	0.8386	EC
1981	-0.0403	0.1664	-0.2424	SD	2005	0.0912	0.0434	2.1033	END
1982	0.0081	0.2432	0.0335	WD	2006	0.0772	0.0352	2.1956	END
1983	0.0238	-0.0987	-0.2419	SND	2007	0.0631	-0.03833	-1.6479	SND
1984	0.0394	0.0583	0.6757	WD	2008	0.0235	-0.0809	-0.2913	SND
1985	-0.0155	0.0811	-0.1912	SD	2009	0.0549	-0.2878	-0.1908	SND
1986	0.0276	-0.0417	-0.6630	SND	2010	0.0736	0.0875	0.8418	EC
1987	0.0063	0.2003	0.03192	WD	2011	0.0719	0.0337	2.1277	END
1988	0.0777	0.1729	0.4496	WD	2012	0.0220	-0.05417	-0.4062	SND
1989	0.0185	-0.1971	-0.0942	SND	2013	0.0323	-0.0307	-1.0534	SND
1990	-0.1943	-0.0346	5.6165	RD	2014	-0.0050	-0.0348	0.1445	WND
1991	0.0320	0.0647	0.4953	WD	2015	-0.0064	-0.1406	0.0455	WND
1992	0.0231	0.1393	0.1662	WD	2016	-0.0057	-0.0653	0.0884	WND
1993	0.0462	0.1638	0.2820	WD	2017	0.0115	0.0203	0.5650	WD
1994	0.0262	-0.0081	-3.2385	SND	2018	0.0190	0.0115	1.6547	END

Source: Computed based on World bank data,2018

It can be inferred that weak decoupling occurred between greenhouse gas emissions per capita and trade openness in majority of the years in India whereas in China both weak and strong decoupling happened to be equally seen. This type of decoupling was possible as trade helps to promote the international movement of production elements and international transfer of technical knowledge, so as to realize the efficient utilization of resources (Helpman,1998). This transfer of technology makes production-energy efficient and also trade ensures that the environmental standards are met with**.**

To conclude

- **Weak decoupling occurred between greenhouse gas emissions per capita and trade openness in majority of the years in India whereas in China both weak and strong decoupling happened to be equally seen.**

4.3.Long run relationship between Gross Domestic Product (GDP) per capita and its determinants (Gross fixed capital formation per capita, trade openness, inflation, population, energy consumption per capita and greenhouse gas emissions per capita) using cointegration analysis

4.3.1 The ADF unit root test of stationarity

It is well known that usual techniques of regression analysis can produce highly misleading conclusion when variables contain stochastic trend (Stock and Watson, 1988). In order to shun spurious regression phenomenon, it is necessary to conduct a unit root test for each variable before the analysis. Determining the order of integration of the series used in the analysis by applying Augmented Dickey-Fuller unit root test is the first step of the empirical analysis.

The following null hypothesis was tested.

H0: The chosen variables GDP per capita, GFCF per capita, trade openness, inflation, population, energy consumption per capita and GHG emissions per capita are not stationary.

Ha: The chosen variables GDP per capita, GFCF per capita, trade openness, inflation, population, energy consumption per capita and GHG emissions per capita are stationary.

The variable was said to be stationary if H_0 was rejected. If H_a was accepted, there was the existence of at least one unit root and the variable was found to be non-stationary. The test is applied again taking the first difference and if needed the second difference of the variable. The ADF test of stationarity was performed on the variables used in the study for India and China based on Intercept, Trend and Intercept.

ADF test of stationarity on the variables used in Model I of the study for India and China was performed based on “Intercept”, “Trend and Intercept”. Table 4.3.1(a) shows the ADF statistics based on Intercept. Using the Intercept criteria the results indicated all the variables used in the model such as GDP per capita, GFCFper capita, trade openness, inflation, population, energy consumption per capita and GHG emissions per capita became stationary only in their first differences for both India and China with their probability values less than 0.05.

The study also carried out the ADF test based on trend and intercept and the results are given in table 4.3.1(b). The results of the unit root with trend and Intercept pointed out clearly that the null hypothesis of a unit root can be rejected at the first difference only in the model for both India and China.

Table 4.3.1(a): Unit Root Test Results based on ADF Statistic using Intercept

Country	Order of difference	ADF t-statistic	Critical Values (5 % level)	p-value	H0	Order of Integration
LGDPpc						
India	Level	4.3086	-2.9237	1	Accept	I(1)
	First Difference	-5.7051	-2.9251	0	Reject	
China	Level	0.3225	-2.9266	0.9771	Accept	I(1)
	First Difference	-3.2281	-2.9266	0.0246	Reject	
LGFCFpc						
India	Level	-1.2782	-2.9237	0.6323	Accept	I(1)
	First Difference	-6.1391	-2.9251	0	Reject	
China	Level	0.4397	-2.9251	0.9826	Accept	I(1)
	First Difference	-4.3411	-2.9251	0.0011	Reject	
TO						
India	Level	-0.6807	-2.9571	0.8376	Accept	I(1)
	First Difference	-3.9604	-2.9604	0.0048	Reject	
China	Level	-2.9028	-2.9237	0.0524	Accept	I(1)
	First Difference	-4.943	-2.9251	0.0002	Reject	
INF						
India	Level	-2.8375	-3.513	0.1921	Accept	I(1)
	First Difference	-4.5462	-2.9237	0.0006	Reject	
China	Level	-2.734	-2.9297	0.0765	Accept	I(1)
	First Difference	-3.9737	-2.9266	0.0034	Reject	
POP						
India	Level	-0.23383	-2.93694	0.9256	Accept	I(1)
	First Difference	-2.64586	-2.9484	0.0437	Reject	
China	Level	-0.1599	-2.9297	0.9359	Accept	I(1)
	First Difference	-3.0063	-2.9297	0.042	Reject	
LENpc						
India	Level	3.7886	-2.9237	1	Accept	
	First Difference	-5.1404	-2.9251	0.0001	Reject	I(1)
China	First	-1.2526	-2.9251	0.9981	Accept	I(1)
	Difference	-4.3629	-2.9251	0.0011	Reject	
LGHGpc						
India	Level	-2.1813	-3.5063	0.4887	Accept	I(1)
	First Difference	-6.9048	-3.5085	0	Reject	
China	Level	-0.1551	-2.9251	0.9368	Accept	I(1)
	First Difference	-10.1367	-2.9251	0	Reject	

Source: Estimates based on World bank data,2018

Table 4.3.1(b):Unit Root Test Results based on ADF Statistic using Trend and Intercept

Country	Order of difference	ADF t-statistic	Critical Values (5 % level)	p-value	H0	Order of Integration
LGDPper capita						
India	Level	-1.6689	-3.5063	0.7496	Accept	I(1)
	First Difference	-8.3447	-3.5085	0	Reject	
China	Level	-3.9248	-3.5063	0.6425	Accept	I(1)
	First Difference	-3.6579	-3.5085	0.0355	Reject	
LGFCFper capita						
India	Level	1.2107	-3.5063	0.8969	Accept	I(1)
	First Difference	-6.1234	-3.5085	0	Reject	
China	Level	-1.091	3.5085	0.9198	Accept	I(1)
	First Difference	-4.4572	-3.5085	0.0046	Reject	
TO						
India	Level	-1.5772	-3.5577	0.7797	Accept	I(1)
	First Difference	-3.8923	-3.5628	0.0246	Reject	
China	Level	-0.9641	-3.5063	0.9394	Accept	I(1)
	First Difference	-5.6505	-3.5085	0.0001	Reject	
INF						
India	Level	-5.1553	-4.1611	0.2006	Accept	I(1)
	First Difference	-8.6839	-4.1657	0	Reject	
China	Level	-4.1427	-3.5107	0.2108	Accept	I(1)
	First Difference	-7.293	-3.5155	0	Reject	
POP						
India	Level	-2.8375	-3.513	0.1921	Accept	I(1)
	First Difference	-4.1858	-3.5366	0.0111	Reject	
China	Level	-2.9303	-3.5155	0.1633	Accept	I(1)
	First Difference	-3.4734	-3.513	0.0489	Reject	
LEN PC						
India	Level	-0.12	-3.5063	0.9931	Accept	I(1)
	First Difference	-6.9287	-3.5085	0	Reject	
China	First	-1.3573	-3.5085	0.8605	Accept	I(1)
	Difference	-4.746	-3.508	0.0002	Reject	
LGHG PC						
India	Level	-0.9648	-3.5063	0.9393	Accept	I(1)
	First Difference	-4.6497	-3.5085	0.0027	Reject	
China	Level	-0.6054	-3.5063	0.9741	Accept	I(1)
	First Difference	-4.4562	-3.5085	0.0046	Reject	

Source: Estimates based on World bank data,2018

4.3.2Johansen Cointegration Test for GDP Per capita and its determinants

The easiest way for selecting lag length is to decide to use a criterion that gives the lowest value. In the present estimation of lag length, Akaike Information Criteria had the lowest value corresponding to lag 2 for India and lag 1 for China. The concept of cointegration can be described as an orderly co-movement among the chosen time series over the long-run. The existence of long run relationship among the variables has to found out if the variables of the study have the same order of integration. It is necessary to test for cointegration if we desire to provide strong and meaningful results. One of the most extensively used approaches to test for cointegration is VAR based Johansen (1992) test. Johansen test allows for more than one co-integrating relationship to be tested unlike Engle-Granger test which permits only one cointegrating relationship and thus is more applicable in this study. To determine the cointegration rank (*r*) of the model and to verify the existence of cointegrating relationship, the trace statistic and the max-eigen value, the two likelihood ratios (LR) test statistics of the Johansen methodology are employed.

Hypothesis for the test of Cointegration

Null Hypothesis (H_o): The determinants of GDP per capita do not exhibit long term relationship.

Alternate Hypothesis (H_a): The determinants of GDP per capita exhibits long term relationship.

Table 4.3.2(a): Unrestricted Cointegration Rank Test (Trace)-India

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value (0.05)	Prob.**
None *	0.986850	549.5798	125.6154	0.0001
At most 1 *	0.907113	359.0026	95.75366	0.0000
At most 2 *	0.872340	254.4424	69.81889	0.0000
At most 3 *	0.794182	163.8735	47.85613	0.0000
At most 4 *	0.723001	94.31981	29.79707	0.0000
At most 5 *	0.572217	37.83525	15.49471	0.0000
At most 6	0.010696	0.473148	3.841466	0.4915

Source: Estimates based on World bank data, 2018
Trace test indicates 6 cointegrating eqn(s) at the 0.05 level;
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

Table 4.3.2(b): Unrestricted Cointegration Rank Test (Trace)-China

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value (0.05)	Prob.**
None *	0.998786	719.5119	125.6154	0.0001
At most 1 *	0.978231	424.1014	95.75366	0.0001
At most 2 *	0.912983	255.7017	69.81889	0.0000
At most 3 *	0.802625	148.2691	47.85613	0.0000
At most 4 *	0.671729	76.87252	29.79707	0.0000
At most 5 *	0.397408	27.86022	15.49471	0.0004
At most 6	0.118977	5.573563	3.841466	0.0182

Source: Estimates based on World bank data,2018
Trace test indicates 6 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug- Michelis (1999) p-values**

The table 4.3.2(a) and 4.3.2(b) gives the estimates of the trace statistic for GDP per capita and the dependent variables GFCF per capita, trade openness, inflation, population, energy consumption per capita and GHG emissions per capita for India and China. The trace statistic was found to be greater than the critical value for At most 5 cointegrating equations for both India and China. Hence the null hypothesis that the determinants of GDP per capita do not exhibit long term relationship is rejected and it is concluded that the determinants of GDP per capita exhibited long term relationship with the presence of atleast 6 cointegrating equations for both India and China.

Table 4.3.2(c): Unrestricted Cointegration Rank Test (Maximum Eigenvalue)-India

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value (0.05)	Prob.**
None *	0.986850	190.5772	46.23142	0.0000
At most 1 *	0.907113	104.5601	40.07757	0.0000
At most 2 *	0.872340	90.56893	33.87687	0.0000
At most 3 *	0.794182	69.55368	27.58434	0.0000
At most 4 *	0.723001	56.48457	21.13162	0.0000
At most 5 *	0.572217	37.36210	14.26460	0.0000
At most 6	0.010696	0.473148	3.841466	0.4915

Source: Estimates based on World bank data,2018
Max-eigenvalue test indicates 6 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

Table 4.3.2(d): Unrestricted Cointegration Rank Test (Maximum Eigenvalue)-China

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value (0.05)	Prob.**
None *	0.998786	295.4105	46.23142	0.0000
At most 1 *	0.978231	168.3997	40.07757	0.0001
At most 2 *	0.912983	107.4326	33.87687	0.0000
At most 3 *	0.802625	71.39662	27.58434	0.0000
At most 4 *	0.671729	49.01230	21.13162	0.0000
At most 5 *	0.397408	22.28666	14.26460	0.0022
At most 6 *	0.118977	5.573563	3.841466	0.0182

Source: Estimates based on World bank data,2018
Max-eigenvalue test indicates 7 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

The table 4.3.2(c) and 4.3.2(d) show the statistic Maximum Eigen value estimated using the Johansen procedure for the variables of the study. The Eigen statistic values were found to be greater than the critical values at Atmost 5 and At most 6 cointegrating equations for India and China respectively. Therefore the null hypothesis is rejected which means that the determinants of GDP per capita do not show evidence of long term relationship and it can be concluded that the variables of the model have a long run equilibrium relationship, with the presence of atleast 6 cointegrating equations for India and atleast 7 cointegrating equations for China. The results of the Johansen cointegration test using the trace statistic and Max-Eigen value statistic show that variables of the model showed a common trend and move together in the long run.

4.3.3 Estimation of long run GDP function using the Normalized Cointegrating Coefficients

Understanding the nature of relationship among the variables is important to know the presence of long run relationship and so the normalized cointegrating coefficients of independent variables of the model for GDP per capita resulting from Johansen cointegration method are given in the table 4.3.3(a) and 4.3.3(b)

Table 4.3.3(a): Normalized cointegrating coefficients from the Cointegration equation-India

Variables	Co-efficients	Standard Errors
LGFCF pc	0.011464	0.0073
TO	-0.00102	9.80E-05
INF	0.007593	0.00026
POP	0.070797	0.01075
LEN pc	-0.27644	0.045653
LGHG pc	0.045653	0.03948

Source: Estimates based on World bank data,2018

Table 4.3.3(b): Normalized cointegrating coefficients from the Cointegration equation-China

Variables	Co-efficients	Standard Errors
LGFCFpc	0.248464	0.02231
TO	0.029722	0.00031
INF	0.037195	0.00072
POP	0.456342	0.01488
LEN pc	3.282923	0.08063
LGHG	-0.57744	0.06016

Source: Estimates based on World bank data,2018

The normalized cointegration coefficients of the cointegrating equation give the long run GDP as a function of the determinants.

For India

LGDP pc=-0.0114 LGFCFpc +0.0010TO - 0.0075INF- 0.0707POP+ 0.2764LEN pc-0.0456LGHG pc

For China

LGDP pc= -0.2484 LGFCF pc -0.0297TO - 0.0371INF- 0.4563POP+ 3.2829LEN pc+0.5774LGHG pc

As per Skerman et al. (2009) the signs are reversed due to normalization process to enable proper interpretation. The coefficients obtained revealed that trade openness and energy consumption per capita have positive impact on the GDP per capita in India during the study period. It denotes that an increase in the values of the above variables will lead to an increase in GDP per capita. The remaining variables such as GFCF per capita, inflation, population and GHG emissions per capita have a negative effect on GDP per capita in India.

For China, GHG emission per capita has positive effects on GDP per capita. GFCF per capita, trade openness, inflation, population and energy consumption per capita have negative impact on GDP per capita. The coefficients obtained from the cointegration equation clearly supports the fact that GDP per capita during the study period for India and China is impacted by GFCF per capita, trade openness, population, inflation, energy consumption per capita and GHG emissions per capita

4.3.4. Estimation of Short run GDP per capita using Vector Error Correction Model (VECM)

The cointegration test for Model I showed that all variables of the model show a cointegrating relationship and Johansen's cointegration equation gives the long run relationship for GDP per capita and its determinants. As usual VECM is constructed based on the error correction term estimated by the cointegration approach to analyse the short run dynamics and the adjustments in the long run for GDP per capita. According to Kumari and Mahakud, (2012), variables used in the model during short run is likely to move from equilibrium and can be explained through the Error Correction Model (ECM) by including stationary residuals from the co-integrating vectors and including its one period lagged values (ECt-1) in an error correction model(cited by Radhika and Devi,2017)

Following the procedure, the dynamic error correction equation of GDP per capita can be specified as:

$$\mathbf{\Delta LGDPpc_{it} = \beta_{oi} + \Sigma\beta_{1i}\Delta LGDPpc_{it-1} + \Sigma\beta_{2i}\Delta LGFCFpc_{it-1} + \Sigma\ \beta_{3i}\Delta TO_{it-1} + \Sigma\ \beta_{4i}\ \Delta INF_{it-1} + \Sigma\ \beta_{5i}\Delta POP_{it-1} + \Sigma\beta_{6i}\Delta LENpc_{it-1} + \Sigma\ \beta_{7i}\Delta GHGpc_{it-1} + \varepsilon_{it}}$$

Where Δ stands for the coefficient of the error correction terms and provides the path of equilibrium in the model and $\boldsymbol{\varepsilon_{it}}$ denotes the noise error term. Here again the error correction term is used as one of the determinants of the VECM function.

A single equation model was estimated using the first differences of the variables. The table 4.3.4(a) and 4.3.4 (b) gives the coefficients of the VECM model.

The error correction coefficient for GDP per capita as dependent variable for India was negative (-0.1476) as in the principle indicating that the series for GDP per capita will converge in the long run. The magnitude shows that GDP per capita will adjust for about 0.15 percent of its total deviations from the long run equilibrium during the short run. A percentage change in two year lagged energy consumption per capita is associated with a 0.68 percent increase in GDP per capita and is significant at 10 percent level.

For China the error correction coefficients of GDP per capita was negative (-0.29) showing the ability to bounce back to equilibrium in the long run. The variable inflation impacted positively on GDP per capita and was statistically significant at 5 percent level.

The estimated error correction model enjoys the minimum goodness of fit with R^2 value being 0.59 and adjusted R^2 of 0.35 for India. The R^2 indicated that for India 59 percent of variations in the dependent variable was accounted for by the variations in the explanatory variables used in the model. For China, the R^2 was 0.43 and adjusted R^2 was 0.29 which indicated that 43 percent of variations in the dependent variable were accounted for by the variations in the explanatory variables used in the model.

The F-statistic value of 2.63 for India and 3.13 for China indicated that the overall model was statistically significant and explains the fact that all the explanatory variables simultaneously explained the variations in the GDP per capita during the study period.

The diagnostic tests on the residuals of the VECM model was also performed using the Breusch-Godfrey Serial Correlation LM test and the LM Statistic indicated that there was absence of autocorrelation.

The Residual Heteroscedasticity Breusch-Pagan-Godfrey test was performed to test heteroscedasticity. The null hypothesis was rejected which implies the fact that the error correction model is free from the problem of heteroscedasticity. It confirmed that the model estimated could be relied upon for making inferences on the impact of chosen variables on GDP per capita.

Table 4.3.4(a): Estimated coefficients of the VECM- India

Error Correction:	DLGDP PC	DLGFCF PC	DTO	DINF	DPOP	DLEN PC	DLGHG PC
CointEq1	-0.147630	2.170890	85.98586	-404.6061	-0.083864	-0.334486	-0.160738
	(0.45715)	(1.72507)	(81.1362)	(137.750)	(0.07723)	(0.24288)	(0.29296)
	[-0.32294]	[1.25844]	[1.05977]	[-2.93725]	[-1.08586]	[-1.37717]	[-0.54867]
DLGDP PC (-1)	-0.353722	0.117057	-26.56142	282.7935	0.031626	0.361327	0.025439
	(0.40285)	(1.52016)	(71.4987)	(121.388)	(0.06806)	(0.21403)	(0.25816)
	[-0.87806]	[0.07700]	[-0.37150]	[2.32967]	[0.46469]	[1.68821]	[0.09854]
DLGDP PC(-2)	-0.274703	1.050655	45.81224	121.2262	0.091383	0.127718	0.041095
	(0.27140)	(1.02414)	(48.1690)	(81.7796)	(0.04585)	(0.14419)	(0.17392)
	[-1.01217]	[1.02589]	[0.95107]	[1.48235]	[1.99301]	[0.88574]	[0.23628]
DLGFCF PC(-1)	-0.084607	-0.862841	37.44496	-8.301220	-0.020273	-0.047193	0.006505
	(0.06749)	(0.25467)	(11.9781)	(20.3360)	(0.01140)	(0.03586)	(0.04325)
	[-1.25365]	[-3.38805]	[3.12611]	[-0.40820]	[-1.77807]	[-1.31617]	[0.15042]
DLGFCF PC(-2)	-0.078257	-0.505198	10.61177	5.415215	-0.020235	-0.019702	0.019056
	(0.06705)	(0.25303)	(11.9010)	(20.2051)	(0.01133)	(0.03563)	(0.04297)
	[-1.16708]	[-1.99658]	[0.89167]	[0.26801]	[-1.78624]	[-0.55304]	[0.44345]
DTO (-1)	0.001664	0.001805	-0.836330	-0.422012	7.02E-05	0.000510	0.001153
	(0.00108)	(0.00407)	(0.19135)	(0.32486)	(0.00018)	(0.00057)	(0.00069)
	[1.54389]	[0.44372]	[-4.37076]	[-1.29905]	[0.38556]	[0.89004]	[1.66820]
DTO (-2)	0.001276	0.000533	-0.270784	0.031566	0.000250	0.000313	0.000321
	(0.00109)	(0.00411)	(0.19354)	(0.32858)	(0.00018)	(0.00058)	(0.00070)
	[1.17053]	[0.12950]	[-1.39914]	[0.09607]	[1.35953]	[0.54027]	[0.45876]
DINF (-1)	0.001102	-0.001232	-0.031979	0.196976	-4.50E-05	0.000913	0.000169
	(0.00126)	(0.00477)	(0.22447)	(0.38109)	(0.00021)	(0.00067)	(0.00081)
	[0.87163]	[-0.25820]	[-0.14247]	[0.51687]	[-0.21045]	[1.35815]	[0.20806]
DINF (-2)	0.000495	0.000835	0.044027	-0.032924	0.000137	0.000362	0.000258
	(0.00078)	(0.00295)	(0.13865)	(0.23539)	(0.00013)	(0.00042)	(0.00050)
	[0.63361]	[0.28316]	[0.31754]	[-0.13987]	[1.03593]	[0.87164]	[0.51525]
DPOP (-1)	-0.145926	4.249368	-38.65292	-37.93204	1.517808	-0.502896	-0.257198
	(0.70512)	(2.66081)	(125.147)	(212.471)	(0.11913)	(0.37463)	(0.45187)
	[-0.20695]	[1.59702]	[-0.30886]	[-0.17853]	[12.7412]	[-1.34239]	[-0.56919]
DPOP (-2)	0.011240	-6.065398	-12.66220	202.4943	-0.835800	0.724571	0.469346
	(0.74480)	(2.81053)	(132.189)	(224.426)	(0.12583)	(0.39571)	(0.47729)
	[0.01509]	[-2.15810]	[-0.09579]	[0.90228]	[-6.64233]	[1.83109]	[0.98335]
DLEN PC(-1)	0.992977	0.931155	-39.58405	-60.44481	0.077769	-0.707152	0.086228
	(0.44524)	(1.68014)	(79.0232)	(134.163)	(0.07522)	(0.23655)	(0.28533)
	[2.23020]	[0.55421]	[-0.50092]	[-0.45053]	[1.03387]	[-2.98939]	[0.30221]
DLEN PC(-2)	0.679981	1.727393	44.01665	-120.8985	0.104829	-0.365032	0.150511
	(0.39626)	(1.49530)	(70.3294)	(119.403)	(0.06695)	(0.21053)	(0.25394)
	[1.71600]	[1.15521]	[0.62586]	[-1.01253]	[1.56588]	[-1.73387]	[0.59271]
DLGHG PC(-1)	-0.453516	1.161671	41.96842	-279.9532	-0.151687	-0.205550	-0.842658
	(0.49226)	(1.85756)	(87.3676)	(148.330)	(0.08316)	(0.26153)	(0.31546)
	[-0.92130]	[0.62538]	[0.48037]	[-1.88737]	[-1.82395]	[-0.78594]	[-2.67122]
DLGHG PC(-2)	-0.127843	0.407324	-82.09369	-64.73756	-0.089156	-0.063463	-0.535726
	(0.36311)	(1.37021)	(64.4457)	(109.414)	(0.06135)	(0.19292)	(0.23269)
	[-0.35208]	[0.29727]	[-1.27384]	[-0.59168]	[-1.45336]	[-0.32897]	[-2.30228]
C	0.000625	-0.008581	-0.212010	-0.055444	-0.000511	0.001173	0.001466
	(0.00237)	(0.00894)	(0.42054)	(0.71398)	(0.00040)	(0.00126)	(0.00152)
	[0.26362]	[-0.95974]	[-0.50414]	[-0.07765]	[-1.27733]	[0.93170]	[0.96569]
R-squared	0.593893						
Adj. R-squared	0.350229						
F-statistic	2.637341						
Akaike AIC	-5.430911						
Schwarz SC	-4.762200						

Source: Estimates based on secondary data

Figures in ( ) are standard error values; figures in [ ] are the "t" statistics

Table 4.3.4(b):Estimated coefficients of the VECM- China

Error Correction:	DLGDP PC	DLGFCFPC	DTO	DINF	DPOP	DLEN PC	DLGHG PC
CointEq1	-0.009658	0.099869	10.11562	-67.63223	-0.044600	0.005660	0.137430
	(0.02196)	(0.06877)	(7.70112)	(10.6595)	(0.14164)	(0.02769)	(0.13075)
	[-0.43983]	[1.45230]	[1.31353]	[-6.34480]	[-0.31489]	[0.20440]	[1.05113]
DLGDP PC(-1)	-0.289647	-0.277448	-3.565433	41.79274	1.522920	-0.253048	-1.423863
	(0.18218)	(0.57052)	(63.8921)	(88.4361)	(1.17508)	(0.22974)	(1.08472)
	[-1.58990]	[-0.48631]	[-0.05580]	[0.47258]	[1.29601]	[-1.10145]	[-1.31265]
DLGFCF PC(-1)	-0.022219	-0.276725	-11.52768	-27.36638	-0.604238	-0.007169	-0.164695
	(0.05589)	(0.17502)	(19.6001)	(27.1294)	(0.36048)	(0.07048)	(0.33276)
	[-0.39757]	[-1.58113]	[-0.58814]	[-1.00873]	[-1.67621]	[-0.10173]	[-0.49494]
DTO (-1)	0.000489	0.002799	-0.279435	-0.151831	0.000185	-0.000263	-0.004415
	(0.00044)	(0.00139)	(0.15534)	(0.21501)	(0.00286)	(0.00056)	(0.00264)
	[1.10305]	[2.01794]	[-1.79889]	[-0.70616]	[0.06478]	[-0.47171]	[-1.67395]
DINF (-1)	0.000872	-0.001085	-0.053794	0.311931	0.000779	0.000385	-0.000767
	(0.00032)	(0.00101)	(0.11271)	(0.15600)	(0.00207)	(0.00041)	(0.00191)
	[2.71427]	[-1.07853]	[-0.47729]	[1.99952]	[0.37559]	[0.95030]	[-0.40084]
DPOP (-1)	-0.021749	-0.005105	-7.019849	11.23365	-0.161307	0.001473	0.101828
	(0.02311)	(0.07238)	(8.10596)	(11.2198)	(0.14908)	(0.02915)	(0.13762)
	[-0.94099]	[-0.07053]	[-0.86601]	[1.00123]	[-1.08200]	[0.05054]	[0.73993]
DLEN PC(-1)	0.012341	-0.947019	56.66091	-133.6818	0.026218	-0.090072	1.097050
	(0.13426)	(0.42046)	(47.0873)	(65.1757)	(0.86601)	(0.16931)	(0.79942)
	[0.09192]	[-2.25233]	[1.20332]	[-2.05110]	[0.03027]	[-0.53198]	[1.37231]
DLGHG PC(-1)	0.033925	0.153504	15.47078	-11.62445	-0.058658	0.040180	-0.668195
	(0.02203)	(0.06898)	(7.72505)	(10.6926)	(0.14208)	(0.02778)	(0.13115)
	[1.54017]	[2.22534]	[2.00268]	[-1.08715]	[-0.41286]	[1.44650]	[-5.09484]
C	0.000618	-0.000623	-0.002836	-0.337256	0.006926	-0.000172	0.000486
	(0.00190)	(0.00594)	(0.66556)	(0.92124)	(0.01224)	(0.00239)	(0.01130)
	[0.32563]	[-0.10482]	[-0.00426]	[-0.36609]	[0.56580]	[-0.07168]	[0.04305]
R-squared	0.432079	0.441584	0.294831	0.676741	0.107263	0.250310	0.551670
Adj. R-squared	0.294401	0.306211	0.123881	0.598375	-0.109159	0.068566	0.442984
F-statistic	3.138335	3.261967	1.724665	8.635673	0.495619	1.377271	5.075820
Akaike AIC	-5.776311	-3.493200	5.943607	6.593775	-2.048107	-5.312402	-2.208135
Schwarz SC	-5.403953	-3.120843	6.315965	6.966133	-1.675749	-4.940044	-1.835778

Source: Estimates based on secondary data
Figures in ( ) are standard error values; figures in [ ] are the “t” statistics

4.4 Variance Decomposition Analysis

Variance decomposition model of the forecast error gives the percentage of unexpected variation in each variation that is produced by shocks from other variables. It indicates the relative impact that a variable has on another. The variance decomposition enables assessment of economic significance of this impact as a percentage of the forecast error for a variable sum to one.

The table 4.4.1(a) shows the variance decomposition results for model GDP per capita and its determinants for India. Over a period of 10 years, the forecast error variance for a particular period is 100. In the short run 100 percent variance is explained by the variable GDP per capita itself meaning strongly endogenous. The remaining variables do not have any influence. From second period onwards, inflation has influence on GDP per capita both in the short run and in the long run with 10.20 percent contribution. Variance contribution of GDP per capita in the long run is 82.6 percent, the variance contribution of the other variables on GDP per capita is as follows; GFCF per capita is about 0.58 percent, trade openness, population, energy consumption per capita and greenhouse gas emissions per capita is 1.34 percent,0.48percent ,1.76 percent and 3 percent respectively. No variable seems to significantly contribute to the change in GDP per capita

For China, 100 percent forecast error variance of GDP per capita is explained by itself in the short run. Population has an influence on GDP per capita from second period onwards. Variance contribution of GDP per capita itself is 58.6 percent and influence by population is 21.4 percent in the long run on GDP per capita. The consecutive tables show how variance of GFCF per capita, inflation, population and GHG emissions per capita are explained by themselves. Trade openness and energy consumption per capita are influenced by GFCF per capita.

Table 4.4.1(a): Variance Decomposition Analysis of GDP per capita -India

Variance Decomposition of LGDP PC								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	0.011297	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.014531	93.09312	0.212346	0.102910	4.061285	0.242040	2.268963	0.019333
3	0.017079	90.83485	0.183504	0.353866	5.922131	0.252848	2.397784	0.055019
4	0.019130	88.57508	0.237076	0.515786	7.655162	0.247684	2.544511	0.224705
5	0.020997	86.76468	0.295092	0.669949	8.995524	0.239537	2.479957	0.555266
6	0.022749	85.59207	0.430718	0.774306	9.552296	0.246889	2.372918	1.030800
7	0.024462	84.70095	0.534131	0.880306	9.798718	0.283392	2.234627	1.567872
8	0.026166	83.96232	0.587115	1.006747	9.918139	0.348682	2.086402	2.090594
9	0.027889	83.27192	0.595522	1.163339	10.04514	0.424991	1.929205	2.569880
10	0.029642	82.60489	0.581778	1.346540	10.20198	0.488331	1.768660	3.007820
Variance Decomposition of LGFCF P C								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	0.042742	36.24761	63.75239	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.058312	47.61096	46.48215	0.566487	4.660220	0.223444	0.008856	0.447888
3	0.071712	59.15364	35.14446	0.813097	3.368518	0.238325	0.107220	1.174737
4	0.082785	64.98238	27.78209	1.454613	3.063950	0.214710	0.240639	2.261619
5	0.091854	67.48099	22.87166	2.251499	3.250747	0.174431	0.373454	3.597222
6	0.098922	68.22291	19.77137	2.958083	3.529705	0.205967	0.506663	4.805301
7	0.103970	68.06864	17.90262	3.534285	3.707336	0.369925	0.622988	5.794207
8	0.107221	67.56238	16.83363	3.953014	3.729361	0.641198	0.707493	6.572920
9	0.109058	66.93127	16.27947	4.240899	3.675090	0.934503	0.754416	7.184352
10	0.109970	66.30036	16.04502	4.430864	3.621629	1.165648	0.772261	7.664220
Variance Decomposition of TO								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	2.110370	8.542982	0.458707	90.99831	0.000000	0.000000	0.000000	0.000000
2	3.166921	3.980674	8.223873	73.19888	8.543062	0.496521	3.763964	1.793029
3	3.948586	3.293263	5.295499	62.91358	19.57798	1.181593	6.190236	1.547845
4	4.472482	4.863439	4.425848	59.28849	18.67565	1.423665	9.920405	1.402503
5	4.947181	6.574115	4.376255	55.63211	17.65973	1.610648	12.80514	1.341996
6	5.374706	7.666186	5.665161	52.31801	16.73545	1.678531	14.59622	1.340446
7	5.727734	8.052364	7.642149	49.76269	15.86076	1.615335	15.73283	1.333867
8	6.003397	7.842687	9.807926	47.91115	15.21715	1.497505	16.43360	1.289980
9	6.203111	7.417826	11.81657	46.59419	14.68833	1.403307	16.86107	1.218711
10	6.343385	7.123888	13.47732	45.57747	14.20502	1.369713	17.06963	1.176957
Variance Decomposition of INF_								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	3.033058	40.27517	0.827572	5.572355	53.32491	0.000000	0.000000	0.000000
2	3.184946	37.88533	3.870054	5.053549	49.86114	0.389508	2.137592	0.802828
3	3.304935	35.19255	7.409244	4.896190	46.63916	0.362307	2.944492	2.556059
4	3.380249	34.18161	7.715734	4.701194	46.26777	0.763890	3.453858	2.915943
5	3.430032	34.06209	7.522257	4.592304	45.43675	1.915505	3.638918	2.832173
6	3.492810	33.52859	8.196257	4.731886	43.88510	2.952623	3.753091	2.952458
7	3.567666	32.66943	9.034904	5.038372	42.81116	3.282029	3.910145	3.253963
8	3.630562	32.00277	9.469218	5.311710	42.37059	3.205252	4.164193	3.476263
9	3.667002	31.75942	9.549735	5.455115	42.03068	3.190107	4.453289	3.561651
10	3.684557	31.70564	9.515022	5.491961	41.67697	3.373521	4.665147	3.571732
Variance Decomposition of POP_								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	0.005022	0.002342	18.76432	2.006318	5.571279	73.65574	0.000000	0.000000
2	0.011727	0.205385	27.62912	1.384159	12.84721	57.33292	0.182716	0.418495
3	0.018942	1.054196	30.05546	1.632878	20.43163	46.28622	0.070779	0.468838
4	0.025751	2.890727	28.28409	1.971570	27.94931	38.36649	0.163889	0.373931
5	0.031774	6.586877	25.32403	2.101647	33.03242	32.28532	0.421644	0.248067
6	0.036988	12.34258	22.18063	2.072391	34.95272	27.51573	0.694930	0.241021
7	0.041663	19.59414	19.22694	1.964762	34.34349	23.60479	0.865341	0.400535
8	0.046022	27.22066	16.65375	1.840368	32.35213	20.35359	0.895909	0.683598
9	0.050133	34.23449	14.52209	1.737217	29.96033	17.68219	0.830303	1.033385
10	0.053976	40.14142	12.79193	1.669652	27.71930	15.51923	0.731769	1.426703
Variance Decomposition of LEN PC								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC

1	0.005253	6.925681	2.271101	10.89565	5.434488	4.482578	69.99050	0.000000
2	0.006625	14.40879	1.428901	9.663039	7.644410	3.645502	61.43273	1.776631
3	0.007983	17.56638	6.266041	7.308059	11.77952	2.956499	51.17681	2.946693
4	0.009564	25.75025	9.333670	5.466706	14.02042	2.427819	38.93816	4.062976
5	0.011283	35.75249	10.98992	4.080882	12.74162	2.164994	29.52573	4.744368
6	0.013133	45.72465	10.86371	3.018615	11.12516	2.108865	22.48304	4.675949
7	0.015054	54.04878	9.722883	2.339884	10.13849	2.120946	17.44478	4.184233
8	0.017007	60.45527	8.318680	2.018821	9.749305	2.044854	13.81353	3.599539
9	0.018947	65.11965	7.079991	1.958195	9.717484	1.853493	11.18410	3.087082
10	0.020820	68.49974	6.110230	2.041430	9.762610	1.608366	9.279167	2.698453
Variance Decomposition of LGHG PC								
Period	**S.E.**	**LGDP PC**	**LGFCF PC**	**TO**	**INF**	**POP**	**LEN PC**	**LGHG PC**
1	0.007200	11.07804	0.650782	4.000098	0.008187	0.101997	28.22742	55.93348
2	0.009080	9.855091	1.743175	4.777467	0.029770	0.067612	24.42883	59.09805
3	0.011389	12.88489	7.338154	3.582968	4.305489	0.101291	18.22278	53.56443
4	0.013677	18.27437	8.122097	2.899809	6.199945	0.138821	13.71532	50.64965
5	0.016110	26.05090	9.137950	2.466085	5.421472	0.166162	10.23021	46.52723
6	0.018637	33.83126	9.150966	2.323757	4.953795	0.224428	7.779879	41.73592
7	0.021177	40.99330	8.487349	2.404553	4.655781	0.257155	6.080767	37.12109
8	0.023703	46.99435	7.685913	2.636587	4.536247	0.240631	4.872278	33.03400
9	0.026172	51.70893	6.962036	2.947201	4.533275	0.199753	4.001257	29.64754
10	0.028541	55.29637	6.399407	3.259701	4.509138	0.177495	3.365495	26.99239

Source: Estimated based on World bank data,2018

Table 4.4.1(b):Variance Decomposition Analysis of GDP per capita an-China

Variance Decomposition of LGDP PC								
Period	**S.E.**	**LGDP PC**	**LGFCF PC**	**TO**	**INF**	**POP**	**LEN PC**	**LGHG PC**
1	0.009570	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.016243	97.93362	0.288028	0.375758	0.081286	0.127449	0.499276	0.694581
3	0.021221	91.86484	0.886317	2.594804	0.818890	0.495458	1.896356	1.443340
4	0.026195	84.16094	1.310486	6.155883	0.708775	2.353239	3.352997	1.957677
5	0.030949	75.91806	1.358549	8.733593	0.595454	5.978094	5.442206	1.974040
6	0.035257	69.07590	1.301659	10.26030	0.485513	9.866447	7.110819	1.899361
7	0.039117	64.29751	1.179186	11.04458	0.396541	13.46952	7.872302	1.740358
8	0.042538	61.21198	1.024012	11.28730	0.354387	16.72696	7.851324	1.544035
9	0.045549	59.47169	0.896162	11.22245	0.327010	19.42610	7.293885	1.362701
10	0.048278	58.66093	0.905053	10.95355	0.302217	21.41621	6.548185	1.213849
Variance Decomposition of LGFCF PC								
Period	**S.E.**	**LGDP PC**	**LGFCF PC**	**TO**	**INF**	**POP**	**LEN PC**	**LGHG PC**
1	0.029513	8.305712	91.69429	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.049357	7.797954	88.19925	0.323470	0.072374	1.627117	1.277266	0.702568
3	0.070130	3.864329	84.65616	0.163105	0.265439	4.188726	4.797577	2.064664
4	0.092217	2.448178	80.62435	0.171541	0.248393	6.977474	7.273520	2.256542
5	0.113878	2.350223	74.95772	0.361560	0.387593	9.691117	10.38425	1.867535
6	0.133477	2.914050	70.42587	0.608542	0.460770	11.15993	12.86000	1.570837
7	0.149645	3.415264	67.73678	0.817860	0.572453	11.70651	14.38286	1.368272
8	0.162556	3.698465	66.27750	1.013714	0.675085	11.82701	15.27626	1.231962
9	0.172732	3.798768	65.69062	1.186794	0.730892	11.71626	15.73336	1.143297
10	0.180724	3.768013	65.64764	1.318290	0.749592	11.48780	15.93585	1.092817
Variance Decomposition of TO								
Period	**S.E.**	**LGDP PC**	**LGFCF PC**	**TO**	**INF**	**POP**	**LEN PC**	**LGHG PC**
1	0.045439	12.33692	17.69612	69.96696	0.000000	0.000000	0.000000	0.000000
2	0.067395	14.52175	27.59595	52.52141	2.033911	1.903870	0.029768	1.393348
3	0.075467	16.45469	30.02912	47.35324	2.479121	1.840519	0.509389	1.333913
4	0.080881	20.16991	28.87661	42.93627	2.621321	2.243957	1.982131	1.169794
5	0.084764	21.72089	27.85731	39.53160	2.529358	4.148720	2.965380	1.246741
6	0.087978	21.78589	27.36558	36.90025	2.382505	5.638276	4.532903	1.394606
7	0.091425	21.47611	27.59838	34.23653	2.225780	6.206361	6.835360	1.421479
8	0.095259	20.92169	28.70888	31.54023	2.051869	6.414518	8.941412	1.421398
9	0.099578	20.06824	30.72448	28.92066	1.882900	6.346446	10.55185	1.505429
10	0.104753	18.95858	33.77643	26.17073	1.701466	5.924620	11.81194	1.656225
Variance Decomposition of INF								

Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	0.132947	9.916699	1.580039	3.094197	85.40907	0.000000	0.000000	0.000000
2	0.158234	7.028285	7.258794	6.498866	65.38431	11.96973	0.663777	1.196236
3	0.173694	6.161320	10.41247	5.395251	56.22244	12.64314	4.583677	4.581705
4	0.185721	5.418566	9.536946	4.720427	50.71424	11.08002	14.50869	4.021109
5	0.194825	5.096857	8.756230	5.996954	46.09302	10.06861	19.89706	4.091261
6	0.201108	4.783645	8.245975	9.308259	43.54164	9.822242	20.45857	3.839668
7	0.204778	4.903637	8.194760	11.24211	42.00931	9.759251	19.98111	3.909829
8	0.208041	5.054227	9.836328	11.54273	40.71721	9.455840	19.43992	3.953747
9	0.213035	4.847708	13.46256	11.11260	38.83212	9.228732	18.64672	3.869565
10	0.219820	4.609454	17.90128	10.43731	36.47180	9.125609	17.70343	3.751112
Variance Decomposition of POP								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	0.020911	1.439361	17.93867	9.477659	0.310998	70.83331	0.000000	0.000000
2	0.035714	0.520125	29.09888	7.640721	0.664940	60.85144	0.555246	0.668646
3	0.046382	0.784833	30.87797	6.449103	1.082319	58.20983	1.719804	0.876143
4	0.054431	1.539596	30.24897	6.353022	1.317010	57.08832	2.732870	0.720223
5	0.060236	2.024877	29.23101	6.792445	1.696963	56.47025	3.068550	0.715901
6	0.063935	2.241856	28.09226	7.502273	1.974726	56.30998	3.034476	0.844432
7	0.065930	2.262689	27.10962	8.278902	2.108923	56.36408	2.874084	1.001701
8	0.066923	2.198218	26.36121	8.939929	2.169709	56.32684	2.853281	1.150815
9	0.067583	2.242934	25.97092	9.354564	2.171286	55.89397	3.092487	1.273840
10	0.068358	2.543256	26.14240	9.441684	2.128297	54.84328	3.540905	1.360173
Variance Decomposition of LEN PC								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	0.012125	2.499348	2.037385	0.884622	1.742369	3.775487	89.06079	0.000000
2	0.020492	1.522820	5.824354	2.760223	1.044583	5.282897	83.31218	0.252943
3	0.027026	1.092707	12.52992	5.748546	0.649947	5.795217	73.69915	0.484519
4	0.032757	1.303913	21.01503	7.563813	0.602525	7.219101	61.65818	0.637442
5	0.038293	1.354364	29.94065	7.159091	0.522535	9.331892	50.94278	0.748692
6	0.043824	1.172361	38.34937	5.854784	0.464573	11.25528	42.02392	0.879719
7	0.049295	0.941433	44.85805	4.637130	0.469608	12.88741	35.24356	0.962810
8	0.054480	0.783403	49.08842	3.874250	0.503091	14.25402	30.51410	0.982709
9	0.059071	0.741707	51.48207	3.540809	0.544019	15.27584	27.45414	0.961408
10	0.062838	0.767379	52.65351	3.467626	0.589613	15.96267	25.63197	0.927226
Variance Decomposition of LGHG PC								
Period	S.E.	LGDP PC	LGFCF PC	TO	INF	POP	LEN PC	LGHG PC
1	0.043790	16.11198	16.86378	4.057033	0.478186	0.359054	3.042430	59.08754
2	0.051845	11.66854	17.37552	4.003226	6.791604	5.586745	7.210292	47.36408
3	0.056080	16.67273	14.91172	7.139609	6.923284	6.444348	6.360946	41.54736
4	0.059536	19.50238	14.04474	9.424115	6.232974	6.375055	7.537744	36.88299
5	0.062793	18.72068	15.41033	10.97843	6.195232	7.013796	8.407033	33.27449
6	0.066015	17.81612	18.37717	11.59825	5.633565	7.706495	8.358913	30.50948
7	0.069715	16.38276	21.89931	10.72650	5.144354	9.613288	8.535290	27.69850
8	0.073924	14.60380	25.37376	9.541474	4.695429	12.15513	8.878104	24.75229
9	0.077745	13.21135	28.05078	8.657108	4.337959	14.21772	9.113913	22.41117
10	0.080720	12.28268	29.78346	8.123669	4.110669	15.66289	9.227638	20.80899

Source: Estimated based on World bank data,2018

4.5. Impulse response Function (IRF)

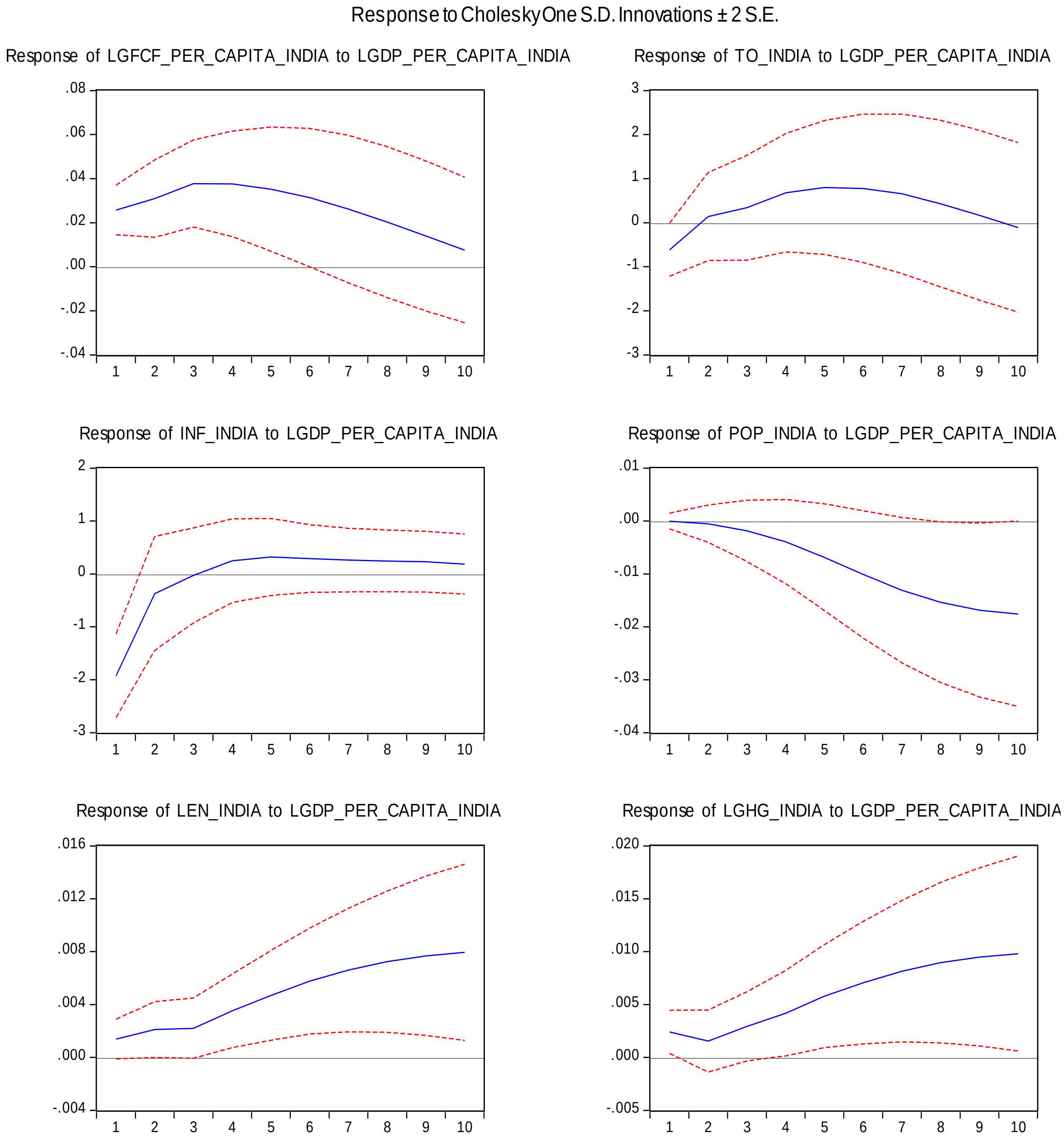
The innovations on the dependent variable cause an impact on all Independent variables in the system and can be investigated using Impulse response analysis. The figures 4.9(a) and 4.9(b) shows the impulse response function of the variables for India and China. The blue line is the impulse response function and redline shows the 95 percent confident intervals in the figure.

Response of GFCF per capita, trade openness, inflation, population, energy consumption per capita and GHG emissions per capita to GDP per capita

The impulse response function of GFCF for India shows a rise initially and a gradual fall till period 10. This implies that one standard deviation shock on GDP per capita will cause an increase in GFCF per capita initially and then a fall in the short and long run. Since the IRF of GFCF per capita lies in the positive region, it can be inferred that the shock on GDP per capita has positive impact on GFCF per capita in the short and long run. The IRF of energy consumption per capita and greenhouse gas emissions per capita also lie in the positive region showing that a shock given on GDP per capita will positively impact them.

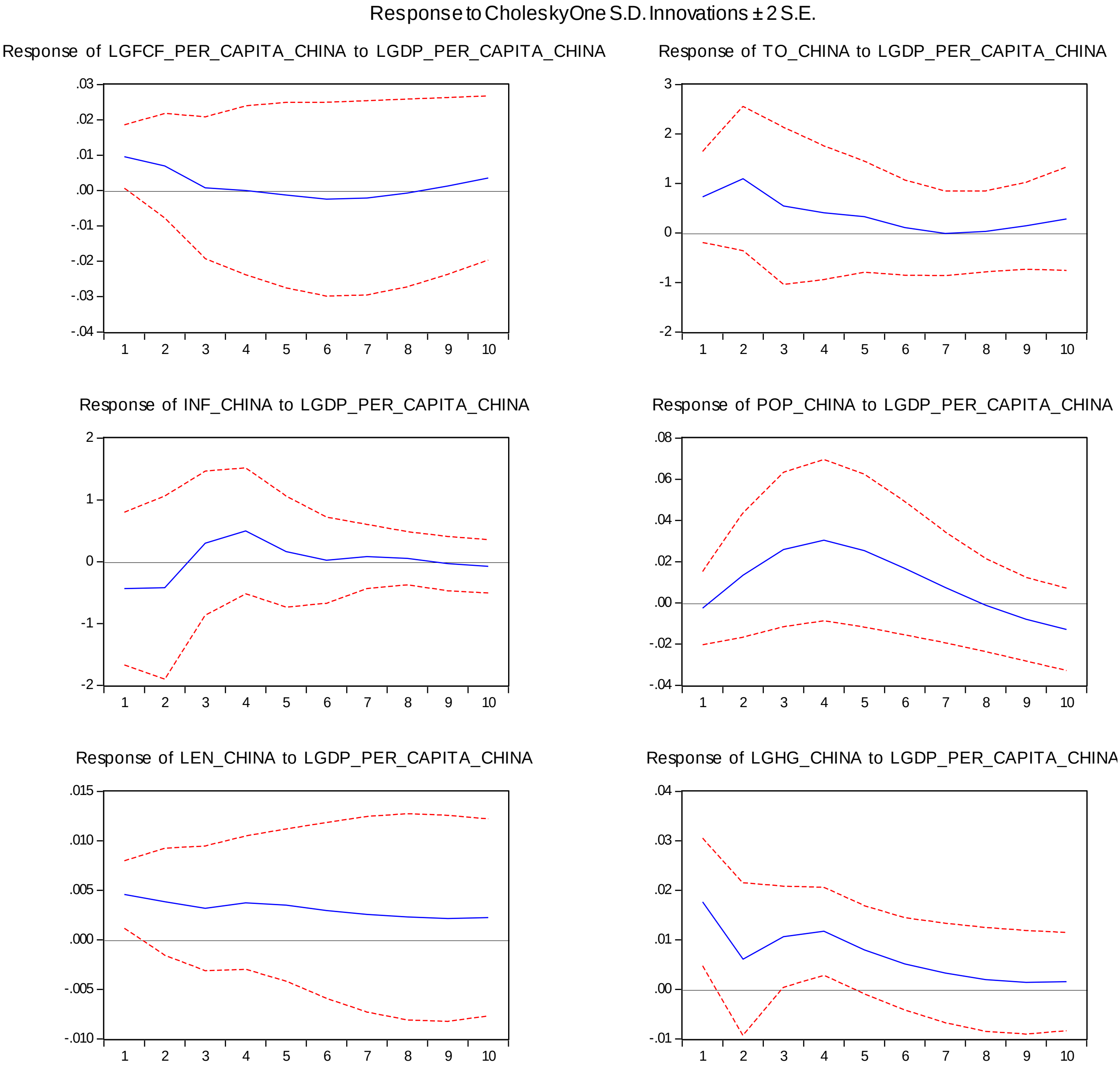
In case of trade openness and inflation, the IRF lies both in negative and positive region implying that the shock on GDP per capita will have an asymmetric impact on trade openness and inflation.

For China, the impulse response function of GFCF per capita, inflation and population lies both in negative and positive region implying that the shock on GDP per capita will have an asymmetric impact on GFCF per capita, inflation and population. The shock on GDP per capita will have positive impact on trade openness, energy consumption per capita and greenhouse gas emissions per capita in short and long run.



Source: World bank,2018

Figure 4.9(a): Impulse Response Function of GDP per capita - India



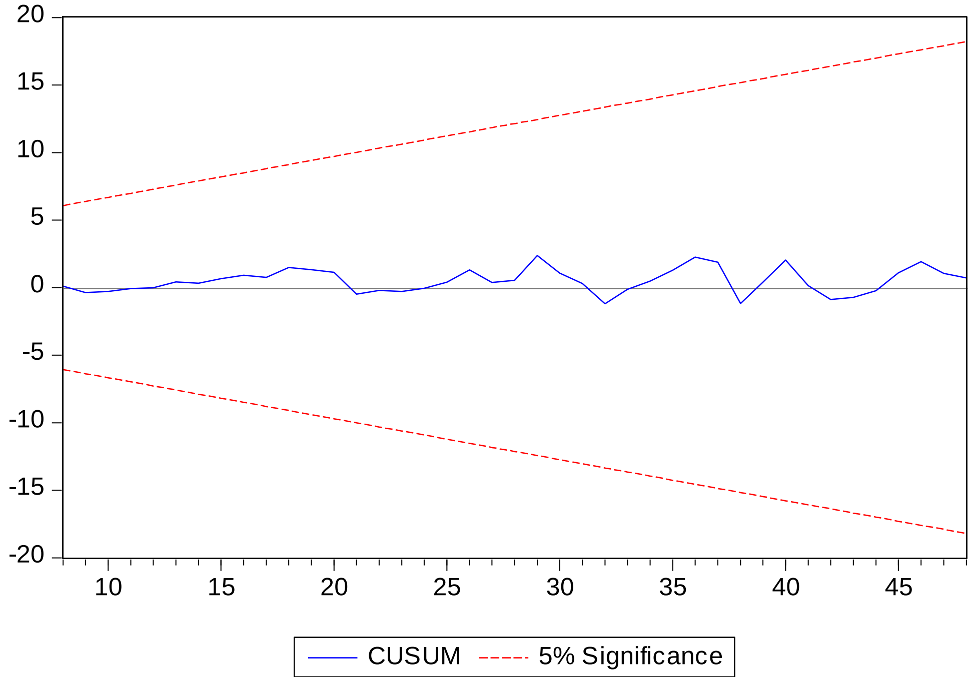
Source: World bank,2018

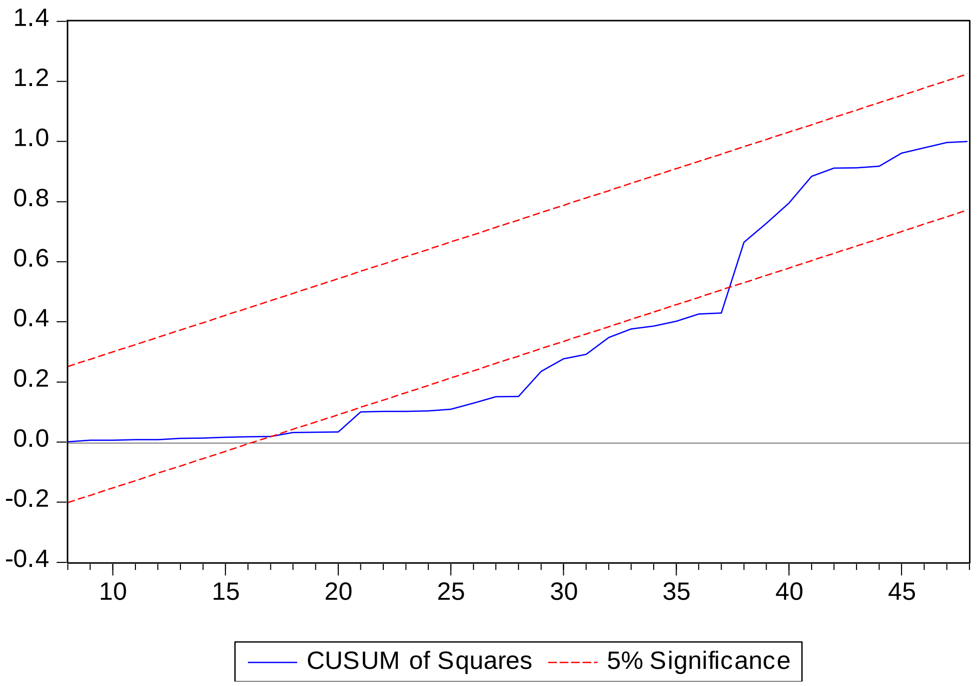
Figure 4.9(b): Impulse Response Function of GDP per capita– China

4.6. Test of Stability

4.6(a) CUSUM and CUSUM Square Test

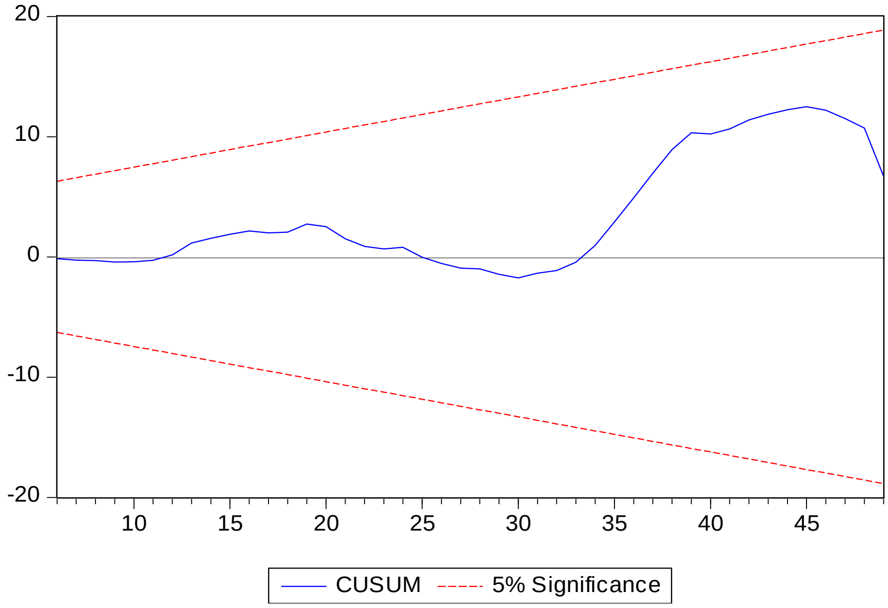
CUSUM test and CUSUM square test were used to test the stability of the GDP per capita and its determinants model.

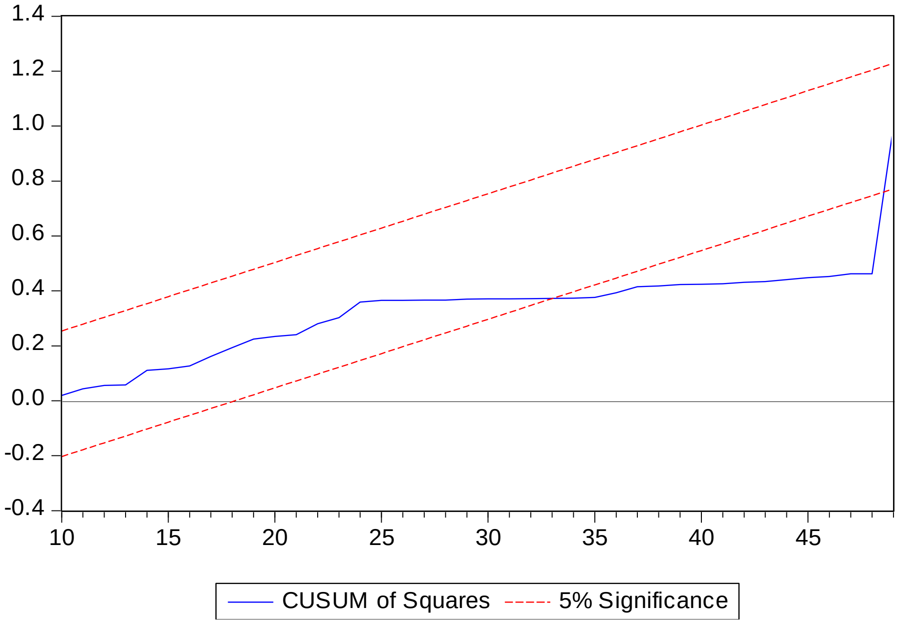




Source: World bank, 2018

Figure 4.10 (a): CUSUM Test AND CUSUM Square Test of GDP per capita-India





Source: World bank,2018

Figure 4.10(b): CUSUM Test and CUSUM SQUARE Test of GDP per capita – China

The CUSUM and CUSUMSQ plot of the residuals generated from the vector error correction model for gross domestic product per capita was used to test the stability of GDP per capita model and the results revealed that the CUSUM plot for GDP per capita was within the 5 percent critical bound levels, indicating that the gross domestic product per capita was found to be stable throughout the study period for both India and China. The CUSUMSQ plot revealed that there was evidence of instability for India from 1980s till 1995 and for China after 1995.This instability could have been the result of the reforms of 80s and 90s and the financial crisis of the 90s.

To conclude

- **Using the "Intercept" and "Trend and Intercept" criteria the results indicated that all the variables used in the model such as GDP per capita, GFCF per capita, trade openness, Inflation, Population, Energy consumption per capita and GHG emissions per capita became stationary only in their first differences for both India and China.**
- **The trace statistic was found to be greater than the critical value for At most 6 cointegrating equations for both India and China. The Eigen values also were greater than the critical value for 6 and 7 cointegrating equations for India and China respectively thus establishing long run relationship between the variables in the model**
- **The error correction coefficient for GDP per capita as dependent variable for India and China was negative as in the principle indicating that the series for GDP per capita will converge in the long run**
- **In the short run for India and China 100 percent variance in GDP per capita is explained by the variable GDP per capita itself meaning strongly endogenous. In the long run 82.6 percent of the variation is explained by GDP per capita itself and 10.20 percent by inflation. For China, in the long run 58.6 percent of the variation is explained by itself and 21.4 percent by population.**
- **For India, SD shock on GDP per capita will cause positive impact on GFCF per capita, energy consumption per capita and greenhouse gas emissions per capita in the short and long run. The innovation given on GDP per capita will cause an asymmetric impact on trade openness and inflation and a negative effect on population. For China, an SD shock on GDP per capita will cause an asymmetric impact on GFCF per capita, inflation and population. The shock on GDP per capita will cause positive impact on trade openness, energy consumption per capita and greenhouse gas emissions per capita.**

- **CUSUM plot for GDP per capita was within the 5 percent critical bound levels, indicating that the gross domestic product per capita was found to be stable throughout the study period for both India and China. The CUSUMSQ plot revealed that there was evidence of instability for India from 1980s till 1995 and for China after 1995.**

4.7. Long run relationship between trade openness and its determinants (Gross domestic product per capita, gross fixed capital formation per capita, exchange rate and population)using cointegration analysis

4.7.1. The ADF unit root test of stationarity

Initially unit root was used to test the stationarity of the variables used in the trade openness model

The following null hypothesis was tested.

H_0: The chosen variables trade openness, GDP pc, GFCF pc, exchange rate and population are not stationary.

Ha: The chosen variables trade openness, GDP pc, GFCF pc, exchange rate and population are stationary.

The present study performed the ADF test of stationarity on the variables used in the trade openness model for India and China based on intercept, trend and intercept. Table 4.7.1(a)and 4.7.1(b) shows the ADF statistics based on “intercept”, “trend and intercept”. Using the “intercept”, “trend and intercept” criteria the results indicated that the variables GDP per capita, GFCF per capita, exchange rate, population and trade openness became stationary only in their first differences for India and China.

Table 4.7.1(a): Unit Root Test Results based on ADF Statistic using Intercept

Country	Order of difference	ADF t-statistic	Critical Values (5 % level)	p-value	H0	Order of Integration
TO						
India	Level	-0.6807	-2.9571	0.8376	Accept	I(1)
	First Difference	-3.9604	-2.9604	0.0048	Reject	
China	Level	-2.9028	-2.9237	0.0524	Accept	I(1)
	First Difference	-4.943	-2.9251	0.0002	Reject	
LGDP PC						
India	Level	4.3086	-2.9237	1	Accept	I(1)
	First Difference	-5.7051	-2.9251	0	Reject	
China	Level	0.3225	-2.9266	0.9771	Accept	I(1)
	First Difference	-3.2281	-2.9266	0.0246	Reject	
LGFCF PC						
India	Level	-1.2782	-2.9237	0.6323	Accept	I(1)
	First Difference	-6.1391	-2.9251	0	Reject	
China	Level	0.4397	-2.9251	0.9826	Accept	I(1)
	First Difference	-4.3411	-2.9251	0.0011	Reject	
POP						
India	Level	-0.23383	-2.93694	0.9256	Accept	I(1)
	First Difference	-2.64586	-2.9484	0.0437	Reject	
China	Level	-0.1599	-2.9297	0.9359	Accept	I(1)
	First Difference	-3.0063	-2.9297	0.042	Reject	
ER						
India	Level	-0.4394	-2.9237	0.8937	Accept	I(1)
	First Difference	-4.6886	-2.9251	0.0004	Reject	
China	Level	-0.7642	-2.9237	0.82	Accept	I(1)
	First Difference	-4.4769	-2.9251	0.0008	Reject	

Source: Estimates based on World bank data,2018

Table 4.7.1(b): Unit Root Test Results based on ADF Statistic using Trend and Intercept

Country	Order of difference	ADF t-statistic	Critical Values	p-value	H0	Order of Integration
TO						
India	Level	-1.5772	-3.5577	0.7797	Accept	I(1)
	First Difference	-3.8923	-3.5628	0.0246	Reject	
China	Level	-0.9641	-3.5063	0.9394	Accept	I(1)
	First Difference	-5.6505	-3.5085	0.0001	Reject	
LGDP PC						
China	Level	-2.9028	-2.9237	0.0524	Accept	I(1)
	First Difference	-4.943	-2.9251	0.0002	Reject	
India	Level	4.3086	-2.9237	1	Accept	I(1)
	First Difference	-5.7051	-2.9251	0	Reject	
China	Level	0.3225	-2.9266	0.9771	Accept	I(1)
	First Difference	-3.2281	-2.9266	0.0246	Reject	
LGFCF PC						
India	Level	-1.2782	-2.9237	0.6323	Accept	I(1)
	First Difference	-6.1391	-2.9251	0	Reject	
China	Level	0.4397	-2.9251	0.9826	Accept	I(1)
	First Difference	-4.3411	-2.9251	0.0011	Reject	
POP						
India	Level	-0.23383	-2.93694	0.9256	Accept	I(1)
	First Difference	-2.64586	-2.9484	0.0437	Reject	
China	Level	-0.1599	-2.9297	0.9359	Accept	I(1)
	First Difference	-3.0063	-2.9297	0.042	Reject	
ER						
India	Level	-0.4394	-2.9237	0.8937	Accept	I(1)
	First Difference	-4.6886	-2.9251	0.0004	Reject	
China	Level	-0.7642	-2.9237	0.82	Accept	I(1)
	First Difference	-4.4769	-2.9251	0.0008	Reject	

Source: Estimates based on World bank data,2018

4.7.2Johansen Cointegration Test for Trade openness and its determinants

To decide the lag length the Akaike Information criterion (AIC) was used as a criterion based on the VAR estimates and the study used the lag of 2 for both India and China as per the criterion for the testing of the cointegration. The model of the Trade openness in India and China is tested for presence of cointegration among the variables using the following hypothesis.

Hypothesis for the test of cointegration

Null Hypothesis (H0): The determinants of trade openness do not exhibit long term relationship.

Alternate Hypothesis (Ha): The determinants of trade openness exhibits long term relationship.

The tables 4.7.2(a) and 4.7.2(b) gives the estimates of the trace statistic for trade openness and the dependent variables GDP per capita, GFCF per capita, exchange rate and population. The trace statistic was found to be greater than the critical value for None and At most 1 cointegrating equation for both India and China respectively. Hence the null hypothesis that the determinants of trade openness do not exhibit long term relationship was rejected and it is concluded that the determinants of trade openness exhibited long term relationship with the presence of at least 1 cointegrating equation for India and atleast 2 cointegrating equations for China.

Table 4.7.2(a):Unrestricted Cointegration Rank Test (Trace)-India

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value 0.05	Prob.**
None *	0.751299	95.59334	69.81889	0.0001
At most 1	0.348596	39.93311	47.85613	0.2249
At most 2	0.273562	22.78808	29.79707	0.2566
At most 3	0.212597	10.00401	15.49471	0.2804
At most 4	0.011024	0.443401	3.841466	0.5055

Source: Estimates based on Secondary data.
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

Table 4.7.2(b): Unrestricted Cointegration Rank Test (Trace)-China

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value 0.05	Prob.**
None *	0.571550	87.52754	69.81889	0.0010
At most 1 *	0.493632	53.62425	47.85613	0.0130
At most 2	0.311452	26.40458	29.79707	0.1171
At most 3	0.210521	11.47776	15.49471	0.1838
At most 4	0.049306	2.022501	3.841466	0.1550

Source: Estimates based on Secondary data.
Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

4.7.2(c):Unrestricted Cointegration Rank Test (Maximum Eigen)-India

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.751299	55.66023	33.87687	0.0000
At most 1	0.348596	17.14503	27.58434	0.5675
At most 2	0.273562	12.78407	21.13162	0.4723
At most 3	0.212597	9.560605	14.26460	0.2424
At most 4	0.011024	0.443401	3.841466	0.5055

Source: Estimates based on Secondary data.
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

4.7.2(d):Unrestricted Cointegration Rank Test (Maximum Eigen)-China

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.571550	33.90328	33.87687	0.0497
At most 1	0.493632	27.21967	27.58434	0.0556
At most 2	0.311452	14.92682	21.13162	0.2941
At most 3	0.210521	9.455260	14.26460	0.2502
At most 4	0.049306	2.022501	3.841466	0.1550

Source: Estimates based on Secondary data.
Max-eigen value test indicates 1 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

The tables 4.7.2 (c) and 4.7.2(d) gives the statistic Maximum Eigen value estimated using the Johansen procedure for the variables of the study. It showed that the Eigen statistic values were found to be greater than the critical values at None cointegrating equations for India and China respectively. Thus the null hypothesis that the determinants of trade openness do not exhibit long term relationship is rejected and it can be concluded that the variables of the model have a long run equilibrium relationship, with the presence of atleast 1 cointegrating equation for both India and China.

The results of the Johansen cointegration test using the trace statistic and Max-Eigen value statistic showed that variables of the model exhibited a common trend and move together in the long run.

4.7.3 Estimation of long run trade openness function using the Normalized Cointegrating Coefficients

The normalized cointegrating coefficients of independent variables of the model for trade openness derived from Johansen cointegration procedure are given in the table 4.7.3(a) and 4.7.3(b).

Table 4.7.3(a): Normalized Cointegrating Coefficients from the Cointegration Equation-India

Variables	Co-efficients	Standard Errors
LGDP pc	-31.6912	4.45314
LGFCF pc	10.0677	1.53412
ER	12.87431	174800
POP	-19.5125	4.69666

Source: Estimates obtained from secondary data.

Table 4.7.3(b): Normalized Cointegrating Coefficients from the Cointegration Equation-China

Variables	Co-efficients	Standard Errors
LGDP pc	-0.32267	0.30046
LGFCF pc	0.051008	0.051008
ER	-0.28088	-0.28088
POP	0.54608	0.23697

Source: Estimates obtained from secondary data.

The normalized cointegration coefficients of the cointegrating equation showed that the trade openness is a function of the determinants. Due to normalization process the signs are reversed for proper interpretation. (Skerman et al,2009).

For India TO= 31.6912 LGDPpc-10.0677LGFCFpc-12.8743 ER+19.5125POP

For China TO=0.3226LGDPpc-0.05101LGFCFpc+0.2809ER-0.5461POP

The coefficients obtained showed that GFCF per capita and exchange rate have negative impact on trade openness in India during the study period. It denotes that an increase in the GFCF per capita and exchange rate will lead to decline in trade openness. GDP per capita and population have a positive effect on trade openness in India.

The coefficients obtained for China revealed that GFCF per capita and population have negative impact on trade openness during the study period. It denotes that an increase in the values of the GFCF per capita and population will lead to decline in trade openness.GDP per capita and exchange rate have positive impact on trade openness in China.

4.7.4 Estimation of Short run Trade openness using Vector Error Correction Model (VECM)

The dynamic error correction equation of trade openness can be specified as:

$$\Delta TOpc_{it} = \beta_{0it} + \Sigma\ \beta_{1i}\Delta TOpc_{it-1} + \Sigma\ \beta_{2i}\Delta LGDPpc_{it-1} + \Sigma\ \beta_{3i}\Delta LGFCFpc^{2}_{it-1} + \Sigma\beta_{4i}\Delta ER_{it-1} + \Sigma\beta_{5i}\Delta POP_{it-1} + \varepsilon t$$

where Δ indicates the coefficient of the error correction terms and gives the direction of equilibrium in the model and εt denotes the noise error term. The error correction term gained in the long run equation of the cointegration process is used as one of the determinants of the VECM function. The coefficients of the VECM model point out the speed of adjustments shown by the respective variables in the short run and are given in the table 4.7.4 (a) and 4.7.4 (b).The estimates obtained specify the change in the trade openness in response to changes in the dependent variables of the model given in their lag forms and the disturbance term of the lag forms. The speed of adjustment is determined by the error correction coefficient within which the model will return to its equilibrium after any disturbances. The coefficient must have a negative sign by rule signifying the ability to spring back to equilibrium. The positive sign specify movement away from equilibrium and depend on the nature of the variables and the system. From the results obtained in VECM, it was found that the error correction coefficient for trade openness as dependent variable for India was negative(-0.0081) as in the principle indicating that the series for trade openness will converge in the long run. An increase in exchange rate by one percent will cause a decline of 0.68 percent intrade openness. An increase in population by one percent will lead to an increase in trade openness by 0.76 percent in the short run. For China, the error correction coefficient for trade openness was negative (-0.0546) as in the principle indicating that the series for trade openness will converge in the long run. The results also reveal that a percent change in lagged trade openness causes 0.36

percent increase in trade openness and is statistically significant at 10 percent level. The estimated error correction model enjoys the minimum goodness of fit with R^2 value being 0.25 and adjusted R^2 of -0.06 for India. The R^2 indicated that for India, 25 percent of variations in the dependent variable were accounted for by the variations in the explanatory variables used in the model. For China, the R^2 was 0.32 and adjusted R^2 was 0.04 which indicated that 32 percent of variations in the dependent variable were accounted for by the variations in the explanatory variables used in the model.

The F-statistic value of 3.80 for India and 4.14for China indicated that the overall model was found to be statistically significant and explains the fact that all the explanatory variables simultaneously explained the variations in the trade openness during the study period for both India and China.

The diagnostic tests on the residuals of the VECM model was also performed using the Breusch-Godfrey Serial Correlation LM Test which indicated that there was absence of autocorrelation.

The residual heteroscedasticity test was also performed. The tests showed that the error correction model is free from the problem of heteroscedasticity thereby increasing the dependability on the model estimated for making inferences on the impact of chosen variables on trade openness.

Table 4.7.4(a):Estimated coefficients of the VECM- India

Error Correction:	D(TO)	D(LGDP PC	D(LGFCF PC)	D(ER)	D(POP)
CointEq1	-0.008104	-0.008114	0.057160	-0.027178	0.002540
	(0.02098)	(0.00681)	(0.02816)	(0.01747)	(0.00023)
	[-0.38625]	[-1.19084]	[2.03015]	[-1.55593]	[10.9159]
D(TO(-1))	0.160834	0.090781	0.016793	0.198460	-0.002700
	(0.18784)	(0.06100)	(0.25206)	(0.15638)	(0.00208)
	[0.85622]	[1.48832]	[0.06662]	[1.26913]	[-1.29597]
D(TO(-2)	0.107268	-0.022357	0.039850	-0.062107	0.003276
	(0.20309)	(0.06595)	(0.27252)	(0.16907)	(0.00225)
	[0.52818]	[-0.33901]	[0.14623]	[-0.36734]	[1.45467]
D(LGDP PC(-1)	0.210398	-0.334318	0.215334	0.572322	-0.017622
	(0.65107)	(0.21141)	(0.87364)	(0.54200)	(0.00722)
	[0.32316]	[-1.58135]	[0.24648]	[1.05594]	[-2.44074]
D(LGDP PC(-2)	0.295789	-0.315792	0.480802	-0.105883	-0.003090
	(0.67930)	(0.22058)	(0.91153)	(0.56551)	(0.00753)
	[0.43543]	[-1.43163]	[0.52747]	[-0.18723]	[-0.41020]
D(LGFCF PC(-1)	-0.142586	0.138575	0.082140	-0.259620	0.014128
	(0.29911)	(0.09713)	(0.40137)	(0.24901)	(0.00332)
	[-0.47670]	[1.42674]	[0.20465]	[-1.04263]	[4.25914]
D(LGFCF PC(-2)	-0.366860	0.003364	-0.252416	0.016372	0.007115
	(0.27658)	(0.08981)	(0.37113)	(0.23025)	(0.00307)
	[-1.32642]	[0.03745]	[-0.68013]	[0.07111]	[2.31970]
D(ER(-1)	-0.681511	0.279517	0.030843	0.019540	0.012998
	(0.46589)	(0.15128)	(0.62516)	(0.38785)	(0.00517)
	[-1.46282]	[1.84764]	[0.04934]	[0.05038]	[2.51580]
D(ER(-2)	-0.056851	-0.101856	-1.250569	0.477920	0.009002
	(0.39674)	(0.12883)	(0.53237)	(0.33028)	(0.00440)
	[-0.14329]	[-0.79063]	[-2.34905]	[1.44701]	[2.04614]
D(POP(-1)	0.756141	-0.969527	-5.333778	3.127843	1.575001
	(4.26618)	(1.38531)	(5.72461)	(3.55153)	(0.04731)
	[0.17724]	[-0.69986]	[-0.93173]	[0.88070]	[33.2912]
D(POP(-2)	0.340946	0.234922	-2.359871	0.955210	-0.889919
	(3.92546)	(1.27467)	(5.26742)	(3.26789)	(0.04353)
	[0.08685]	[0.18430]	[-0.44801]	[0.29230]	[-20.4431]
C	0.031637	0.013626	-0.024343	0.023653	-0.002082
	(0.01813)	(0.00589)	(0.02433)	(0.01509)	(0.00020)
	[1.74489]	[2.31445]	[-1.00056]	[1.56706]	[-10.3572]
R-squared	0.246462	0.415114	0.347816	0.352549	0.996594
Adj. R-squared	-0.060536	0.176827	0.082111	0.088773	0.995206
F-statistic	3.802814	1.742074	1.309033	1.336545	718.1800
Akaike AIC	-3.643868	-5.893458	-3.055754	-4.010547	-12.64737
Schwarz SC	-3.132003	-5.381593	-2.543889	-3.498682	-12.13551

Source: Estimates based on secondary data

Figures in ( ) are standard error values; figures in [ ] are the "t" statistics

Table 4.7.4(b):Estimated coefficients of the VECM- China

Error Correction:	D(TO)	D(LGDP PC)	D(LGFCF PC)	D(ER)	D(POP)
CointEq1	-0.054621	0.004843	0.021882	0.296545	0.025950
	(0.08696)	(0.02117)	(0.06755)	(0.04543)	(0.03476)
	[-0.62814]	[0.22871]	[0.32392]	[6.52818]	[0.74660]
D(TO(-1))	0.359644	0.015760	0.203266	-0.197060	-0.004418
	(0.19049)	(0.04638)	(0.14799)	(0.09951)	(0.07614)
	[1.88799]	[0.33980]	[1.37354]	[-1.98030]	[-0.05803]
D(TO(-2))	-0.181944	-0.079287	-0.297939	-0.099488	-0.093455
	(0.19362)	(0.04714)	(0.15042)	(0.10115)	(0.07739)
	[-0.93970]	[-1.68180]	[-1.98073]	[-0.98362]	[-1.20753]
D(LGDP PC(-1)	0.307884	0.225152	-0.529601	-0.000568	0.485363
	(0.83693)	(0.20378)	(0.65019)	(0.43720)	(0.33454)
	[0.36787]	[1.10487]	[-0.81453]	[-0.00130]	[1.45086]
D(LGDP PC(-2)	-1.547009	0.060371	0.339165	-0.194083	-0.032312
	(0.83984)	(0.20449)	(0.65245)	(0.43873)	(0.33570)
	[-1.84202]	[0.29523]	[0.51983]	[-0.44238]	[-0.09625]
D(LGFCF PC(-1)	-0.368060	0.056658	0.448361	0.202552	-0.104972
	(0.31152)	(0.07585)	(0.24201)	(0.16273)	(0.12452)
	[-1.18151]	[0.74697]	[1.85267]	[1.24469]	[-0.84303]
D(LGFCF PC(-2)	0.275552	0.066654	0.211542	0.653319	0.135621
	(0.32231)	(0.07848)	(0.25039)	(0.16837)	(0.12883)
	[0.85494]	[0.84934]	[0.84485]	[3.88027]	[1.05270]
D(ER(-1)	0.036236	0.083632	0.037109	0.172441	0.029910
	(0.24024)	(0.05849)	(0.18663)	(0.12550)	(0.09603)
	[0.15084]	[1.42975]	[0.19883]	[1.37406]	[0.31147]
D(ER(-2))	0.090900	0.055719	-0.098230	0.189816	-0.004101
	(0.24873)	(0.06056)	(0.19323)	(0.12993)	(0.09942)
	[0.36546]	[0.92004]	[-0.50836]	[1.46088]	[-0.04125]
D(POP(-1))	-0.316340	-0.007963	-0.129532	-0.168931	0.548265
	(0.49137)	(0.11964)	(0.38173)	(0.25668)	(0.19641)
	[-0.64380]	[-0.06656]	[-0.33933]	[-0.65813]	[2.79147]
D(POP(-2))	0.617141	0.092425	0.159798	-0.343162	-0.218675
	(0.47420)	(0.11546)	(0.36839)	(0.24772)	(0.18955)
	[1.30143]	[0.80048]	[0.43377]	[-1.38530]	[-1.15368]
C	0.066160	0.022428	0.019917	-0.012354	-0.025358
	(0.03185)	(0.00775)	(0.02474)	(0.01664)	(0.01273)
	[2.07735]	[2.89226]	[0.80499]	[-0.74253]	[-1.99193]
R-squared	0.318003	0.402910	0.343245	0.715128	0.508458
Adj. R-squared	0.040152	0.159652	0.075678	0.599069	0.308200
F-statistic	4.144510	1.656304	1.282839	6.161772	2.539018
Akaike AIC	-2.747238	-5.572629	-3.252193	-4.045923	-4.581237
Schwarz SC	-2.235373	-5.060764	-2.740328	-3.534058	-4.069371

Source: Estimates based on secondary data
Figures in ( ) are standard error values; figures in [ ] are the "t" statistics

4.8. Variance Decomposition Analysis

Variance decomposition model of the forecast error helps to obtain the percentage of unexpected variation in each variable that is caused by shocks from other variables. Table 4.8.1 (a) and 4.8.1(b) shows the variance decomposition analysis of trade openness and its determinants in India and China respectively. In India, in the short run 100 percent variance is explained by the variable trade openness meaning it is strongly endogenous. The remaining variables do not have any influence. From second period onwards, GDP per capita and GFCF per capita have influence on trade openness both in the short run and in the long run. Variance contribution of trade openness on itself in the long run is 50 percent, the variance contribution of GFCF per capita is about 0.58 percent, variance contribution of GDP per capita, GFCF per capita, population and exchange rate is 24 percent, 16 percent,8 percent and 1 percent respectively. The consecutive table shows that the variance of GDP per capita is explained to the amount of 88.29 percent by itself. GFCF per capita is influenced both by itself (28.48 percent) and by population (29 percent). Exchange rate is also explained by the variable itself in the long run

For China, 100 percent forecast error variance of trade openness is explained by itself in the short run. GFCF per capita has an influence on GDP per capita from second period onwards. Variance contribution of trade openness on itself is 67 percent and GFCF per capita contributes 23 percent to the trade openness in the long run. Over the long period the other variables GDP per capita, GFCF per capita and population are explained by itself to the tune of 54.39 percent, 56.56 percent and 46.7 percent respectively. Exchange rate is influenced by both GFCF per capita (44 percent) and trade openness (44 percent).

Table 4.8.1(a):Variance Decomposition Analysis of Trade openness-India

Variance Decomposition of TO:						
Period	**S.E.**	**TO**	**LGDP PC**	**LGFCF PC**	**POP**	**ER**
1	0.025892	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.034346	89.22018	3.053434	6.919243	0.154361	0.652780
3	0.036535	88.79987	2.699006	6.897311	0.813189	0.790626
4	0.037475	87.97647	2.572924	6.678672	1.962649	0.809282
5	0.038310	84.50719	2.498144	7.734199	4.155164	1.105298
6	0.039735	78.67264	3.195156	10.80907	6.075277	1.247851
7	0.042235	70.85246	5.565496	14.87168	7.371153	1.339211
8	0.045571	63.23431	10.30257	17.18543	7.931284	1.346408
9	0.049551	56.55088	16.75240	17.19332	8.120547	1.382854
10	0.053983	50.78009	23.94150	15.54326	8.225249	1.509906
Variance Decomposition of LGDP PC						
Period	**S.E.**	**TO**	**LGDP PC**	**LGFCF PC**	**POP**	**ER**
1	0.011885	7.632701	92.36730	0.000000	0.000000	0.000000
2	0.014361	5.648197	93.82416	0.106509	0.407058	0.014081
3	0.016840	4.304551	94.69433	0.089333	0.703401	0.208388
4	0.018918	3.722036	94.10077	0.573293	1.436241	0.167663
5	0.021083	3.326345	93.28734	1.349070	1.884146	0.153101
6	0.023338	3.230044	91.77091	2.678610	2.187871	0.132562
7	0.025710	3.297850	90.41617	3.873640	2.282502	0.129837
8	0.028164	3.492880	89.29843	4.793529	2.284276	0.130881
9	0.030668	3.716783	88.61784	5.289023	2.241899	0.134451
10	0.033191	3.923611	88.29352	5.447645	2.203083	0.132143
Variance Decomposition of LGFCF PC						
Period	**S.E.**	**TO**	**LGDP PC**	**LGFCF PC**	**POP**	**ER**
1	0.041044	0.137736	15.64885	84.21342	0.000000	0.000000
2	0.057601	0.521677	8.374745	74.96429	5.313416	10.82587
3	0.074851	0.317865	5.088044	72.86892	8.022054	13.70312
4	0.089046	0.234946	3.837812	64.81904	12.25989	18.84831
5	0.100984	0.241116	3.443341	57.78825	15.99271	22.53459
6	0.111622	0.558814	3.418171	50.39200	19.63870	25.99232
7	0.121556	1.354121	3.266426	43.89536	22.78673	28.69737
8	0.131708	2.769541	2.924906	38.07200	25.41590	30.81766
9	0.142657	4.688336	2.497648	32.97047	27.49072	32.35283
10	0.155070	6.865274	2.170043	28.48956	29.06219	33.41293
Variance Decomposition of POP						
Period	**S.E.**	**TO**	**LGDP PC**	**LGFCF PC**	**POP**	**ER**
1	0.001005	9.185721	12.65704	8.724075	69.43317	0.000000
2	0.002365	11.19529	20.06271	16.58554	50.60789	1.548563
3	0.004146	13.19110	28.66710	19.59993	35.69378	2.848098
4	0.006104	14.76074	36.60077	18.42008	26.89684	3.321570
5	0.008116	16.00537	43.46912	15.29565	21.66931	3.560551
6	0.010128	16.76040	49.09574	11.74025	18.57475	3.828857
7	0.012138	16.97815	53.29111	8.655308	16.83350	4.241941
8	0.014159	16.74667	56.01270	6.389519	16.01218	4.838937
9	0.016211	16.23329	57.39477	4.906697	15.84808	5.617156
10	0.018309	15.60949	57.69701	3.992439	16.15671	6.544357
Variance Decomposition of ER:						
Period	**S.E.**	**TO**	**LGDP PC**	**LGFCF PC**	**POP**	**ER**
1	0.015501	0.020642	19.77943	6.391201	8.378120	65.43060
2	0.031683	0.016487	6.172932	63.16274	3.316251	27.33159
3	0.048871	0.087304	8.361030	60.89891	5.575426	25.07733
4	0.065733	0.050928	10.09025	58.66229	7.635323	23.56121
5	0.081087	0.065981	12.55041	52.06982	10.45591	24.85787
6	0.094693	0.160545	14.37983	45.81647	13.14505	26.49811
7	0.107054	0.483038	15.55478	39.85288	15.71971	28.38960
8	0.118590	1.137732	15.85813	34.80147	18.04047	30.16220
9	0.129935	2.186456	15.35160	30.55917	20.12381	31.77896
10	0.141646	3.564492	14.18963	27.06965	21.98251	33.19372

Sources: Estimates based on World bank data,2018

Table 4.8.1(b):Variance Decomposition Analysis of Trade openness-China

Variance Decomposition of TO						
Period	S.E.	TO	LGDP PC	LGFCF PC	POP	ER
1	0.049339	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.073730	94.75621	0.511420	4.291102	0.215849	0.225419
3	0.084898	87.26320	1.188316	10.24083	1.126204	0.181443
4	0.090602	81.46193	1.301978	14.61983	2.380244	0.236019
5	0.094471	77.69475	1.201942	17.24361	3.553066	0.306639
6	0.097807	75.13078	1.154637	18.84079	4.582653	0.291136
7	0.101016	73.06767	1.165348	19.93298	5.532789	0.301207
8	0.104201	71.16433	1.221258	20.84033	6.397533	0.376549
9	0.107457	69.31530	1.328354	21.78225	7.092046	0.482052
10	0.110920	67.47955	1.485220	22.90603	7.534791	0.594408
Variance Decomposition of LGDP PC						
Period	S.E.	TO	LGDP PC	LGFCF PC	POP	ER
1	0.012562	12.35874	87.64126	0.000000	0.000000	0.000000
2	0.019648	16.23798	81.17842	0.173999	0.024135	2.385469
3	0.025491	18.12839	77.96141	0.304899	0.387361	3.217945
4	0.030243	19.93198	75.15954	0.431099	1.584181	2.893201
5	0.034298	21.83704	71.81955	0.699345	3.260387	2.383683
6	0.037910	23.43293	68.26071	1.179384	5.142613	1.984367
7	0.041202	24.57991	64.77397	1.804728	7.137452	1.703940
8	0.044266	25.44777	61.36030	2.473607	9.201731	1.516588
9	0.047199	26.25188	57.91947	3.159050	11.26340	1.406203
10	0.050091	27.12057	54.39165	3.911661	13.21626	1.359852
Variance Decomposition of LGFCF PC						
Period	S.E.	TO	LGDP PC	LGFCF PC	POP	ER
1	0.037930	0.795755	26.03345	73.17079	0.000000	0.000000
2	0.056826	0.370366	21.57597	77.71387	0.159485	0.180311
3	0.070481	1.769661	20.98062	75.94494	1.089431	0.215346
4	0.083172	7.083617	19.58355	70.39306	1.899399	1.040374
5	0.095887	13.78154	17.64232	64.52161	2.130791	1.923743
6	0.108171	19.29010	16.05389	60.36668	2.044511	2.244815
7	0.119864	23.03047	15.02355	57.91125	1.882685	2.152043
8	0.130984	25.31314	14.45992	56.56279	1.734239	1.929903
9	0.141466	26.62865	14.24616	55.79344	1.615147	1.716603
10	0.151219	27.38529	14.29824	55.25157	1.518055	1.546851
Variance Decomposition of POP						
Period	S.E.	TO	LGDP PC	LGFCF PC	POP	ER
1	0.019541	10.59270	5.229576	7.898049	76.27967	0.000000
2	0.034426	15.60521	1.757010	18.96366	62.76414	0.909985
3	0.044966	16.10874	1.321151	24.62580	56.61845	1.325854
4	0.051871	17.16890	1.335910	26.75492	53.49723	1.243030
5	0.056553	19.20998	1.278286	27.28085	51.17227	1.058612
6	0.059758	21.31249	1.183378	27.31533	49.21185	0.976955
7	0.061724	22.67487	1.109863	27.29423	47.86844	1.052596
8	0.062713	23.20102	1.095497	27.24178	47.18766	1.274039
9	0.063120	23.20667	1.177301	27.10504	46.92186	1.589125
10	0.063335	23.04979	1.378634	26.92152	46.72405	1.926009
Variance Decomposition of ER:						
Period	S.E.	TO	LGDP PC	LGFCF PC	POP	ER
1	0.035344	2.363589	0.785973	9.807976	7.378099	79.66436
2	0.048425	4.336282	1.188312	11.55420	4.496117	78.42509
3	0.057610	13.52971	1.118209	15.70728	3.382882	66.26192
4	0.070605	26.83766	0.784428	23.01041	2.633992	46.73350
5	0.087149	34.81850	0.538198	30.98441	2.187348	31.47155
6	0.104112	38.18043	0.396236	37.11925	1.863307	22.44078
7	0.119912	40.04460	0.302577	40.91564	1.554482	17.18270
8	0.134354	41.66301	0.244085	42.93175	1.268457	13.89270
9	0.147631	43.13291	0.235822	43.91645	1.051275	11.66354
10	0.159888	44.26925	0.296322	44.44247	0.932962	10.05899

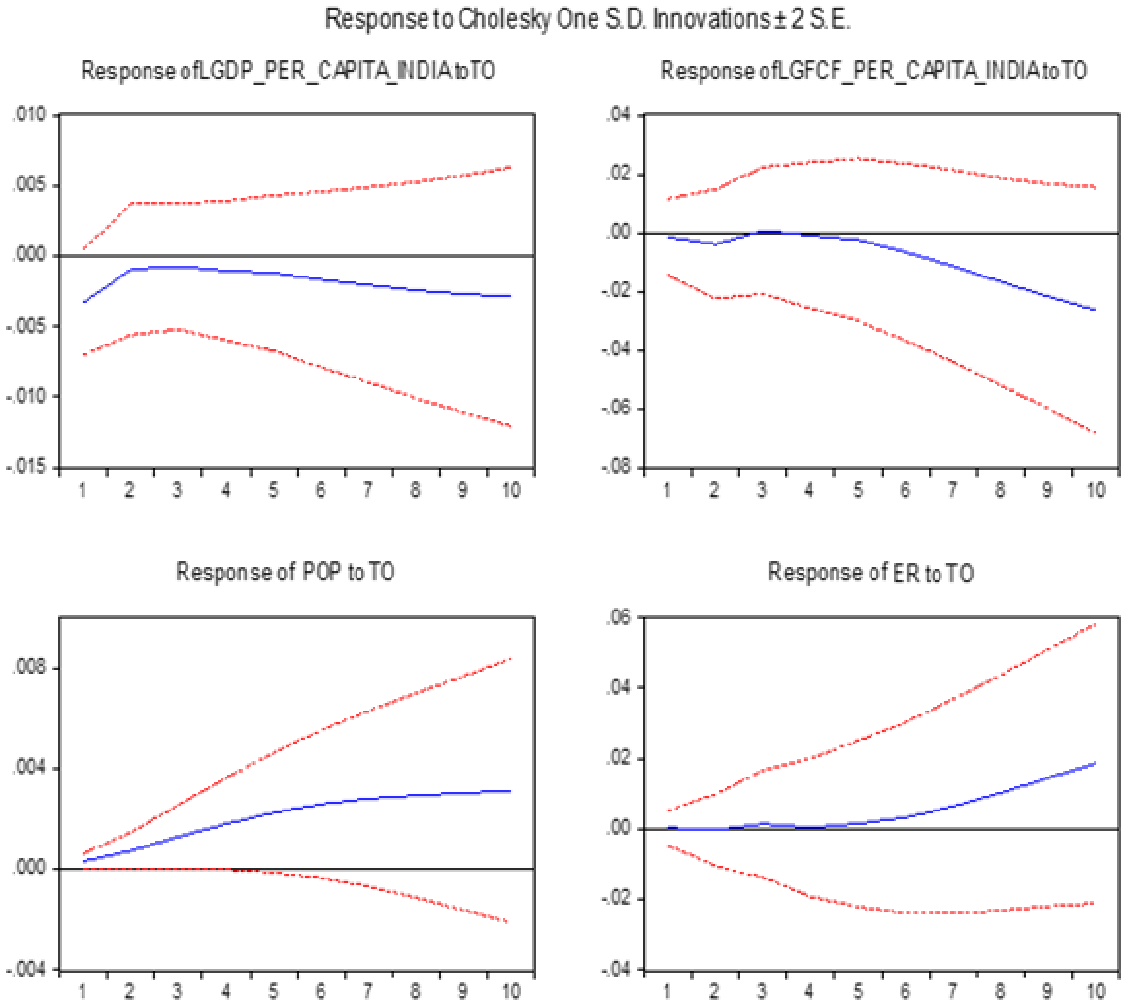
Sources: Estimates based on World bank data,2018

4.9 Impulse Response Function

The effect of innovations in all variables in the system on trade openness can be investigated using impulse response analysis. The figures 4.13 (a) and 4.13 (b) show the Impulse response function of the variables for India and China. The blue line is the impulse response function and redline shows the 95 percent confident intervals in the figure.

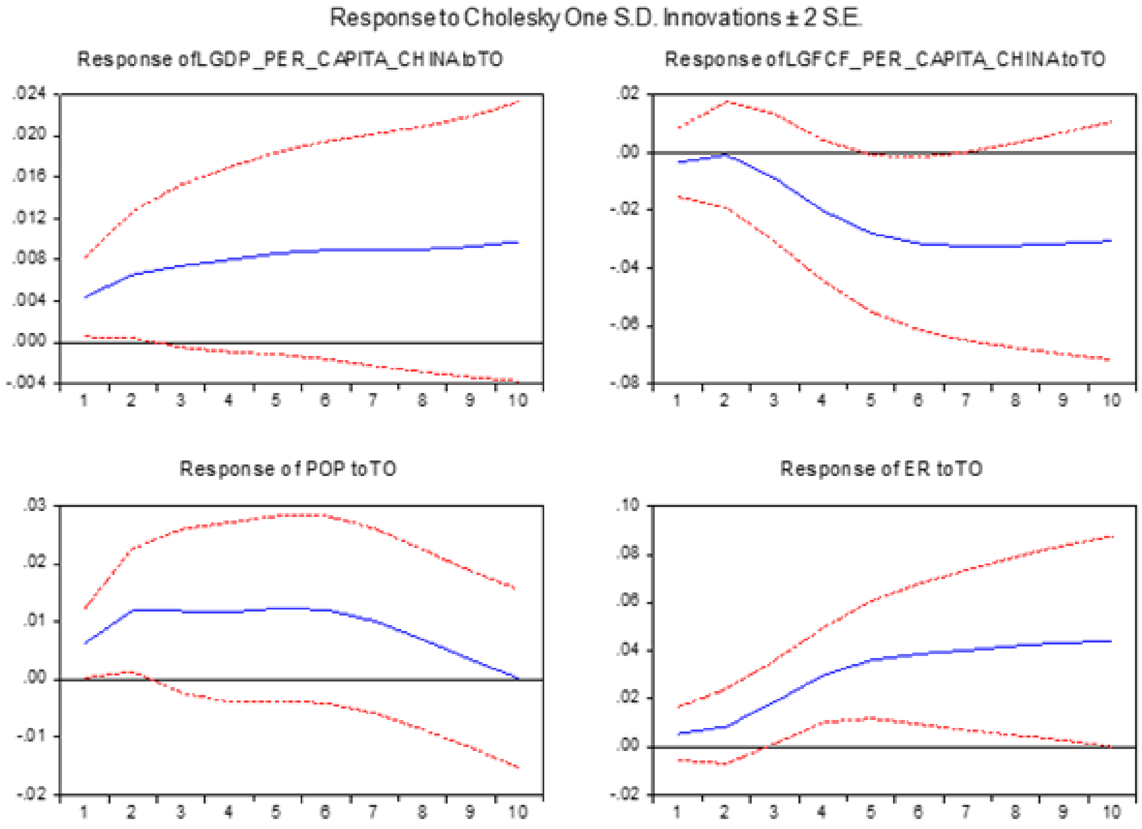
The IRF of GDP per capita is negative both in the short run and long run for India. For China the response is positive both in the short run and long run. The GFCF per capita is negative both in the short run and long run for India and China. The population variable is positive throughout the period in both India and China. The response of exchange rate (ER) is stable initially and stays in the positive region in the long run for India. For China the exchange rate response was positive in both short run and long run.

It can be inferred that a standard deviation shock on trade openness will cause a positive impact on population and exchange rate in India. The innovation given to trade openness will cause a negative impact on GDP per capita and GFCF per capita. For China, an SD shock on trade openness will cause positive impact on GDP per capita, population ad exchange rate and a negative impact on GFCF per capita.



Source: Computed based on World Bank data

Figure 4.11(a): Impulse Response Function of Trade Openness - India

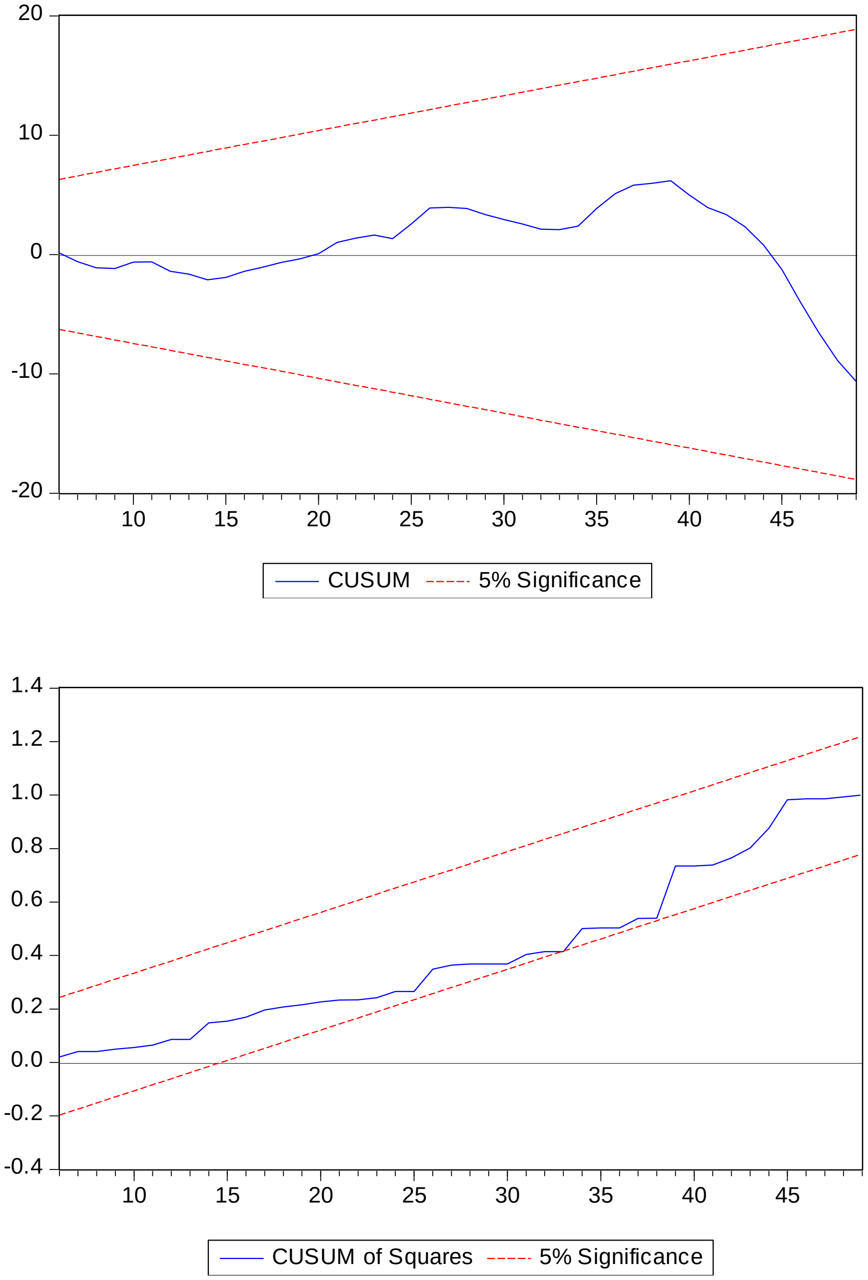


Source: Computed based on World Bank data,2018

Figure 4.11(b): Impulse Response Function of Trade Openness- China

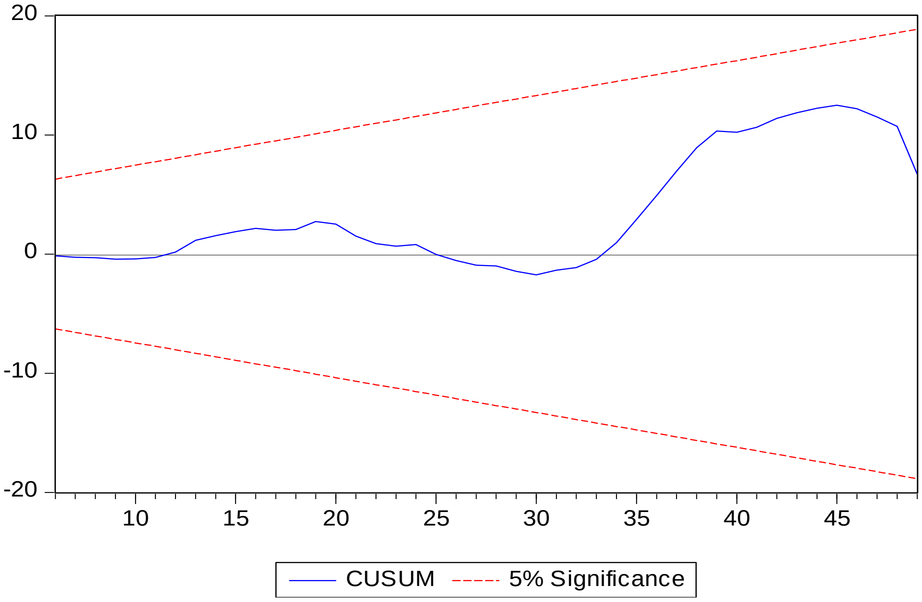
4.10. Test of Stability

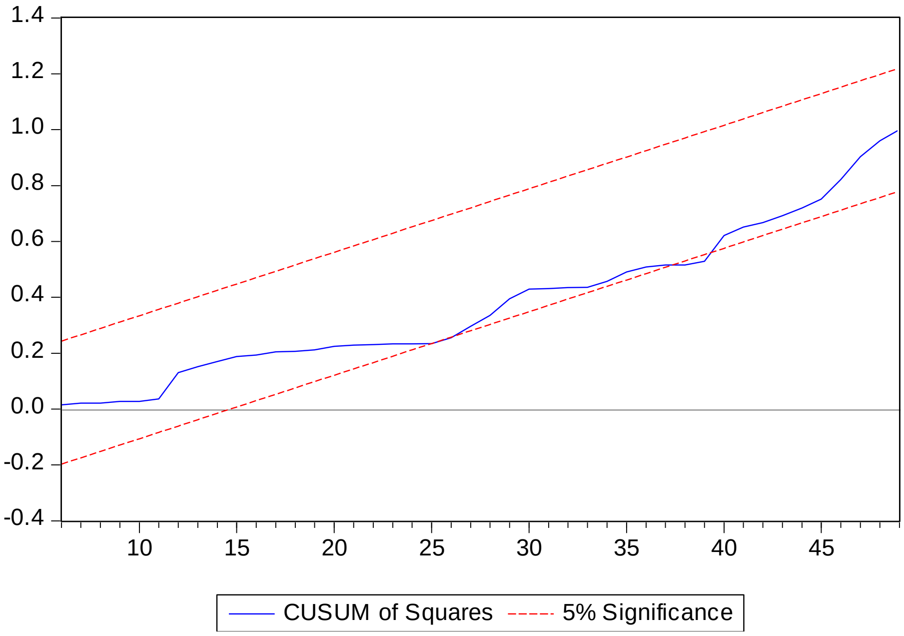
CUSUM AND CUSUM square plot was performed to test the stability of the trade opennessmodel. The residuals from the error correction model were used to create CUSUM and CUSUM square plot.



Source: World bank data,2018

Figure 4.12(a): CUSUM Test and CUSUM Square Test of Trade openness-India





Source: World bank data,2018

Figure 4.12(b): CUSUM Test and CUSUM Square Test of Trade openness - China

The CUSUM and CUSUMSQ plot of the residuals generated from the vector error correction model for trade openness was used to test its stability and the results revealed that the CUSUM plot and CUSUM square plot for trade openness was within the 5 percent critical bound levels, indicating that the trade openness was found to be stable throughout the study period for both India and China.

To conclude

- **Using the "Intercept" and "Trend and Intercept" criteria the results indicated that all the variables used in the model such as trade openness, GDP per capita, GFCF per capita, exchange rate and population became stationary only in their first differences for both India and China.**
- **The trace statistic was found to be greater than the critical value for 1 and 2 cointegrating equations respectively for India and China. The Eigen values also were greater than the critical value for 1 cointegrating equation for both India and China thus establishing long run relationship between the variables in the model**
- **The error correction coefficient for trade openness as dependent variable for India and China was negative as in the principle indicating that the series for trade openness will converge in the long run**
- **In the short run for India and China 100 percent variance in trade openness is explained by the variable trade openness itself meaning strongly endogenous. In the long run 50 percent of the variation is explained by trade openness itself and 24 percent by GDP per capita. For China, in the long run 67 percent of the variation in trade openness is explained by the variable itself and 23 percent by GFCF per capita.**
- **As per the impulse response analysis a standard deviation shock on trade openness will cause a positive impact on population and exchange rate in India in the long run. The innovation given to trade openness will cause a negative impact on GDP per capita and GFCF per capita. For China, an SD shock on trade openness will cause positive impact on GDP per capita, population and exchange rate and a negative impact on GFCF per capita.**
- **The CUSUM plot and CUSUM square plot for trade openness was within the 5 percent critical bound levels, indicating that the trade openness was found to be stable throughout the study period for both India and China.**

4.11. Long run relationship between Greenhouse Gas Emissions and its determinants (Gross domestic product per capita, Gross domestic product per capita square, Energy consumption and Trade openness) using cointegration analysis

4.11.1 The ADF unit root test of stationarity

The stationarity of the variables included in the model pertaining to long run relationship between GHG per capita and its determinants were based on unit root test.

For this the following null hypotheses was tested.

H_0: The chosen variables GDP per capita, GDP per capita square, GHG emissions per capita, energy consumption per capita and trade openness are not stationary.

H_a: The chosen variables GDP per capita, GDP per capita square, GHG emissions per capita, energy consumption per capita and trade openness are stationary.

Table 4.11.1(a) shows the ADF statistics based on Intercept. Using the Intercept criteria, the results indicated that all the variables such as GDP per capita, GDP per capita square, GHG emissions per capita, energy consumption per capita and trade openness became stationary only in their first differences for India and China and became significant at five percent levels.

Table 4.11.1(a): Unit Root Test Results based on ADF Statistic using Intercept

Country	Order of difference	ADF t-statistic	Critical Values (5 % level)	p-value	H0	Order of Integration
LGDP PC						
India	Level	4.3086	-2.9237	1	Accept	I(1)
	First Difference	-5.7051	-2.9251	0	Reject	
China	Level	0.3225	-2.9266	0.9771	Accept	I(1)
	First Difference	-3.2281	-2.9266	0.0246	Reject	
LGDP PC^2						
India	Level	5.3848	-2.92378	1	Accept	I(1)
	First Difference	-5.00112	-2.92517	0.0001	Reject	
China	Level	1.060202	-2.92662	0.9966	Accept	I(1)
	First Difference	-2.76982	-2.92662	0.0405	Reject	
LGHGPC						
India	Level	1.1228	-2.9237	0.9972	Accept	I(1)
	First Difference	-6.771	-2.9251	0	Reject	
China	Level	-0.1551	-2.9251	0.9368	Accept	I(1)
	First Difference	-10.1367	-2.9251	0	Reject	
LEN PC						
India	Level	3.7886	-2.9237	1	Accept	I(1)
	First Difference	-5.1404	-2.9251	0.0001	Reject	
China	First	-1.2526	-2.9251	0.9981	Accept	I(1)
	Difference	-4.3629	-2.9251	0.0011	Reject	
TO						
India	Level	-0.6807	-2.9571	0.8376	Accept	I(1)
	First Difference	-3.9604	-2.9604	0.0048	Reject	
China	Level	-2.9028	-2.9237	0.0524	Accept	I(1)
	First Difference	-4.943	-2.9251	0.0002	Reject	

Source: Computed based on World Bank data,2018

ADF test based on “trend and intercept “was also performed and the results are given in table 4.11.1(b). The results of the unit root with trend and intercept pointed out clearly that the null hypothesis of a unit root can be rejected at the first difference for all variables such as GDP per capita, GDP per capita square, GHG emissions per capita, energy consumption per capita and trade openness meaning that all the variables were found to be stationary only at their first differences for India and China.

Table 4.11.1(b):Unit Root Test Results based on ADF Statistic using Trend and Intercept

Country	Order of difference	ADF t-statistic	Critical Values (5 % level)	p-value	H0	Order of Integration
LGDP PC						
India	Level	-1.6689	-3.5063	0.7496	Accept	I(1)
	First Difference	-8.3447	-3.5085	0	Reject	
China	Level	-3.1264	-3.5107	0.1125	Accept	I(1)
	First Difference	-3.6579	-3.5085	0.0355	Reject	
LGDP PC^2						
India	Level	-0.98357	-3.50637	0.9367	Accept	I(1)
	First Difference	-8.27028	-3.50851	0	Reject	
China	Level	-2.68959	-3.51074	0.2455	Accept	I(1)
	First	-3.04969	-3.51074	0.0305	Reject	
LGHG PC						
India	Level	-2.1813	-3.5063	0.4887	Accept	I(1)
	First Difference	-6.9048	-3.5085	0	Reject	
China	Level	0.3432	3.5085	0.4325	Accept	I(1)
	First Difference	-3.5074	-3.5063	0.0499	Reject	
LENPC						
India	Level	-0.12	-3.5063	0.9931	Accept	I(1)
	First Difference	-6.9287	-3.5085	0	Reject	
China	First	-1.3573	-3.5085	0.8605	Accept	I(1)
	Difference	-4.746	-3.508	0.0002	Reject	
TO						
India	Level	-1.5772	-3.5577	0.7797	Accept	I(1)
	First Difference	-3.8923	-3.5628	0.0246	Reject	
China	Level	-0.9641	-3.5063	0.9394	Accept	I(1)
	First Difference	-5.6505	-3.5085	0.0001	Reject	

Source: Computed based on World Bank data,2018

4.11.2Johansen Cointegration Test for GHG emissions per capita and its determinants

Akaike Information criterion (AIC) was used to choose the lag length and this study used the lag of 1 for India and 2 for China for the testing the cointegration in the GHG emissions per capita and its determinants model. The model of the GHG emissions per capita in India and China is tested for presence of cointegration among the variables using the following hypothesis.

Hypothesis for the test of cointegration

Null Hypothesis (H_0): The determinants of GHG do not exhibit long term relationship.

Alternate Hypothesis (Ha): The determinants of GHG exhibits long term relationship.

Table 4.11.2(a): Unrestricted Cointegration Rank Test (Trace)-India

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	Prob.**
None *	0.638875	110.7498	69.8188	0
At most 1*	0.549277	70.00859	47.85613	0.0001
At most 2*	0.473865	38.13249	29.79707	0.0044
At most 3	0.248316	12.44461	15.49471	0.1368
At most 4	0.02535	1.027057	3.841466	0.3109

Source: Estimates from Secondary data
Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
***denotes rejection of the hypothesis at the 0.05 level**
****Mackinnon-Haug-Michelis(1999) p-values**

Table 4.11.2(b): Unrestricted Cointegration Rank Test (Trace)- China

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.598865	97.83854	69.81889	0.0001
At most 1 *	0.472985	61.30022	47.85613	0.0017
At most 2 *	0.466515	35.67916	29.79707	0.0094
At most 3	0.206326	10.54618	15.49471	0.241
At most 4	0.032048	1.302891	3.84146	0.2537

Source: Estimates from Secondary data
Trace test indicates 3 cointegrating eqns at the 0.05 level
***denotes rejection of the hypothesis at the 0.05 level**
**** MacKinnon-Haug-Michelis(1999)p-values**

The trace statistic for GHG per capita and the dependent variables such as GDP per capita, GDP per capita square, energy consumption per capita and trade openness can be seen in the above table 4.11.2(a) and 4.11.2(b). The trace statistic was found to be greater than the critical value at most 2 cointegrating equations for both India and China. Hence the null hypothesis that the determinants of GHG per capita do not show signs of long term relationship is rejected and it is concluded that the determinants of GHG per capita exhibited long term association with atleast 3 cointegrating equations for both India and China.

Table 4.11.2(c): Unrestricted Cointegration Rank Test (Maximum Eigenvalue)-India

Hypothesized No. of CE(s)	Eigenvalue	Maximum Eigen Statistic	Critical Value	Prob.**
None *	0.638875	40.74119	33.87687	0.0065
At most 1*	0.549277	31.8761	27.58434	0.0132
At most 2*	0.473865	25.68788	21.13162	0.0106
At most 3	0.248316	11.41755	14.2646	0.1345
At most 4	0.02535	1.027057	3.84114	0.3109

Source: Estimates from Secondary data
Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

Table 4.11.2 (d): Unrestricted Cointegration Rank Test (Maximum Eigenvalue)-China

Hypothesized No. of CE(s)	Eigenvalue	Maximum Eigen Statistic	Critical Value	Prob.**
None *	0.598865	36.53831	33.87687	0.0235
At most 1	0.472985	25.62106	27.58434	0.0873
At most 2	0.466515	25.13298	21.13162	0.0129
At most 3	0.206326	9.243288	14.2646	0.2665
At most 4	0.032048	1.302891	3.841466	0.2537

Source: Estimates from Secondary data
Max-Eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
*** denotes rejection of the hypothesis at the 0.05 level**
****MacKinnon-Haug-Michelis (1999) p-values**

The Johansen method estimated the statistic Maximum Eigen value for the variables of the study presented in the above table 4.11.2(c) and 4.11.2(d)showed that the Eigen statistic values were greater than the critical values at atmost 2 for India and None for China. Therefore the null hypothesis that the determinants of GHG emissions per capita do not exhibit long term relationship is rejected and it can be concluded that the variables of the model have a long run equilibrium relationship, with the presence of atleast 3 cointegrating equations for India and 1 for China. The Johansen cointegration test results using the trace statistic and Max-Eigen value statistic showed that the series are associated and combined in a linear manner which implies that even if there are shocks in the short run influencing movement in the individual series, they would converge with time in the long run. It can be concluded that variables of the model showed a common trend and move together in the long run. The presence of long run relationship is in agreement with Ozturk and Uddin (2012), Ali et al(2017), Iskandar (2019),Jain et al. (2019).

4.11.3 Estimation of long run GHG emissions function using the Normalized Cointegrating Coefficients

It is important to understand the nature of relationship among the variables once the presence of long run relationship is confirmed and hence the normalized cointegrating coefficients of independent variables of the model for GHG emissions per capita derived from Johansen cointegration procedure for India and China are given in the table 4.11.3(a) and 4.11.3(b).

Table 4.11.3(a): Normalized Cointegrating Coefficients from the Cointegration equation-India

Variables	Co-efficients	Standard Errors
LGDP pc	-0.18226	0.00295
LGDP2 pc^2	-0.30028	0.03443
LEN pc	0.403208	0.03513
TO	3.92E-05	0.000099

Source: Estimates from secondary data

Table 4.11.3(b): Normalized Cointegrating Coefficients from the Cointegration equation-China

Variables	Co-efficients	Standard Errors
LGDP pc	-1.03477	0.40008
LGDP pc^2	0.000153	0.00074
LEN pc	-0.79751	0.41693
TO	-0.00585	0.0018

Source: Estimates from secondary data

The normalized cointegration coefficients obtained from the cointegrating equation present the long run GHG Emissions as a function of the determinants .

For India LGHG = 0.18226LGDP + 0.30028LGDP^2 - 0.40320LEN - 0.0000392TO

For China LGHG = 1.034770LGDP- 0.000153LGDP^2 + 0.797506LEN + 0.005850TO

Due to normalization process, the signs are reversed to enable proper interpretation(Skerman et al,2009).According to the EKC hypothesis, the sign of coefficient of GDP per capita is supposed to be positive and that of squared GDP per capita should be negative. The study found that for China, the effects of GDP per capita and GDP per capita square on greenhouse gas emissions per capita are positive and negative respectively thus confirming the inverted U shape for the study period in accordance with EKC theory and empirical research by Jalil and Mahmu (2009), Halkos, G. and Tzeremes(2011), Xu et al. (2018), Hao et al. (2019). But for India there is no evidence of such a relationship between greenhouse gas emissions per capita and gross domestic product similar to the results of Makarrabbi et al. (2017).

GHG emissions per capita is the target variable. The coefficients obtained from cointegration revealed that GDP per capita and GDP per capita square have positive impact on the GHG emissions per capita in India and GDP per capita. Energy consumption per capita and trade openness have positive impact for China in the long run. It denotes that an increase in the values of the above variables will lead to increase in greenhouse gas emissions.

Energy consumption per capita and trade openness have a negative effect on GHG Emissions per capita for India and for China. GDP per capita square has negative effect on GHG emissions per capita.

The coefficients obtained from the cointegration equation is adequate to explain the fact that GHG emissions per capita during the study period for India is impacted by GDP per capita, GDP per capita square, energy consumption per capita and trade openness.(Osiobe 2019, Yazdi and Dariani 2019, Tong et al., 2020, Khan et al., 2020).The impacts of these variables stress that both India and China must devise more stringent measures to bring about a balance between their need for economic development and environment sustainability by switching over to energy efficient methods(Ozturk and Uddin,2012). China being known as world factory produces on a large scale and exports. High pollution in China is due to its free trade policies. Ignoring environmental laws may prove detrimental for China as well as the world.

4.11.4 Estimation of Short run GHG emissions per capita using Vector Error Correction Model (VECM)

The results of the cointegration test performed in the study showed that all variables of the model exhibit a cointegrating relationship and Johansen's cointegration equation gives the long run relationship for GHG emissions per capita and its determinants. After estimating the error correction term in the cointegration process, the next step is to build the VECM to examine the short run dynamics and the adjustments in the long run for GHG emissions per capita. VECM describes how the examined model is adjusting in each time period towards its long-run equilibrium state. The dynamic specification of the VECM allows the deletion of the insignificant variables, while the error correction term is retained (Mishra and Pradhan, 2011).

Following the procedure, the dynamic error correction equation of GHG emissions per capita can be specified as:

$$\Delta LGHGpc_{it} = \beta_{0it} + \Sigma\ \beta_{1i}\Delta LGHGpc_{it-1} + \Sigma\ \beta_{2i}\Delta LGDPpc_{it-1} + \Sigma\ \beta_{3i}\Delta LGDPpc^{2}_{it-1} + \Sigma\beta_{4i}\Delta LENpc_{it-1} + \Sigma\beta_{5i}\Delta TO_{it-1} + \varepsilon t$$

where Δ indicates the coefficient of the error correction terms and gives the direction of equilibrium in the model and εt denotes the noise error term. The error correction term gained in the long run equation of the cointegration process is used as one of the determinants of the VECM function. The coefficients of the VECM model point out the speed of adjustments shown by the respective variables in the short run and are given in the table 4.11.4(a) and 4.11.4(b).The estimates obtained specify the change in the GHG Emissions per capita in response to changes in the dependent variables of the model given in their lag forms and the disturbance term of the lag forms. The speed of adjustment is determined by the error correction coefficient within which the model will return to its equilibrium after any disturbances. The coefficient must have a negative sign by rule signifying the ability to spring back to equilibrium. The positive sign specify movement away from equilibrium and depend on the nature of the variables and the system. The best value of the VECM coefficients lies between 0 and 1, but not more than 2.

From the results obtained in VECM, it was found that the error correction coefficient for GHG Emissions per capita as dependent variable for India was negative (-0.4860) as in the theory indicating that the series for GHG emissions per capita will converge in the long run. The variable one year lagged trade openness is associated with 0.001 percent increase in GHG emissions per capita in India and is statistically significant at 5 percent level.

For China it was found that the error correction coefficient for GHG emissions per capita was negative (-0.2917) as in the principle indicating that the series for GHG emissions per capita will converge in the long run. The adjustment coefficient which corrects the previous period deviation and the magnitude shows that GHG emissions per capita will adjust for about 0.29 percent of its total deviations from the long run equilibrium during the short run. A percent change in two year lagged GHG per capita by itself will lead to 0.30 percent decrease in GHG emissions per capita and is statistically significant at 10 percent level.

The estimated error correction model enjoys the minimum goodness of fit with R^2 value being 0.48 and adjusted R^2 of 0.39 for India. The R^2 indicated that for India 48 percentage of variations in the dependent variable was accounted for by the variations in the explanatory variables used in the model. For China, the R^2 was 0.65 and adjusted $R^2$was 0.51 which indicated that 65 percent of variations in the dependent variable were accounted for by the variations in the explanatory variables used in the model.

The results revealed that overall model was statistically significant at 1 percent level revealed by the F-statistic value of 5.125 for India and 4.67 for China. It confirms the fact that all the explanatory variables together explained the variations in the GHG emissions per capita during the study period for both India and China

The Breusch-Godfrey Serial Correlation LM Test was performed on the VECM residuals and the LM Statistic pointed out that there was absence of autocorrelation.

Residual Heteroscedasticity Breusch-Pagan-Godfrey Test was conducted to test the heteroscedasticity. The null hypothesis was that the residuals were heteroscedastic. It showed that the error correction model is free from the problem of heteroscedasticity, validating that the model estimated could be relied upon for making inferences on the impact of selected variables on GHG emissions per capita.

Table 4.11.4(a): Estimated coefficients of the VECM- India

Error Correction:	D(LGHG)	D(LGDP PC)	D(SGDP PC)	D(LEN PC)	D(TO)
CointEq1	-0.486067	-1.753245	-1.390799.	0.921787	46.47048
	(0.37920)	(0.64733)	(1715142)	(0.26895)	(99.0636)
	[-1.28183]	[-2.70843]	[-0.81089]	[3.42738]	[0.46910]
D(LGHG_INDIA(-1))	-0.114344	0.902677	697567.6	-0.346438	-13.27675
	(0.25007)	(0.42690)	(1131098)	(0.17737)	(65.3302)
	[-0.45724]	[2.11450]	[0.61672]	[-1.95324]	[-0.20323]
D(LGDP_PC_INDIA(-1))	0.065991	-0.421021	188923.4	0.049588	-89.61855
	(0.13631)	(0.23270)	(616553.)	(0.09668)	(35.6110)
	[0.48412]	[-1.80929]	[0.30642]	[0.51291]	[-2.51660]
D(SGDP_PC_INDIA(-1))	-3.47E-02	4.26E-09	-0.526135	-6.82E-08	8.62E-05
	(6.8E-02)	(1.2E-07)	(0.30849)	(4.8E-08)	(1.8E-05)
	[-0.5102]	[0.03660]	[-1.70552]	[-1.40928]	[4.83637]
D(LEN_ PC_INDIA(-1))	-0.390528	-0.888087	461149.2	0.168905	-68.87238
	(0.32357)	(0.55237)	(1463534)	(0.22949)	(84.5312)
	[-1.20693]	[-1.60778]	[0.31509]	[0.73599]	[-0.81476]
D(TO_INDIA(-1))	0.001085	-0.000378	-1459.979	0.000452	-0.293080
	(0.00052)	(0.00089)	(2359.16)	(0.00037)	(0.13626)
	[2.08079]	[-0.42453]	[-0.61886]	[1.22118]	[-2.15087]
C	0.000608	0.000720	6231.160	0.000783	-0.217512
	(0.00134)	(0.00228)	(6049.84)	(0.00095)	(0.34943)
	[0.45461]	[0.31547]	[1.02997]	[0.82513]	[-0.62248]
R-squared	0.482394				
Adj. R-squared	0.388283				
F-statistic	5.125835				
Akaike AIC	-6.601085				
Schwarz SC	-6.305532				

Source: Estimates based on World Bank data, 2018
Figures in ( ) are standard error values; figures in [ ] are the "t" statistics
***Denotes significant at 1 percent level**

Table 4.11.4(b): Estimated coefficients of the VECM- China

Error Correction:	D(LGHG)	D(LGDP PC)	D(SGDP PC)	D(LEN PC)	D(TO)
CointEq1	-0.291787	-0.003010	2291319.	0.053965	3.314236
	(0.15414)	(0.03215)	(347690.)	(0.03258)	(7.92523)
	[-1.89305]	[-0.09364]	[6.59013]	[1.65662]	[0.41819]
D(LGHG_CHINA(-1))	-0.726023	0.071908	-1696298.	-0.021669	18.07651
	(0.20829)	(0.04344)	(469849.)	(0.04402)	(10.7097)
	[-3.48561]	[1.65526]	[-3.61030]	[-0.49224]	[1.68786]
D(LGHG_CHINA(-2))	-0.303130	0.062878	-735015.1	-0.066274	8.096785
	(0.18941)	(0.03950)	(427262.)	(0.04003)	(9.73899)
	[-1.60038]	[1.59165]	[-1.72029]	[-1.65557]	[0.83138]
D(LGDP_PC_CHINA(-1))	-0.790971	-0.399127	3428997.	-0.194111	-26.34887
	(0.98787)	(0.20603)	(2228365)	(0.20878)	(50.7933)
	[-1.81296]	[-1.93718]	[1.53880]	[-0.92974]	[-0.51875]
D(LGDP_PC_CHINA(-2))	-0.246860	-0.034555	2111928.	0.192927	-12.69265
	(0.96971)	(0.20225)	(2187401)	(0.20494)	(49.8596)
	[-0.25457]	[-0.17086]	[0.96550]	[0.94138]	[-0.25457]
D(SGDP_PC_CHINA(-1))	0.000000143	3.92E-09	-0.781081	-3.16E-08	4.10E-06
	(9.0E-08)	(1.9E-08)	(0.20213)	(1.9E-08)	(4.6E-06)
	[1.59466]	[0.20987]	[-3.86422]	[-1.66839]	[0.88939]
D(SGDP_PC_CHINA(-2))	0.000000145	-1.21E-08	-1.191804	-4.39E-08	-1.28E-05
	(9.3E-08)	(1.9E-08)	(0.20952)	(2.0E-08)	(4.8E-06)
	[1.55840]	[-0.62613]	[-5.68826]	[-2.23870]	[-2.68348]
D(LEN _PC(-1))	0.396020	-0.166114	-1518563.	-0.217878	-12.12258
	(0.86997)	(0.18144)	(1962408)	(0.18386)	(44.7311)
	[0.4552]	[-0.91551]	[-0.77383]	[-1.18502]	[-0.27101]
D(LEN_PC(-2))	-0.198242	0.016099	-1056988.	-0.189254	-46.30179
	(0.81809)	(0.17062)	(1845378)	(0.17290)	(42.0635)
	[-0.24232]	[0.09436]	[-0.57278]	[-1.09461]	[-1.10076]
D(TO(-1))	0.000846	7.01E-05	-37587.47	-0.000111	-0.418248
	(0.00343)	(0.00072)	(7738.03)	(0.00072)	(0.17638)
	[0.24658]	[0.09796]	[-4.85750]	[-0.15321]	[-2.37128]
D(TO(-2))	0.001610	-4.64E-05	-38264.90	0.000211	-0.079559
	(0.00333)	(0.00069)	(7506.40)	(0.00070)	(0.17110)
	[0.48384]	[-0.06680]	[-5.09764]	[0.30055]	[-0.46499]
C	-0.026475	0.001328	287229.6	0.007571	0.695533
	(0.01910)	(0.00398)	(43083.8)	(0.00404)	(0.98205)
	[-1.38616]	[0.33336]	[6.66677]	[1.87553]	[0.70825]
R-squared	0.655313	0.304438	0.687706	0.421470	0.585154
Adj. R-squared	0.514885	0.021061	0.560475	0.185772	0.416142
F-statistic	4.666533	1.074321	5.405179	1.788181	3.462210
Akaike AIC	-2.210347	-5.345358	27.04762	-5.318899	5.669591
Schwarz SC	-1.698482	-4.833493	27.55948	-4.807034	6.181456

Source: Estimates based on secondary data
Figures in ( ) are standard error values; figures in [ ] are the "t" statistics
***Denotes significant at 1 percent level**

4.12 Variance Decomposition Analysis

Variance decomposition model of the forecast error helps to obtain the percentage of unexpected variation in each variable that is caused by shocks from other variables. It indicates the relative impact that a variable has on another. The variance decomposition enables evaluation of economic significance of this impact as a percentage of the forecast error for a variable sum to one.

The table 4.12.1(a) shows the variance decomposition results for model GHG emissions per capita and its determinants for India. Over a period of 10years, the forecast error variance for a particular period is 100. In the short run 100 percent of forecast error variance GHG emissions per capita is explained by the variable (GHG emissions per capita) itself meaning strongly endogenous. The remaining variables do not have any influence implying strongly exogenous. From second period onwards, GDP per capita square (30.75 percent) has influence on GHG emissions per capita both in the short run and in the long run. Variance contribution of GHG per capita on itself is 57.3 percent; the variance contribution of GDP per capita is only about 9.18 percent showing weak influence on GHG pc in the long run. Variance contribution of energy consumption per capita and trade openness (TO) is 0.58 percent and 2.18 percent respectively which is very meagre. In the long run, the variance of the explanatory variables GDP per capita, GDP per capita square and trade openness are explained by the variables themselves as seen in the consecutive tables. Energy per capita alone is explained by GDP pc square

For China, 100 percent forecast error variance of GHG emissions per capita is explained by itself in the short run. Energy consumption per capita has a strong influence on GHG emissions per capita from second period onwards. Variance contribution of GHG emissions per capita itself is 56.1 percent and of Energy consumption per capita is 15.63 percent. In China all the explanatory variables such as GDP per capita, GDP per capita square, energy consumption per capita and trade openness are explained by themselves in the long run as can be seen in the consecutive tables.

Table 4.12.1(a):Variance Decomposition for GHG Emissions pc of India

Variance decomposition of LGHG PC						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc 2	LEN pc	TO
1	0.007724	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.011074	92.93078	0.210988	2.816322	1.010201	3.031707
3	0.012817	86.27537	0.622762	8.723818	0.783321	3.594730
4	0.014179	80.02811	0.992904	15.13761	0.837721	3.003654
5	0.015219	75.50398	1.709461	19.37001	0.802366	2.614186
6	0.016046	71.44206	2.696846	22.77591	0.733563	2.351618
7	0.016746	67.53407	4.008834	25.58926	0.684707	2.183128
8	0.017362	63.88140	5.521952	27.84609	0.646553	2.104003
9	0.017920	60.49228	7.257845	29.53193	0.610586	2.107353
10	0.018444	57.30835	9.181595	30.75186	0.576382	2.181808
Variance decomposition of LGDP PC						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc 2	LEN pc	TO
1	0.010617	0.472466	99.52753	0.000000	0.000000	0.000000
2	0.013685	2.596142	85.60145	8.032172	0.003854	3.766381
3	0.016699	2.302671	80.81197	11.12489	0.502379	5.258089
4	0.019173	1.843281	77.22030	14.46506	0.609482	5.861867
5	0.021488	1.471139	76.00725	15.93850	0.607988	5.975120
6	0.023640	1.325950	75.06244	16.99098	0.524572	6.096056
7	0.025712	1.424695	74.39057	17.55515	0.444709	6.184874
8	0.027690	1.731849	73.69094	17.93005	0.390722	6.256439
9	0.029589	2.212644	72.97247	18.14556	0.380566	6.288760
10	0.031410	2.833635	72.15551	18.29734	0.432101	6.281412
Variance decomposition of LGDP PC ^{2}						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc 2	LEN pc	TO
1	0.001006	48.20883	0.475108	51.31606	0.000000	0.000000
2	0.001509	60.78413	1.116931	36.50776	0.169629	1.421552
3	0.001845	57.34097	2.043712	37.04538	0.130573	3.439359
4	0.002090	51.72641	4.837550	39.20327	0.337904	3.894869
5	0.002286	46.83585	7.686206	41.26246	0.419072	3.796415
6	0.002452	42.43042	11.10400	42.37891	0.405120	3.681549
7	0.002604	38.30323	14.63138	43.03277	0.364490	3.668128
8	0.002749	34.56835	18.15052	43.23422	0.327076	3.719829
9	0.002889	31.32565	21.46452	43.09713	0.302930	3.809774
10	0.003025	28.57428	24.52442	42.67942	0.305694	3.916187
Variance decomposition of LEN PC						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc 2	LEN pc	TO
1	0.006075	49.29373	0.547007	50.03663	0.122628	0.000000
2	0.009160	62.06499	1.084075	34.98387	0.416826	1.450231
3	0.011195	58.80957	2.086245	35.17403	0.361272	3.568887
4	0.012681	53.15107	5.006649	37.05818	0.674704	4.109399
5	0.013874	48.19840	8.048144	38.87538	0.825296	4.052780
6	0.014891	43.70146	11.69995	39.79940	0.831335	3.967856
7	0.015826	39.45009	15.50054	40.28425	0.778448	3.986671
8	0.016723	35.56465	19.30833	40.34072	0.714390	4.071910
9	0.017594	32.16327	22.91485	40.07874	0.647550	4.195595
10	0.018449	29.25441	26.26266	39.55666	0.590936	4.335328
Variance decomposition of TO						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc 2	LEN pc	TO
1	0.028708	1.070207	0.446727	0.045436	1.056432	97.38120
2	0.042250	5.405889	5.710566	0.042713	3.742429	85.09840
3	0.048743	7.116051	9.525734	0.117638	4.877724	78.36285
4	0.053566	8.515736	15.67975	0.688188	4.502394	70.61393
5	0.057784	10.17313	21.37083	0.874018	3.903987	63.67803
6	0.061554	11.82867	26.23569	0.836144	3.443923	57.65558
7	0.064700	13.25523	29.86847	0.757382	3.121816	52.99710
8	0.067400	14.46265	32.58995	0.713228	2.912218	49.32195
9	0.069750	15.51775	34.55503	0.729321	2.804029	46.39387
10	0.071819	16.45536	35.94103	0.810911	2.782008	44.01069

Source: Computed based on World bank data,2018

Table 4.12.1(b): Variance Decomposition for GHG emissions pc of China

Variance Decomposition of LGHG_PC_						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc ^{2}	LEN pc	TO
1	0.045846	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.047913	94.21622	0.301003	0.203450	4.355623	0.923709
3	0.049994	88.10395	0.479018	1.333471	8.703577	1.379981
4	0.053243	79.18139	0.663101	3.742458	11.34640	5.066644
5	0.056643	70.31271	1.100499	6.270468	13.23213	9.084186
6	0.059399	63.96898	1.806189	8.107052	14.73183	11.38595
7	0.061499	60.18711	2.626182	9.228349	15.62791	12.33044
8	0.063064	58.10065	3.459766	9.888301	15.91646	12.63482
9	0.064223	56.90705	4.303502	10.28377	15.84475	12.66092
10	0.065112	56.13585	5.179885	10.50810	15.63512	12.54104
Variance Decomposition of LGDP_PC						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc ^{2}	LEN pc	TO
1	0.010578	4.982560	95.01744	0.000000	0.000000	0.000000
2	0.016276	5.591388	92.62384	1.373523	0.181912	0.229335
3	0.021620	3.342020	90.76018	2.430121	3.141534	0.326145
4	0.026794	2.700736	86.47491	3.021925	7.022785	0.779645
5	0.031773	2.568690	81.86177	3.414805	10.43250	1.722230
6	0.036581	2.583624	77.75880	3.657298	13.00247	2.997809
7	0.041204	2.718896	74.48024	3.728842	14.84061	4.231409
8	0.045592	2.983104	72.07490	3.637815	16.12728	5.176906
9	0.049700	3.329907	70.43389	3.431697	16.99832	5.806189
10	0.053510	3.686602	69.39421	3.166190	17.56067	6.192328
Variance Decomposition of LGDP PC ^{2}						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc ^{2}	LEN pc	TO
1	0.056326	5.193027	93.09150	1.715474	0.000000	0.000000
2	0.090265	5.750707	87.28234	6.404037	0.345626	0.217286
3	0.123138	3.236441	83.59615	9.125743	3.681104	0.360559
4	0.155793	2.617160	78.33961	10.50020	7.567266	0.975769
5	0.187916	2.609556	73.31029	11.25972	10.68589	2.134540
6	0.219343	2.816879	69.21187	11.58139	12.85614	3.533729
7	0.249666	3.194733	66.23652	11.52281	14.29295	4.752979
8	0.278415	3.722755	64.29321	11.17000	15.21412	5.599918
9	0.305278	4.321509	63.17311	10.63232	15.76847	6.104589
10	0.330184	4.897227	62.66208	10.00295	16.06872	6.369013
Variance Decomposition of LEN PC						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc 2	LEN pc	TO
1	0.011776	9.017685	13.71156	0.134689	77.13606	0.000000
2	0.017926	13.64349	8.219918	2.328474	74.41859	1.389527
3	0.022952	10.58405	6.197134	7.419764	67.98951	7.809542
4	0.028093	8.251930	5.383112	12.93663	57.14764	16.28069
5	0.032561	6.202030	5.769158	17.06455	49.82487	21.13940
6	0.036061	5.430422	6.929762	19.62737	45.47372	22.53873
7	0.038778	6.007659	8.410108	21.03455	42.31655	22.23114
8	0.040909	7.184544	10.00073	21.77571	39.65621	21.38281
9	0.042615	8.374415	11.66964	22.14843	37.37184	20.43567
10	0.044035	9.374020	13.42241	22.27343	35.43000	19.50014
Variance Decomposition of TO						
Period	S.E.	LGHG pc	LGDP pc	LGDP pc 2	LEN pc	TO
1	0.039603	10.64169	3.777785	9.331325	1.374643	74.87456
2	0.057240	14.00739	7.414728	8.019607	5.145753	65.41252
3	0.064394	11.74897	12.42926	6.569384	12.86334	56.38903
4	0.069846	13.60864	14.92487	5.771722	17.13200	48.56276
5	0.072884	14.43875	16.30114	5.868169	18.28595	45.10598
6	0.074642	14.23292	17.45996	6.303843	18.32778	43.67550
7	0.076042	13.83330	18.57590	6.972181	18.09776	42.52086
8	0.077366	13.44161	19.58066	7.943148	17.82802	41.20656
9	0.078671	13.04829	20.34581	9.184566	17.55293	39.86840
10	0.079918	12.65127	20.86009	10.55880	17.29090	38.63894

Source: Computed based on World bank data,2018

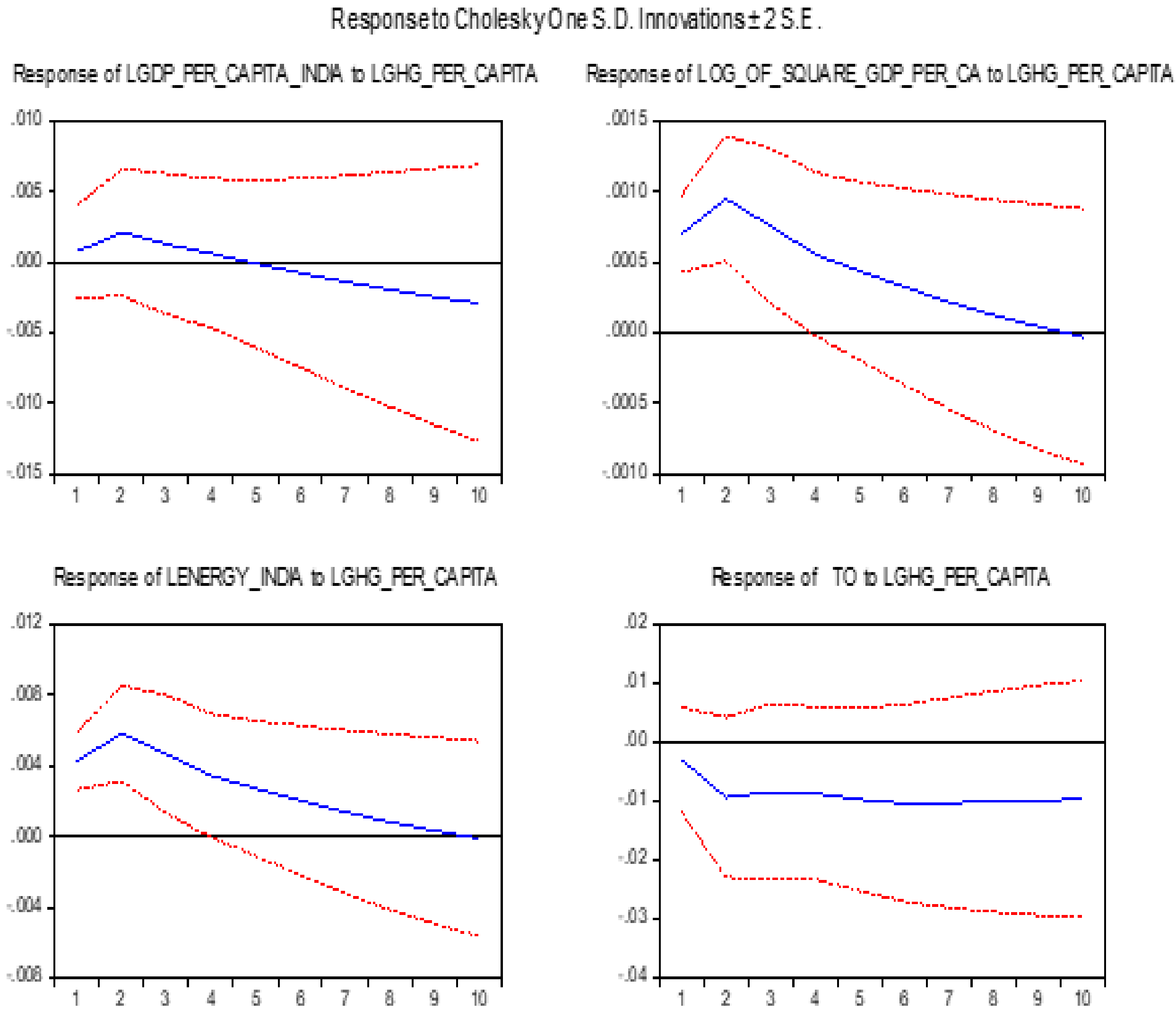
4.13 Impulse Response Function

The effect of innovations in all variables in the system on greenhouse gas emissions can be investigated using impulse response analysis. The figures 4.13 (a) and 4.13 (b) show the impulse response function of the variables for India and China. The blue line is the impulse response function and redline shows the 95 percent confident intervals in the figure.

Response of GDP per capita, GDP per capita square, energy consumption per capita and trade openness to GHG emissions per capita for India and China

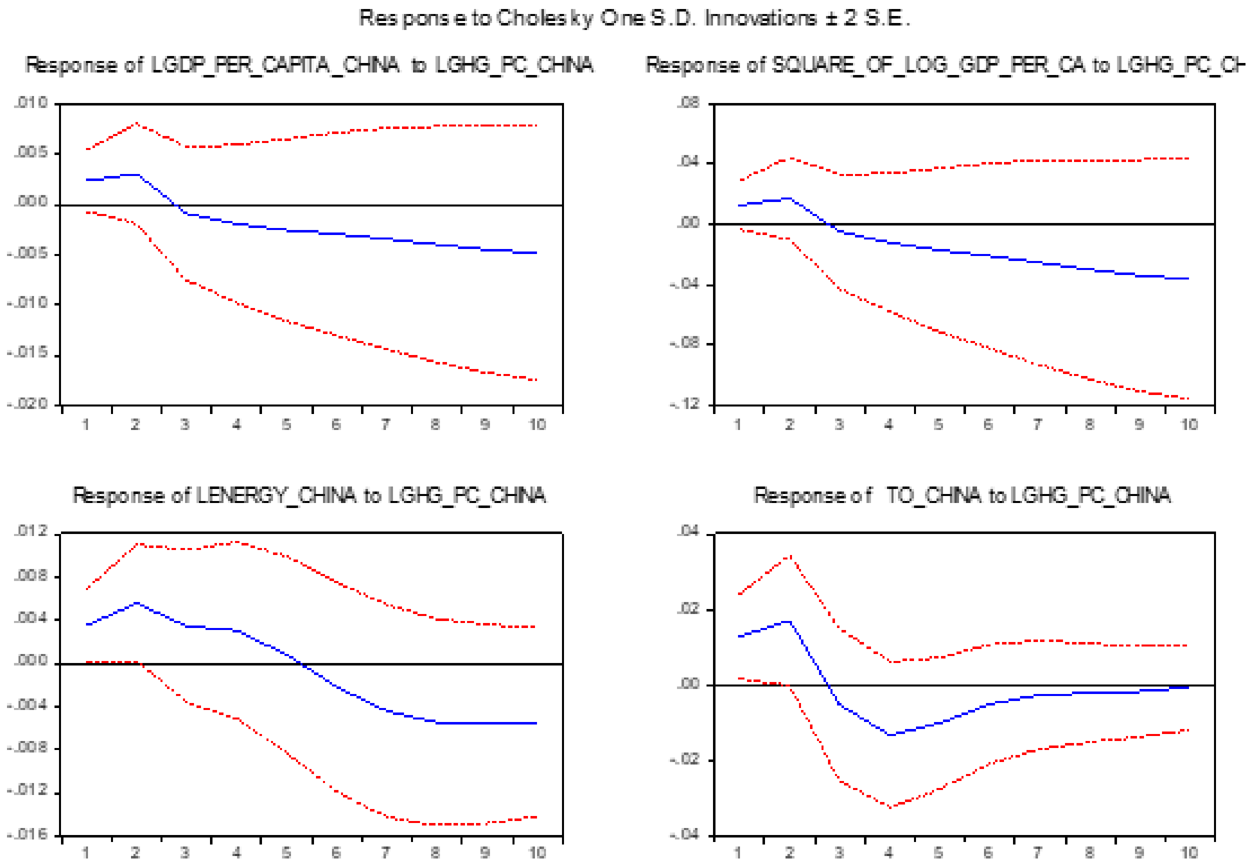
The impulse response function of GDP pc in both India and China is almost the same. In India, it initially increases in the short run, then declines in the 2^{nd} period, becomes stable while nearing the 5^{th} period attains negative region after that. In China the response of GDP pc is positive and increasing till 2^{nd} period, declines in the third period, becomes stable in the short run and attains negative in the long run. The response of GDP pc^2 initially is positive but gradually falls till period 9 and becomes negative in the 10^{th} period for India. In the case of China, the IRF of GDP pc^2 is same as the response of GDP per capita, first it is positive and stable and then becomes negative in the long run. It can be inferred that in India any shock on greenhouse gas emissions will cause a positive impact on gross domestic product per capita square and energy consumption per capita and negative effect on trade openness. An innovation on greenhouse gas emissions will cause an asymmetric impact on gross domestic product per capita in India. For China an innovation on greenhouse gas emissions per capita will cause an asymmetric impact on GDP per capita, GDP per capita square, energy consumption per capita and trade openness. The figure clearly shows how the economic growth inhibits greenhouse gas emissions in the long run especially for China supporting the EKC hypothesis but the decoupling happens to be slower in India comparatively. $GDPpc^2$ in India and China shows the same effects as their GDP pc responses.

The energy consumption per capita is mostly in the positive region for India showing the positive effect of energy consumption per capita on GHG emissions per capita. The result indicates how energy consumption causes environmental degradation. For China it is initially positive and increases till period 2, then falls slowly after period 5 becoming zero and then negative in the long run. China's energy conservation policy seems to have made the response negative in the long run. The IRF of trade openness to GHG emissions pc for India is negative throughout both in the long run and short run implying that as the country becomes more open to trade, the GHG pc emissions seems to decline. Same is the case with China in the long run as the IRF is positive in the short run but falls into negative region in the long run.



Source: Computed based on World bank data

Figure 4.13(a): Impulse Response Function of GHG emissions pc- India

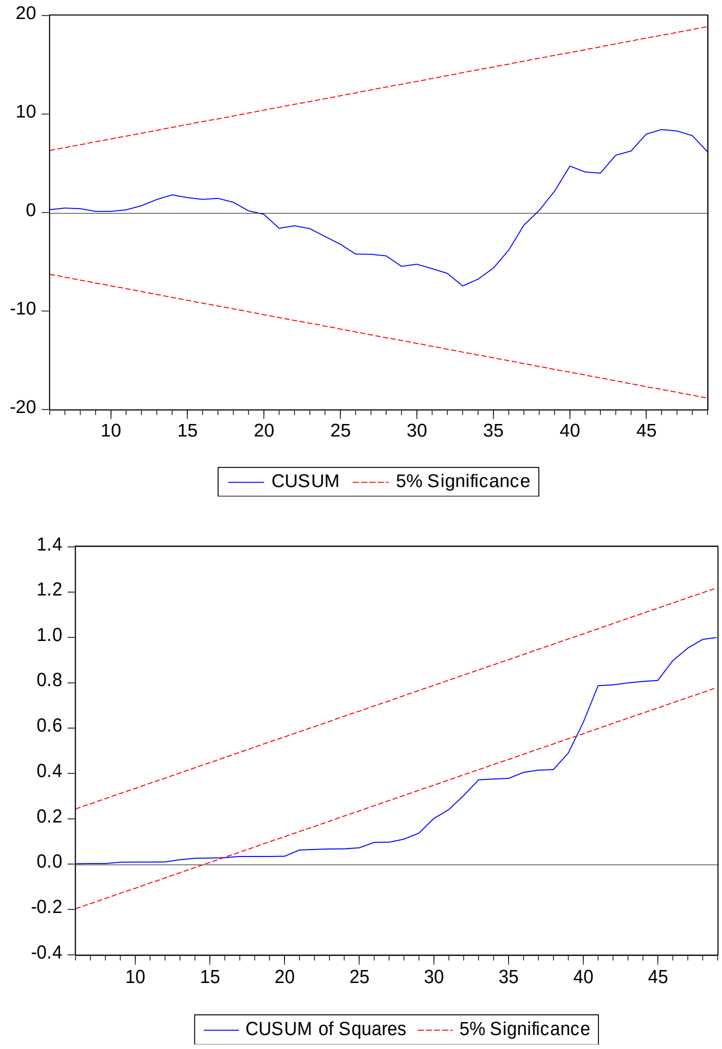


Source: Computed based on World bank data,2018

Figure 4.13(b): Impulse Response Function of GHG emissions pc- China

4.14 Test of Stability

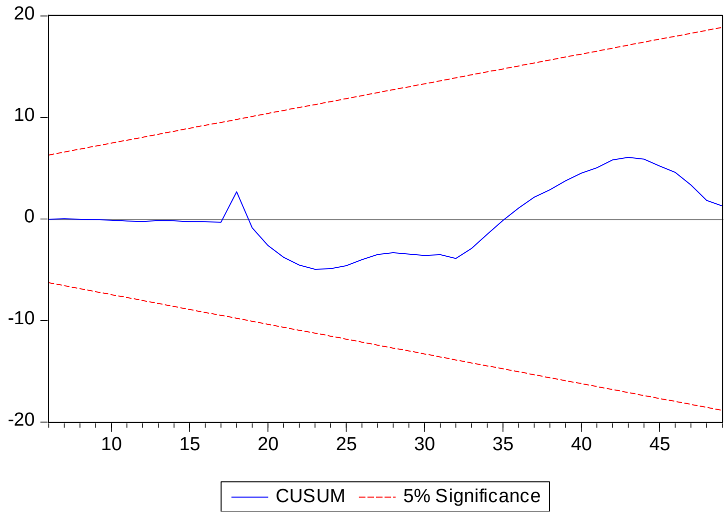
The CUSUM and CUSUMSQ plot of the residuals generated from the vector error correction model for greenhouse gas emissions per capita in India was used to test the stability of the model.

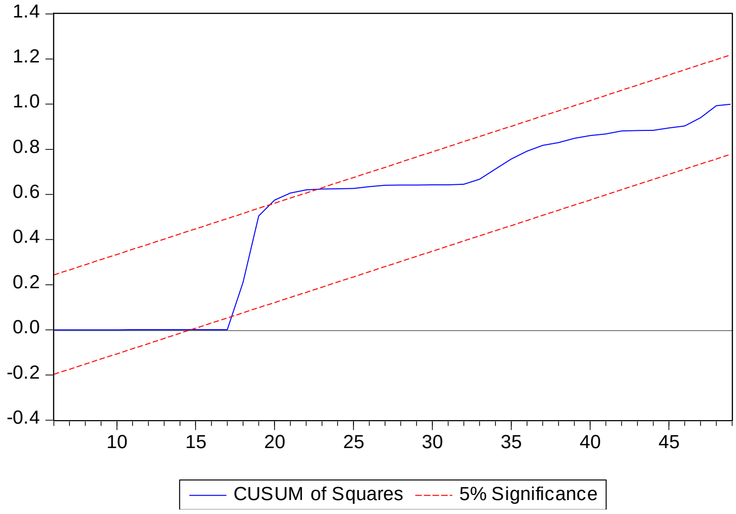


Source: World bank data,2018

Figure 4.14(a): CUSUM Test and CUSUM Square Test-India

The CUSUM plot for GHG emissions per capita was within the 5 percent critical bound levels, indicating that the greenhouse gas emissions per capita was found to be stable throughout the study period. The CUSUMSQ plot revealed that there was evidence of temporal instability for both India and China.





Source: World bank data,2018

Figure 4.14(b): CUSUM Test and CUSUM Square Test –China

To conclude

- **Using the "Intercept" and "Trend and Intercept" criteria the results indicated that all the variables used in the model such as GDP per capita, GDP per capita square, energy consumption per capita and trade openness became stationary only in their first differences for both India and China.**
- **The trace statistic was found to be greater than the critical value for 3 cointegrating equations forboth India and China. The Eigen statistic values also were greater than the critical value for 3 cointegrating**

equation for India and 1 for China thus establishing long run relationship between the variables in the model.

- **For China, the effects of GDP per capita and GDP per capita square on greenhouse gas emissions per capita are positive and negative respectively thus confirming the inverted U shape for the study period in accordance with EKC theory and empirical research by Jalil and Mahmu (2009), Halkos, G. and Tzeremes(2011), Xu et al. (2018), Hao et al. (2019). But for India there is no evidence of such a relationship between greenhousegas emissions per capita and gross domestic product similar to the results of Makarrabbi et al. (2017).**
- **The error correction coefficient for GHG emissions per capita as dependent variable for India and China was negative as in the principle indicating that the series for GHG emissions per capita will converge in the long run.**
- **In the short run for India and China 100 percent variance in GHG emissions per capita is explained by the variable GHG emissions per capita itself meaning strongly endogenous. In the long run 57.3 percent of the variation is explained by GHG emissions per capita itself and 30.75 percent by GDP per capita square. For China, in the long run 56.1 percent of the variation in GHG emissions per capita is explained by the variable itself and 15.63 percent by energy consumption per capita.**
- **It can be inferred that in India any shock on greenhouse gas emissions will cause a positive impact on gross domestic product per capita square and energy consumption per capita and negative effect on trade openness in the short and long run. An innovation on greenhouse gas emissions will cause an asymmetric impact on gross domestic product per capita in India. For China an innovation on greenhouse gas emissions per capita will cause an asymmetric impact on GDP per capita, GDP per capita square, energy consumption per capita and trade openness.**

- **The CUSUM plot for GHG emissions per capita was within the 5 percent critical bound levels, indicating that the greenhouse gas emissions per capita was found to be stable throughout the study period. The CUSUMSQ plot revealed that there was evidence of temporal instability for both India and China.**

4.15 Granger Causality Test of analyzing the direction of relationship among the variables

The existence of long term and short term relations among the variables are given by the cointegration test and the VECM analysis clearly. But the direction of relationship is not found in these analyses. For more meaningful predictions it is advisable to analyse the causal relationship among the variables both the dependent and independent variables in the study. The Granger (1987) causality test helps to identify the direction and causality of relationship among the variables. The pair wise Granger Causality test was performed between the chosen variables GHG emissions per capita, GDP per capita, GDP per capita square, trade openness and energy consumption per capita.

If the P value is more than 0.05 or 0.01 then Ho is accepted. If the p value is less than 0.05, 0.01 or 0.10, the null hypothesis is rejected, inferring that X Granger causes Y. The estimated F statistics and the P values for the variables and the decision on the causality are presented in table 4.15.1(a) and 4.15.1(b).

Table 4.15.1(a):Pair wise Granger Causality Test Statistics–India

S.No.	Null Hypothesis	Obs	F-Statistic	Prob.	Causality Exists
1	LGDP PC does not Granger Cause LGHG PC	47	2.89043	0.0667	Y
2	LGHG PC does not Granger Cause LGDP PC		0.28596	0.7527	
3	LGDP PC^2 does not Granger Cause LGHG PC	47	2.67015	0.081	Y
4	LGHG PC does not Granger Cause $LGDPPC^2$		0.25372	0.7771	
5	LEN PC does not Granger Cause LGHG PC	47	2.86697	0.0681	Y
6	LGHG PC does not Granger Cause LEN PC		1.36447	0.2666	
7	TO does not Granger Cause LGHGPC	47	1.17928	0.3175	N
8	LGHG PC does not Granger Cause TO		1.13392	0.3314	
9	$LGDPPC^2$ does not Granger Cause LGDP PC	47	1.10297	0.3413	N
10	LGDP PC does not Granger Cause LGDP PC^2		1.07676	0.3499	
11	LEN PC does not Granger Cause LGDP PC	47	2.33958	0.1088	N
12	LGDP PC does not Granger Cause LEN PC		1.84931	0.1699	
13	TO does not Granger Cause LGDP PC	47	0.09122	0.9130'	N
14	LGDP PC does not Granger Cause TO		2.28344	0.1144	
15	LEN PC does not Granger Cause LGDP PC^2	47	1.90876	0.1609	N
16	LGDP PC^2 does not Granger Cause LEN PC		1.77758	0.1815	
17	TO does not Granger Cause LGDP PC^2	47	0.09694	0.9078	Y
18	LGDP PC^2 does not Granger Cause TO		2.47142	0.0967	
19	TO does not Granger Cause LEN PC	47	0.69708	0.5037	N
20	LEN PCdoes not Granger Cause TO		0.80276	0.4548	

Source: Estimates Calculated based on secondary data. Y = Yes, N = No

Table 4.15.1(b):Pair wise Granger Causality Test Statistics–China

S.No.	Null Hypothesis	Obs	F-Statistic	Prob.	Causality exists
1	LGDP PC does not Granger Cause LGHGPC	47	2.89875	0.0662	Y
2	LGHG PC does not Granger Cause LGDPPC		0.36256	0.698	
3	LGDP PC^2does not Granger Cause LGHG PC	47	3.14005	0.0536	Y
4	LGHG PC does not Granger Cause LGDP PC^2		0.27405	0.7616	
5	LEN PC does not Granger Cause LGHG PC	47	9.22925	0.0005	Y
6	LGHG PC does not Granger Cause LEN PC		5.20725	0.1095	
7	TO does not Granger Cause LGHG PC	47	4.59207	0.0157	Y
8	LGHG PC does not Granger Cause TO		0.21472	0.8076	
9	LGDP PC^2does not Granger Cause LGDP PC	47	3.74679	0.0318	Y
10	LGDP PC does not Granger Cause LGDP PC^2		4.37866	0.0187	
11	LEN PC does not Granger Cause LGDP PC	47	0.12997	0.8785	N
12	LGDP PC does not Granger Cause LEN PC		2.38838	0.1041	
13	TO does not Granger Cause LGDP PC	47	1.91926	0.1594	N
14	LGDP PC does not Granger Cause TO		0.22234	0.8016	
15	LEN PC does not Granger Cause LGDP PC^2	47	0.55066	0.5807	N
16	LGDP PC does not Granger Cause LEN PC		1.18191	0.3167	
17	TO does not Granger Cause LGDP PC^2	47	2.91888	0.065	Y
18	LGDP PC^2 does not Granger Cause TO		0.07991	0.9233	
19	TO does not Granger Cause LEN PC	47	2.81450	0.0713	Y
20	LEN PC does not Granger Cause TO		0.34485	0.7103	

Source: Estimates Calculated based on secondary data. Y = Yes, N = No

Table 4.15.1 (a) and Table 4.15.1 (b) show the following results

Granger's causality was tested for only Model III as it had all the three important variables of the study. The results revealed unidirectional relationship between the following variable pairs for India such as

- Gross domestic product per capita & greenhouse gas emissions per capita,
- Gross domestic product per capita square & greenhouse gas emissions per capita,
- Energy consumption per capita & greenhouse gas emissions per capita,
- Gross domestic product per capita square &trade openness

For China the following pairs had unidirectional relationship.

- Gross domestic product per capita & greenhouse gas emissions per capita,
- Gross domestic product per capita square & greenhouse gas emissions per capita,
- Trade openness & greenhouse gas emissions per capita,
- Trade openness & gross domestic product per capita square
- Trade openness & energy consumption per capita.
- Energy consumption per capita & greenhouse gas emissions per capita,

The pair which showed bidirectional causality was

- Gross domestic product per capita square &gross domestic product per capita.

The causality running from gross domestic product per capita to greenhouse gas emissions in both India and China revealed that all steps taken to improve growth will increase the emissions. When the countries grow the consumption of energy is more and therefore emissions increase as can be seen from the unidirectional causality between energy consumption per capita and green house gas emissions per capita in both India and China. The results for China clearly show how trade openness is the cause for increase in gross domestic product per capita, energy consumption per capita and green house gas emissions per capita.(Jun et al,2020)

To conclude

- **Gross domestic product per capita and its square caused green house gas emissions per capita in both India and China**
- **Energy consumption per capita caused green house gases emissions per capita in India and China.**
- **GDP per capita caused trade openness in India whereas trade openness caused GDP per capita square, greenhouse gas emissions per capita and energy consumption per capita in China.**