CHAPTER-5

ENERGY CONSUMPTION AND GROSS INDUSTRIAL VALUE-ADDED LINKAGES IN THE INDIAN MANUFACTURING SECTOR: A DISAGGREGATE APPROACH

In the previous chapter, two sets of variables were investigated for their functional relationship. One set of variables included fuel consumption, fixed capital, labor, profit, and the net value-added and the second set of variables included industrial net output, fuel consumption, fixed capital, and labor. Based on this, the degree of cause-and-effect relationship among variables was ascertained. This chapter analyses the relationship between the final fuel consumption and industrial gross value added. However, the total fuel consumption is treated in a disaggregated manner, unlike the previous chapter where fuel consumption was taken in an aggregate manner, i.e., total fuel consumption by the manufacturing industry.

5.1 Introduction

It is asserted that energy is the primary input for economic growth and the modern era's industrial progress. There are two reasons for this. First, the growth of an economy hinges on the availability of cost-effective and environmentally efficient energy sources. Second, the level of economic development has been seen to be dependent on energy consumption. In this regard, Indian industries are not an exception. In 2021, the industrial sector reported almost 41% of total energy consumption in India. This being so, the change in energy consumption to responsive change in gross industrial value-added can capture both the industrial sector structure and how efficiently the energy has been used in this sector.

For India, in the past few decades, the energy–G.D.P. elasticity has been greater than unity; for every 1per cent increase in G.D.P., the energy consumption increased by more than 1per cent. In contrast, industrial energy consumption elasticity has been less than unity (India's National Integrated Energy Policy 2005). It indicates that the industrial sector is relatively more efficient in the use of energy than the economy as a whole. This has been attributed to improved technology, energy use efficiency, inter-fuel substitution, modernization, upgrading technology, and Perform, Achieve & Trade (PAT). Against these facts, the Indian economy ranks third in world energy consumption, and Indian industries continue to be dependent on conventional production processes heavily reliant on energy. With the current reform initiatives like Make in India, whose principal objective is to put manufacturing at its growth model's heart. A government target of increasing the manufacturing sector's share in the gross domestic product from approximately 15 percent to 25 percent by the beginning of the next decade can be expected to a significant increase in demand for energy. Further, a continuous program involving infrastructure construction (roads and national highways) is likely to support energy demand growth. Thus, a robust dual-functional relationship between industrial expansion and energy consumption can be expected in the near future.

In the said context, the present chapter attempts to analyze the energy consumption by Indian industries both at aggregate and disaggregate levels from 2001 to 2021. As the utilisation of aggregate energy data does not accommodate the intensity or extent to which a sector depends on various energy sources and as the employment of aggregate energy data may not be able to index the impact of a specific energy type on industrial production, following Yang (2000) in this chapter the disaggregate forms of energy are also used for the comparisons of the intensity of causal relationships. Thus, the chapter's primary objective is to empirically examine the relative impact of industrial production and energy consumption at both aggregated and disaggregated levels concerning oil, natural gas, and electricity.

The rest of the structure of the chapter includes the literature review on energy consumption and industrial value-added, the data source and methodology, the results and discussion, and the research outcomes.

5.2 Literature Review

For a long time, the classical growth theories asserted that economic growth is dependent on labor and capital only, but considering the oil embargo of 1973-74 and the continued rise in energy prices challenged the thought and brought out a significant role of energy resources in the industrial production processes (Pindyck, 1979). It was Georgescu (1972) who was one of the first to emphasize energy as a critical input in manufacturing activities. According to him, optimum energy use improves efficiency and productivity. Since then, several studies were undertaken to analyze the nexus between energy input and economic output. Kraft and Kraft (1978) conducted one of the pioneering works on the causal relationship between energy input and economic growth using the time series data for the United States economy from the year 1947 to 1974. He used a bi-variate causality test to determine the causality between energy input and economic growth. He identified a positive relationship between GNP growth and an increase in energy use. In another study, Yu and Erol (1987) studied the cause-and-effect relationship between energy consumption and real G.N.P. for developed countries like Canada, France, Germany, the U.K, Italy, and Japan. By employing the Granger and Sims test of causality methods, they found a bi-directional causality between two variables in the Japanese economy and no causal relationship between the two variables for developed countries like the U.K and France. Whereas, the study on Germany and Italy found that increased GNP led to increased energy consumption and this was vice-versa in the case of Canada.

Similarly, many other studies have been undertaken at the global level to investigate the relationship between energy consumption and industrial output vis-à-vis economic growth. Some of these studies like Glasure (1998), Soytas and Sari (2003), Lee (2006), and Zamani (2009) for various periods for economies such as South Korea, Singapore, Turkey, Argentina, and Iran saw a bi-directional relationship among energy and output. These studies mostly used models such as the Engle-Granger Causality Test, Error Correction Model, and ARDL Bound Test. In contrast, other researchers like Hondroyiannis et al. (2002), Lee (2006), and Jorbert and Karanfil (2007) used Engle-Granger, Granger Causality Test, Johnsen's Multivariate Co-integration Technique, Co-integration and Vector Error Correction Model (VECM), for economies such as United Kingdom, France, Sweden, Germany, U.S.A., and Turkey. They found no causality between energy consumption and output. Whereas, few other studies done by Bradley and Ugur (2007) for economies such as Japan, Turkey, and United States for different research periods have shown uni-directional causality between energy and output.

Apart from the above-cited studies at global levels, researchers have also endeavored to study and predict the relationship between energy consumption and industrial output concerning India's GDP at the local levels. In one such study, Ghosh (2002) using time series data on variables such as electricity use and economic growth (per capita), observed that there is a long-run causality occurring from output to energy consumption. As opposed to this, Bhattacharya and Paul (2004) applied alternative econometric time series models such as Engle-Granger, Granger Causality Test, and Johnsen's Multivariate Co-integration Technique. They found that bi-directional causality exists between energy consumption and economic growth. Tiwari (2011) for the sample period of 1970-2007 used time-series data and came out with the result that in the long run that there is a causal relationship between GDP and energy consumption. Govindaraju and Tang (2013) for the sample period of 1965-2009 studied the linkages between coal consumption and real GDP per capita, where the results indicated no long-run relationship between energy and income. Still, there is a short-run relationship between income and energy.

Vidyarthi (2013) analyzed the period from 1971-2009 adopting the Johansen approach on time series data of energy consumption, real GDP, and carbon emissions. The results indicated that there is a long-run linkage from energy to income, but a short-run linkage from income to energy. Abbas and Choudhary (2013) studied the area from 1972 to 2008 and found that the aggregate level increase in GDP demanded more energy consumption both in the long run and in the short run. Whereas, at the disaggregated level, they found bi-directional causality between income and energy consumption. Bildirici and Bakirtas (2014), between 1980 and 2011, used a combination of different energy sources such as coal, natural gas, and oil consumption with real GDP by applying the ARDL model. Their results indicated bi-directional relation running from energy to output for coal and oil. Nain et al. (2015), on the other hand, used time-series data at aggregate and disaggregate levels on electricity consumption and real GDP by applying ARDL Bound Test. Their results indicated that there was no long-run relationship at the aggregate level, but a short-run relationship between energy and income.

The study conducted by Singh and Vashishta (2020) examined the relationships between per capita energy consumption and per capita GDP in India for the reference period from 1971 to 2015. The empirical analysis was conducted using the three-stage Johnson Co-integration, Vector Auto-regression, and Granger Causality Test. The outcome of the study showed unidirectional causality occurring from per capita GDP per unit capita energy consumption and this was absent in the long-term equilibrium relationship between per capita energy consumption and per capita GDP in India.

A similar study by Tirwaria et al. (2021) examined the direction of the Granger-causal relationship between electricity consumption and economic growth at the State and Sectorial levels in India. In the investigation, the Panel Co-integration Tests with the structural break, the Heterogeneous Panel Causality Test, and the Panel VAR-based impulse-response model have been used. The study evaluated agricultural and industrial sectors on their energy dependence and contribution to output for eighteen major Indian states for the reference period from 1961 to 2015. The results prove a long-term relationship between economic growth and electricity consumption only in the agriculture sector. Further, the results disclose the presence of unidirectional Granger causality running in the direction of overall economic growth to electricity consumption at the aggregate State level. However, focus on the sectoral level depicts a unidirectional causal relationship flowing from electricity consumption to economic growth for the agriculture sector and economic growth to electricity consumption for the industrial sector.

The survey of the literature of existing studies shows heterogeneity between the energy input relationship with economic growth/industrial output. The findings of multiple studies vary at large. These differences could be accorded to different methodologies used, sets of variables, and various individual research periods. Further, the previous studies mostly covered the sample period up to 2018 and primarily used the ARDL model. The earlier studies were mainly undertaken for heavy industries such as steel, aluminum, cement, paper, etc. It is in this context that the present chapter aims to investigate the energy use and industrial gross value-added relationship using Vector Error Correction Model both at aggregate and disaggregate levels, covering twenty-three clusters of industries listed in the Annual Survey of Industries.

5.3 Data Source and Methodology

The study spans the years 2001 to 2021, and a group of 23 industries has been selected. The essential information was collected from India's Annual Industrial Survey. The study covers a period from 2001 to 2021; a cluster of 23 industries has been chosen. The data includes Energy Total Industrial Fuel Consumption (IFC), Industrial Coal consumption (ICC), Industrial Electricity Consumption (IEC), Industrial Petroleum Consumption (IPC), Other Industrial Oil Consumption (IOC), and Industrial Value Added (IVA). IFC, ICC, I.E.C., I.P.C., I.O.C., and I.V.A. values are expressed at the 2011-2012 constant prices. All the factors have been converted into natural logs following Chang et al. (2001) and to achieve stationary in the variance-covariance matrix.

As the empirical evaluation of the relationship between energy consumption and Industrial value-added involves cross-section time-series data analysis, the first step is to conduct a unit root test to check the data's stationary and non-stationary data. Along with this, optimum lag structure selection has been performed with the help of the Akaike Information Criterion (A.I.C.). The obtained lag length has been imputed in the Johansen co-integration test. Here two types of panel unit root tests have been undertaken, one on the standard unit process with Levin Lin and Chu (L.L.C.) and the other on the individual unit root process using Im, Pesaran, and Shin (I.P.S.), Fisher-augmented Dickey-fuller (A.D.F., 1979) and Phillips Perron test (P.P,1988). The P.P. test considers the series' heteroscedastic dimension hypothesis, while the A.D.F. test deals with autocorrelation. Based on the above tests, the order of integration of the series has been determined. After that, an attempt has been made to investigate the possibility of cointegration between variables through Johansens (1988) and Maddala & Wu (1999) tests of cointegration. Maddala and Wu (1999) used Fisher's (1932) result to propose an alternative approach to test for cointegration in panel data by combining tests from individual cross-section tests to obtain a test statistic for the full panel.

Thus, if π_i is the *p*-value from an individual co-integration test for a cross-section i, then under the null-hypothesis for the whole panel,

$$-2\sum_{i=1}^{N} log_e\,(\pi_i) \quad \dots\dots\dots\dots\dots\dots.\,(1)$$

is distributed as $x_2^2 N$

The chi^2 value is based on Mackinnon-Haug-Michelis's (1999) p-value for Johansen's co-integration Trace test and Maximum Eigenvalue Test.

The evidence of co-integration has been identified through the outcome of Johansen's co-integration test. Although co-integration indicates Granger causality at least in one direction, it does not mean the direction of causality between variables. Thus to find out the direction of the Granger causality among indicated variables, the Vector Error Correction Model (VECM) has been undertaken. To establish VECM, the differencing of the V.A.R. is performed. In the process of differencing the V.A.R., we lose a lag; hence the VECM model has been defined as follows:
At first, we consider a bi-variate relationship.

$$Y_t = \mu + \beta_1 X_t + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots.\,(2)$$

With Engle and Granger (1987) help, we try to connect the co-integration and Error Correction Model (E.C.M.) by converting the above equation.
Hence co-integration equation between Y_t and X_t are formulated as follows:

$$\varepsilon_t = Y_t - \mu - \beta_1 X_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\,(3)$$

The Error Correction Models for Y_t and X_t are as follows:

$$\Delta giva_t = \alpha + \sum_{i-1}^{k-1} \beta_i \Delta Ingiva_{t-i} + \sum_{j=1}^{K-1} \emptyset_j \Delta Intifc_{t-j} + \sum_{k=1}^{k-1} \varphi_k \Delta Inicc_{t-k} + \sum_{l=1}^{k-1} \sigma_l \Delta Iniepv_{t-l} + \sum_{m-1}^{k-1} \vartheta_m \Delta Iniofc_{t-m} + \sum_{n-1}^{k-1} \theta_n \Delta Inipp_{t-n} + \gamma_1 ECT_{t-1} + u_{1t} \dots\dots\dots\dots (4)$$

$$\Delta Intifc_t = a + \sum_{i=1}^{k-1} \beta_i \Delta Ingiva_{t-i} + \sum_{j=1}^{k-1} \emptyset_j \Delta Intifc_{t-j} + \sum_{k=1}^{k-1} \varphi_k \Delta Inicc_{t-k} + \sum_{l=1}^{k-1} \sigma_l \Delta Iniepv_{t-l} + \sum_{m=1}^{k-1} \vartheta_m \Delta Iniofc_{t-m} + \sum_{n-1}^{k-1} \theta_n \Delta Inipp_{t-n} + \gamma_2 ECT_{t-1} + u_{2t} \dots\dots\dots\dots . (5)$$

$$\Delta Inicc_t = b + \sum_{i=1}^{k-1} \beta_i \Delta Ingiva_{t-i} + \sum_{j=1}^{k-1} \emptyset_j \Delta Intifc_{t-j} + \sum_{k=1}^{k-1} \varphi_k \Delta Inicc_{t-k} + \sum_{l=1}^{k-1} \sigma_l \Delta Iniepv_{t-l} + \sum_{m=1}^{k-1} \vartheta_m \Delta Iniofc_{t-m} + \sum_{n-1}^{k-1} \theta_n \Delta Inipp_{t-n} + \gamma_3 ECT_{t-1} + u_{3t} \dots\dots\dots\dots\dots . (6)$$

$$\Delta Iniepv_t = c + \sum_{i-1}^{k-1} \beta_i \Delta Ingiva_{t-i} + \sum_{j-1}^{k-1} \emptyset_j \Delta Intifc_{t-j} + \sum_{k-1}^{k-1} \varphi_k \Delta Inicc_{t-k} + \sum_{l-1}^{k-1} \sigma_l \Delta Iniepv_{t-l} + \sum_{m-1}^{k-1} \vartheta_m \Delta Iniofc_{t-m} + \sum_{n-1}^{k-1} \theta_n \Delta Inipp_{t-n} + \gamma_4 ECT_{t-1} + u_{4t} \dots\dots\dots\dots\dots\dots . (7)$$

$$\Delta Iniofc_t = d + \sum_{i-1}^{k-1} \beta_i \Delta Ingiva_{t-i} + \sum_{j-1}^{k-1} \emptyset_j \Delta Intifc_{t-j} + \sum_{k-1}^{k-1} \varphi_k \Delta Inicc_{t-k} + \sum_{l-1}^{k-1} \sigma_l \Delta Iniepv_{t-l} + \sum_{m-1}^{k-1} \vartheta_m \Delta Iniofc_{t-m} + \sum_{n-1}^{k-1} \theta_n \Delta Inipp_{t-n} + \gamma_5 ECT_{t-1} + u_{5t} \dots\dots\dots\dots\dots\dots .. (8)$$

$$\Delta Inipp_t = e + \sum_{i-1}^{k-1} \beta_i \Delta Ingiva_{t-i} + \sum_{j-1}^{k-1} \emptyset_j \Delta Intifc_{t-j} + \sum_{k-1}^{k-1} \varphi_k \Delta Inicc_{t-k} + \sum_{l-1}^{k-1} \sigma_l \Delta Iniepv_{t-l} + \sum_{m-1}^{k-1} \vartheta_m \Delta Iniofc_{t-m} + \sum_{n-1}^{k-1} \theta_n \Delta Inipp_{t-n} + \gamma_6 ECT_{t-1} + u_{6t} \ldots\ldots\ldots\ldots\ldots (9)$$

k-1= the optimal lag length is reduced by 1

$\beta_1, \emptyset_j, \varphi_k, \vartheta_m, \theta_n =$ Short-run dynamic coefficient of the model's adjustment long-run equilibrium

γ_i= the velocity of the adjustment parameter with a negative sign.

ECT_{t-1}= the error correction term is the lagged value of the residuals derived from the co-integrating regression of the dependent variable on the regressors. It incorporates long-run inference obtained from a long-run co-integration association.

u_{it}= Residuals in the equation.

$\Delta Y_t = \sum_{i=1}^{n} \alpha_i \, \Delta Y_{t-i} + \sum_{j=1}^{n} \beta_j \, \Delta X_{t-j} + u_{1t}$……………. (10)

$\Delta X_t = \sum_{i=1}^{n} \alpha_i \, \Delta X_{t-i} + \sum_{j=1}^{n} \delta_j \, \Delta Y_{t-j} + u_{2t}$……………. (11)

Eq. (10) shows that Y's current value is associated with its past values and X's past values. At the same time, Eq. (11) denotes that ΔX is associated with the past values themselves and ΔY.Thenull hypothesis in Eq. (10) is $\beta_j = 0$, which says, "ΔX does not Granger cause ΔY". Similarly, the null hypothesis in Eq. (11) is δ_j =0, and states,"ΔY does not Granger cause ΔX." The rejection or non-rejection of the null hypothesis is rested on the F-statistics.

5.4 Results and Discussion

The results are derived after performing appropriate models, as articulated above. The panel unit test, namely, Levin, Lin, and Chu (2002): Im, Pesaran, and Shin (2003); and panel augmented Dickey-Fuller (A.D.F.) (Maddala and Wu, 1999) are worked out, and the test result has been presented in the Table-5.1. The test result reveals that the series is integrated with I(1), which means the given series is stationary at the first difference, which means that the variables are distinctively integrated of order 1 or I (1).

Table-5.1, Panel Unit Root Test

	Levin, Lin & Chu t*		ADF		PP	
Variables	Level	First difference	Level	First difference	Level	First difference
GIVA	13.4	11.43*	1.047	219.07*	0.722	305.21*
PCTIFCV	16	11.23*	2.412	234.485*	1.063	286.27*
PCICCW	9.574	4.607*	0.724	58.091*	0.002	47.355*
PCIEPV	17.78	9.457*	0.817	191.34*	0.701	274.82*
PCIPPV	7.708	15.95*	2.957	306.848*	1.239	382.75*
PCIOFCV	6.499	18.64*	11.128	364.462*	5.644	431.8*

Each test employs an intercept and not the trend. * Indicates significance level at 1%. Levin, Lin, and Chu (2002)-presume a typical unit root process, Fisher Type test using A.D.F. and P.P. Test (Maddala and Wu (1999) and Choi (2001))- presumes individual unit root process. Each A.D.F. statistic is accounted for the small-time lag length, which has been selected based on the minimum Akaike Information Criterion. The Phillips–Perron test employs the identical models as the Dickey-Fuller tests, but uses a non-parametric correction, due to Newey and West (1987), to deal with the potential serial correlation. We chose the lag truncation for this non-parametric correction with a help of an automated bandwidth estimator using the Bartlett kernel (Andrews 1991). The test statistics for both the Dickey-Fuller and Phillips–Perron tests have the same distributions. Critical levels are represented in Hamilton (1994) and Enders (1995).

For the cointegration test, the Hypothesis is stated as

H_0=No co-integration between industrial gross value added and energy consumption both at aggregate and disaggregate level.

H_1=H_0 is not true

The Co-integration test has been implemented on the level form of the variables and not on their first difference (Table 5.2).

Table-5.2: Johansen Fisher Panel Co-integration Test

Variables	H_0=r	Trace Test	Eigen Test)
1.(IVA,TFC)	0	115.2	114.5
	1	52.76	52.76
2.(IVA,ICC)	0	83.85	82.63
	1	50.71	50.71
3.(IVA,IEC)	0	112	116
	1	41.64	41.64
4. (IVA, IOFC)	0	98.34	92.17
	1	62.88	62.88
5.(IVA,IPP)	0	114.1	103.5
	1	71.33	71.33

r -indicates the number of cointegration relationships. The critical values for maximum Eigenvalue and trace test statistics are given by Johansen and Juselius (1990)

Through the Johansen Maximum Likelihood approach (Table-5.2), we have investigated whether there is a long-run co-integration relationship between industrial value-added and industrial energy inputs, both at aggregate and disaggregate levels. The outcome of the Eigenvalue and trace tests reject the null hypothesis of no co-integration vectors. Still, they do not deny the doctrine of a co-integrating vector (i.e., r=1) at a 5 % level of significance for models (1), (2), (3), (4), and (5). The results record that the I.V.A. and energy consumption in the industry both at aggregated and disaggregated levels are co-integrated; therefore, we can conclude that both the series tend together in the long run. It posits that the pairs of said variable series are in a long-run relationship.

Table-5.3: Short Run Causal Effect Revealed by the t-statistics of Error Correction Term,

			Coefficient	Std. Error	t-Statistic	Prob.
InGIVA	1	C(4)	0.118894	0.086133	1.380346	0.1676
		C(6)	0.498032	0.164476	3.027996	0.0025
		C(8)	0.024984	0.073283	0.340926	0.7332
		C(10)	-0.015811	0.0226	-0.69959	0.4843
		C(12)	-0.076841	0.050152	-1.53214	0.1256
InPCTIFCV	2	C(16)	0.18817	0.054543	3.449911	0.0006
InPCCVV	3	C(30)	0.030355	0.018355	1.653741	0.0983
InPCIEPV	4	C(44)	0.127027	0.048756	2.605331	0.0092
InPCIOFCV	5	C(58)	0.271607	0.126714	2.14347	0.0322
InPCIPPV	6	C(72)	0.271243	0.068515	3.958861	0.0001

Table-5.4: Long Run Causal Effect Revealed by the t-statistics of E.C.T.,

Model		Coefficient	Std. Error	t-Statistic	Prob.
InGIVA	C(1)	-0.191877	0.053712	-3.57235	0.0004
InTIFCV	C(15)	0.003308	0.002168	1.526045	0.1271
InCCV	C(29)	0.003162	0.000729	4.335113	0.000
InIEPV	C(43)	-0.004866	0.001938	-2.51135	0.0121
InIOFCV	C(57)	0.013077	0.005036	2.596854	0.0095
InIPPV	C(71)	0.00928	0.002723	3.408126	0.0007

The long-run causal relationship indicated by t-statistics of error correction term reveals a robust causal relationship between energy consumption and gross industrial value added at aggregate and disaggregate levels. The models (as shown in Table-5.4) InGIVA, InCC, and InIEP have a causal relationship among the variable in the long run. At the disaggregated level increase in gross industrial value-added has a positive impact on the demand for coal consumption and electricity consumption at a 5% significance level.

$$ECT_{t-1} = \left[Y_{t-1} - \emptyset_j X_{t-1} - \varphi_k R_{t-1} \ldots..\right] \ldots \ldots \ldots \ldots \ldots \ldots .(12)$$

The co-integrating equation and long-run model are error correction term equations signifying long-run relationships among the variables.

$$ECT_{t-1} = [1.0Ingiva_{t-1} - 0.9658Intifc_{t-1} - 7.7101Inicc_{t-1} + 3.6819Iniep_{t-1} + 0.94418Inofc_{t-1} - 4.8951Inipp_{t-1} + 68.731]$$

The above ECT_{t-1} of the co-integrating equation can be interpreted in elasticity form as a 1% change in total industrial energy consumption will increase the gross industrial value added by 0.9658 percent. Similarly, a 1 percent change in industrial coal consumption will influence a change in gross industrial value added by 7.710 percent. Thus, coal consumption has a significant influence on gross industrial value-added. In the same way, a percentage change in Industrial petroleum product consumption increases the gross industrial value added by 4.89 percent. On the contrary, industrial electricity and other-fuel consumption harm the gross industrial value-added.

The short-run association among the variables is expressed below:

$$\Delta giva_t = \alpha + \sum_{i-1}^{k-1} \beta_i \Delta Ingiva_{t-i} + \sum_{j=1}^{K-1} \emptyset_j \Delta Intifc_{t-j} + \sum_{k=1}^{k-1} \varphi_k \Delta Inicc_{t-k} + \sum_{l=1}^{k-1} \sigma_l \Delta Iniepv_{t-l} + \sum_{m-1}^{k-1} \vartheta_m \Delta Iniofc_{t-m} + \sum_{n-1}^{k-1} \theta_n \Delta Inipp_{t-n} + \gamma_1 ECT_{t-1} + u_{1t}$$

$$\Delta giva_t = -0.191877\Delta Ingiva_{t-i} + 0.118894\Delta Intifc_{t-j} + 0.498032\Delta Inicc_{t-k} + 0.024984\Delta Iniepv_{t-l} - 0.015811\Delta Iniofc_{t-m} - 0.076841\Delta Inipp_{t-n} + 0.003339ECT_{t-1} + 0.069971$$

The adjustment co-efficient, which denotes that the previous period's deviation from long-run equilibrium, is corrected in the current period as an adjustment speed of 0.003339,

In the short-run (shown in Table-5.3), a percentage change in TIFC is associated with 0.1188 increases in GIVA on an average Ceteris Paribus, and a percentage change in I.C.C. is associated with 0.49 increases in GIVA on an average Ceteris Paribus, a percentage change in IEPV is associated with 0.0249 increase in GIVA on an average Ceteris Paribus. In contrast, a percentage change in IOFC is associated with a -0.0158 decrease in GIVA on an average Ceteris Paribus. Similarly, a percentage change in I.P.P. is associated with a -0.076 reduction in GIVA on an average Ceteris Paribus.

Granger/Wald Causality test on lagged explanatory variables

H0: lagged coefficient (s)=0

H1: lagged coefficient (s)#0

Decision Criteria: Reject the null hypothesis if the Prob-value of the chi2 statistic is < 0.05

Table-5.5: V.E.C. Granger Causality, Block Exogeneity Wald Tests

Model	Variable influence	Chi-sq	Prob.
GIVA	INICCVV	14.424	0.0007
TIFCV	INGIVA	13.229	0.0013
ICCVV	INGIVA	2.8164	0.2446
IEPV	INGIVA	7.1022	0.0287
IOFCV	INGIVA	6.3978	0.0408
IPPV	INGIVA	23.063	0.000

The null hypothesis (as shown in Table-5.5) tells that the lagged co-efficiency of ICCV does not cause GIVA, against the alternative that the lagged co-efficient of ICCV has a causal effect on GIVA. Looking at the chi-sq results and the probability value, the obtained p-value (0.0007) being more significant than the p-value of the chi-2 statistic (<0.05), we accept that ICCV does not have a short-run causal effect on GIVA. However, at a 10% level of significance, ICCV has short-run causality on GIVA. In contrast, GIVA has a short-run causal effect on total industrial fuel consumption, electricity consumption, petroleum consumption, and other fuel consumption at a 5% level of significance.

Pair-wise Granger causality test on the direction of causality

H0: no Granger – causality

H1: the null hypothesis is not true

Decision criteria: Reject the null hypothesis if the Prob-value of the F-statistics is <0.05

To know the direction of causality

Table:5.6 Pair-wise Granger causality test on the direction of causality

Null Hypothesis:	F-Statistic	Prob.	Direction of causality
INTIFCV does not Granger Cause INGIVA	1.4599	0.2335	Uni-directional causality running from GIVA to TIFCV
INGIVA does not Granger Cause INTIFCV	6.70204	0.0014	
INICCVV does not Granger Cause INGIVA	10.8724	3.00E-05	Uni-directional causality running from I.C.C. to GIVA
INGIVA does not Granger Cause INICCVV	2.30372	0.1012	
INIEPV does not Granger Cause INGIVA	1.2565	0.2857	Uni-directional causality running from GIVA to IEC
INGIVA does not Granger Cause INIEPV	6.1478	0.0023	
INIOFCV does not Granger Cause INGIVA	2.42366	0.0899	No causality, independent relationship
INGIVA does not Granger Cause INIOFCV	4.7221	0.0094	
INIPPV does not Granger Cause INGIVA	2.6995	0.0684	Uni-directional causality running from GIVA to IPPC
INGIVA does not Granger Cause INIPPV	8.82099	0.0002	

5.5 Conclusion and Policy Implications:

The present chapter examined the interlinkages between energy inputs and industrial value-added for Indian industries for the sample period of 2001-2021. It explored the relationship both at the aggregate and dis-aggregate levels upon finding the presence of integrated series at the level through the panel unit root test. The Johansen Maximum Likelihood approach indicated strong co-integration of the variables. The co-integration results recorded that the GIVA and energy input in the industry both at aggregate and disaggregate levels are co-integrated, and the combination of the following series such as I.V.A. and T.F.C.; I.V.A. and I.C.C.; I.V.A. and I.E.C.; I.V.A. and IOFC; I.V.A. and I.P.P.; tending together in the long run. Hence, posited that the pairs of investigated variable series are in a long-run relationship. Later, to find out the direction of the Granger causality between variables, VECM has been undertaken. In long-run, the results of VECM showed that InGIVA, InCC, and InIEC have cause-and-effect relationships among the variables in the long-run. At the disaggregated level, an increase in gross industrial value-added has a positive impact on the demand for coal usage and electricity consumption at a 5% significance level. These findings are similar to Akhmat and Zaman (2013) and Bildirci (2014) for coal usage and economic growth. But at the same time, the results contradict the finding of Nain, Ahmed, and Kamaiah (2015). Their conclusion for the industrial sector at disaggregates level revealed no long-run relationship between Energy and Income.

Moreover, the short-run VECM results showed short-run causality running from GIVA to industrial fuel consumption, electricity consumption, and petroleum consumption, which meant expanding industrial production, and demands for more energy inputs in the short-run. Moreover, the Granger Causality test reveals the direction of causality running from GIVA to TIFCV, GIVA to I.E.C., GIVA to IPPC, and I.C.C. to GIVA.

Based on the above empirical results, we know that the Gross industrial value-added is delivered primarily through energy consumption. The industrial sector's energy intake remains as high as 50% of the total available commercial energy. Coal & electricity is used as a critical component in industrial production both in the short-run and long-run. Energy-intensive manufacturing such as pulp & paper, basic chemicals, refining, iron & steel, nonferrous metals & nonmetallic mineral seems to be energy dependent for decades ahead. Hence the policymakers must fulfill two objectives. First, balance the demand for and supply of energy and safeguard the environment from the negative externalities of excessive energy consumption. This requires a focus on industrial energy efficiency and scope for saving energy by adopting energy-efficient technology (EETs), substitution for conventional sources of energy, renewable energy Technology (RETs), and best operating practices (B.O.P.s).

Moreover, the current Indian economic thought of being "a self-reliant India" (Atmanirbhar Bharat) will double energy consumption in the near future and widen the energy deficit. Hence in time to come, India needs to design robust energy policies such as reducing dependency on fossil fuels, particularly petroleum and coal, and moving towards renewable energy sources, including hydrogen. This will make India a manufacturing hub, creating global competitiveness, and Atmanirbhar Bharat achievable.

This chapter enclosed an important revelation that coal & electricity is used as a critical component in industrial production both in the short-run and long-run. Many energy-intensive industries such as pulp & paper, and basic metals such as steel, iron, aluminum, chemical, refining, and cement seemingly striving toward more energy dependent for the decades ahead. However, against the availability of conventional energy and its negative externality on the environment, it is warranted that attention to the use of renewable energy and energy efficiency is given. Hence in the forthcoming, sixth chapter the level of energy intensity and efficiency in the manufacturing sector is analyzed with the help of A DEA-Based Malmquist Productivity Analysis.

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