CHAPTER - 4

AN ANALYSIS OF INDUSTRIAL GROSS VALUE ADDED AND ENERGY CONSUMPTION OF INDIAN MANUFACTURING INDUSTRIES: A FIXED AND RANDOM EFFECT APPROACH

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The third chapter described the Indian energy scenario and its sectoral implications, once we had observed each variable and their statistical distribution, both of these investigative stances removed uncertainty regarding the factors and energy's relationship to the industrial sector specifically and the Indian economy generally.

Using methods like fixed and random effect models, Trans-log production function, and Allen elasticity of factor substitution, the current chapter continues further to statistically explore the relationship between industry and energy in two parts with two sets of variables. The purpose is to find out the functional relationship among variables and to know the energy elasticity to industrial output and industrial output elasticity to energy use.

4.1 Introduction

India's industrialization has rapidly grown since the IInd Five-Year Plan was put into place, creating a high demand for energy utilization. At the present, the energy used by industry accounts for about 43% of the energy supply. (Energy Balance Statistics, 2021). This is also because essential energy-intensive industries like pulp and paper, cement, fertilizer, iron and steel, and aluminum are constantly seeing increases in investment (Bhattacharya and Copper 2010). However, the continuous rise in energy use has a significant impact on Green House Gases, especially CO_2. To drastically reduce energy intensity, it is necessary to modify consumption with low utilization. It is also important to note that India pledged at the Conference of Parties (CoP26) to decrease its estimated total carbon emissions by 1 billion tones by 2030, reduce the carbon intensity of its economy by less than 45% by the end of the decade, and achieve net-zero carbon emissions by 2070. Given this, it is even more important to examine the energy use and industrial outputs of energy-intensive industries in India, including those that produce basic metal, beverages, chemical products, coke and refinery, fabricated metal, machinery and equipment, textiles, non-metallic mineral products, paper, and paper products, pharmaceutical medical products, and paper and paper products.

Following the above, the objectives of the present chapter are described below.

4.2 Objectives

1. To evaluate the trends in the volume of energy use and energy intensity of output in industrial sectors.

2. To observe the real price of energy trend throughout the reference period

3. To understand the functional relationship between industrial gross value-added and energy consumption.
4. To study the influence of fixed capital, labor, and energy on industrial gross value-added.
5. To test whether the Random or Fixed Model fits the data well in measuring the energy consumption and industrial gross value-added for Indian Industries.
6. To calculate the share of energy to growth
7. To measure the degree of price elasticity of demand for energy

Based on the above objectives the following main hypothesis has been framed and tested

4.3 Hypotheses

1. Higher energy consumption leads to higher industrial output.
2. The higher the real energy price, the lower the energy demand.

4.4 Review of Related Literature

Numerous studies have examined the functional link between energy and output since the 1970s. And over time, these investigations have used a variety of approaches. They have primarily used production and energy-related aggregate data. The majority of this research discovered a causality running from energy consumption to output in both industrialised and developing nations. There is a large amount of literature on this subject that is currently available, however, a few recent reviews are presented below.

Ewing et al. (2007) investigated the effect of disaggregate energy consumption on industrial output in the United States. Monthly data on energy, employment, and real output was collected and the generalized variance decomposition approach was employed to assess the relative impacts of energy and employment on real output. Their results suggested that unexpected shocks like price falls or rises, on coal, natural gas, and fossil fuel energy sources have the highest impacts on the variation of output, while several renewable sources indicated considerable explanatory power as well. However, their results revealed that none of the energy sources explained more of the forecast error variance of industrial output than employment.

Similarly, Asghar (2008) investigated the causal relationship between GDP and disaggregated forms of energy for five South Asian Countries namely; Pakistan, India, Sri Lanka, Bangladesh, and Nepal. The research was undertaken by using Error Correction Model and Toda and Yamamoto (1995) approach. Results revealed that for Pakistan a unidirectional Granger causality ran from coal to GDP, and unidirectional Granger causality ran from GDP to electricity consumption and total energy consumption and for India, no causality in either direction between GDP and different energy consumption was captured. Whereas for Sri Lanka there was unidirectional Granger causality running from GDP to electricity consumption and total energy consumption. And Bangladesh showed a unidirectional Granger causality from GDP to electricity consumption and from gas consumption to GDP. Finally, Nepal detected a causal direction from petroleum to GDP.

Qasim (2012) studied the relationship between disaggregated energy consumption and industrial output in Pakistan by employing the Johansen Method of Cointegration. The findings agree on the positive effect of disaggregated energy consumption on industrial output. Pinpointedly a bidirectional causality was found in the case of oil consumption, whereas unidirectional causality was in the case of electricity consumption to industrial output. Moreover, unidirectional causality has been found from industrial output to coal consumption. However, there was no causality between gas consumption and industrial output. In the end, the study suggested that depending on conventional energy is risky for industrial sector hence the economy should look for alternative energy sources such as solar and wind to boost clean industrial growth.

Whereas, Ramakrishna, G. & Rena, R. (2013) attempted to overview the energy scenario of India in terms of energy consumption, energy security, and energy efficiency. Growth trends and the changes in growth trends of these variables were estimated for the period 1981 to 2010. The evaluation tested the causal relationship between energy consumption and GDP both at aggregate and disaggregate levels using cointegration and Vector Error Correction (VECM) methods. The empirical outcomes revealed that India is energy scarce economy, despite the continuous increase in energy efficiency. The study also revealed that energy consumption and GDP are bidirectionally related at the aggregate level.

In contrast, Mohanty and Chaturvedi (2015) conducted a study to find out whether electricity energy consumption influences economic growth or vice versa for the Indian economy for the period from 1970–1971 to 2011–2012. After employing, the two-step Engle-Granger technique and Granger causality Block exogeneity Wald test, the study indicated that it is the electricity energy consumption that drives economic growth both in the short run and long run. Further using the dynamic OLS (DOLS) method, the elasticity of electricity consumption on economic growth was estimated at 0.86 and the elasticity of economic growth on electricity consumption was estimated at 1.19.

Korhan et al. (2015), on the other hand, evaluated the relationship among the oil price, inflation, Gdp, and industrial output for Turkey's economy for the reference period of 1961 to 2012. Three different tests, namely unit root, co-integration, and causality tests, have been used to estimate the relationship among the variables. The results of Phillips-Perron (PP) as a unit root test suggested that all the variables under testing were integrated into order one; I (1). Johansen co-integration results asserted a long-run relationship among these variables and the Granger causality test revealed the unidirectional relationship between oil price to industrial production.

Sankaran et al. (2019) concentrated on analysing the functional relationship between manufacturing value added and energy consumption. The variables chosen under the study were per capita income, exports, imports, and exchange rates for ten economies: Morocco, Philippines, Sri Lanka, Kenya, Bangladesh, Bolivia, Cameroon, India, and Peru for the period from 1980 to 2016. The ARDL bounds test approach of cointegration was employed along with Toda-Yamamoto Granger causality test to find out the relationship between electricity consumption and industrial output. The results proved that for countries like Bangladesh, Bolivia, Morocco, and India there was a unidirectional causality from energy consumption to manufacturing output.

Abbasi et al. (2020) carried out their research in two ways. Firstly, they employed Vector Error Correction Model (VECM) to estimate electricity consumption in Pakistan's economy during 1970–2018 to find out the relationship between variables such as electricity consumption, price, and real gross domestic product. Secondly, they tried to decompose cumulative shock if any on each variable using a Dynamic Variance Decomposition Technique. The empirical estimation showed that the variables under study were co-integrated. The results also revealed the long-run relationship between electricity consumption, price, and real gross domestic product in the industrial sector. Further, the two methods employed revealed that the VECM analysis confirmed with variance decomposition method by its results.

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 Aviral Kumar 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 can be categorized as some of them considered energy in aggregate form, to report a few Soytas (2007); Asghar (2008); Qasim 2012). Others reported the energy in disaggregate form namely, Mohanty (2015); Chaturvedi (2015); Rena (2013); Korhan (2015); Sankaran (2019); Abbas (2020), and Singh (2020). Of the above literature, some showed unidirectional causality, like Asghar (2008) for Pakistan, from coal to GDP, for Sri Lanka from GDP to energy, for Bangladesh from GDP to energy, and for Nepal from petroleum to GDP. Qasim (2012) industrial output to oil consumption. Sankaran (2019) reported unidirectional for Bangladesh, Bolivia, Morocco, and India. Whereas the study by Gollagari (2013) reported a bidirectional causality from energy consumption to GDP. These differences could be accorded to different methodologies used, sets of variables, and various individual research periods. It is in this context that the present chapter aims to investigate the energy use and industrial gross value-added along with variables such as price level, fixed capital, and labor relationship using the Fixed and Random Effect Models.

4.5 Data Sources

The main source of data for the analysis is the 'Annual Survey of Industries of India' database from 2001 to 2021. The data of manufacturing industry-wise consumption of energy input such as coal, natural gas, petroleum products, and electricity is collected in the form of physical units. The data of labor employed, fixed capital, and gross value-added is considered in monetary value. This information is collected from various sources such as Petroleum and Natural Gas Statistics published by the Ministry of Petroleum and Natural Gas, Government of India; and Energy Statistics of various years, published by the Ministry of Statistics and Programme Implementation, Government of India.

4.6 Methodology of Analysis

The panel data used here include variables such as fuel intensity, fuel consumption, fixed capital, labor, profit, and net value-added. Data about the above variables have been taken from the Annual Survey of Industries for the reporting period from 2001 to 2021. It is a long panel and has many periods (large T) but a limited number of industries (Cameron and Trivedi, 2009). The data is balanced in a balanced panel. All industries have measurements in all periods. In a contingency table of cross-sectional and time-series variables, each cell has only one frequency. Therefore, the total number of observations is eleven industries over twenty years (11*20) and it is a fixed panel. (Greene 2008).

First, descriptive statistics of the panel data have been explored to obtain the summary of statistics. The analysis began by using the pooled (OLS), which is a linear regression with no fixed or random effect and assumes a constant intercept and slopes regardless of group and period.

OLS: $Industrial\ Gross\ Value\ Added_i(IGVA)$

$$= \beta_0 + \beta_1 fuelconsumed_i + \beta_2 fixed\ capital_i + \beta_3 labour_i + \varepsilon_i$$

The pooled OLS model was found to be fitting the data well at the 0.05 significance level (F=996.35) and P<0001). R^2 of 0.9401 denotes that this model accounts for 93 percent of the total variance in the gross value-added in the industries. However, we need to worry if each industry or year has a different return of gross industrial value-added, and its intercept differs from other industries. This has led to conducting three types of fixed effect estimations: One, (LSDV-with dropping a dummy; two, LSDV1-no intercept but all the dummies and three, LSDV2-subject to constraint). On the other hand, what if the disturbance term alters across industries and years? This makes it a prerequisite to conducting the random effect model.

Hence, firstly the Least Square Dummy Variable (LSDV) model has been conducted by introducing group (industries) dummy variables D1 to D11. The D11 was omitted to avoid multi-collinearity. The regressors and dummies are allowed to be correlated in fixed effect estimation.

LSDV model: $Gross\ Industrial\ Value\ Added_i = \beta_0 + \beta_1 fuel_i + \beta_2 fixed\ capital_i + \beta_3 labour_i + +u_1 d_1 + u_2 d_2 + u_3 d_3 + u_4 d_4 + u_5 d_5 + u_6 d_6 + \cdots + u_{11} d_{11} + \varepsilon_i$

The u1-u11 are respective parameter estimates of group dummy variables D1-D11.

Secondly, estimation of LSDV1 is undertaken, with an inclusion of all dummies but with suppressed intercept (i.e., intercept to be zero). Its functional form is,

$$Gross\ Value\ Added_i = \beta_1 fuel_i + \beta_2 fixedcapital_i + \beta_3 labour_i + \mu_1 d_1 + \mu_2 d_2 + \mu_3 d_3 + \mu_4 d_4 + \mu_5 d_5 + \cdots \mu_{11} d_{11} + \varepsilon_i$$

Thirdly, the estimation of LSDV2 is worked upon that includes the intercept and all dummies but with a restriction that the sum of parameters of all dummies is equal to zero. The functional form of LSDV2 is,

$$Gross\ Value\ Added_i = \beta_0 + \beta_1 fuel_i + \beta_2 fixedcapital_i + \beta_3 labour_i + \mu_1 d_1 + \mu_2 d_2 + \mu_3 d_3 + \mu_4 d_4 + \mu_5 d_5 + \cdots \mu_{11} d_{11} + \varepsilon_i$$

$$Subject\ to: \mu_1 d_1 + \mu_2 d_2 + \mu_3 d_3 + \mu_4 d_4 + \mu_5 d_5 + \cdots \mu_{11} d_{11} = 0$$

Among all the three estimates of fixed effect models, the LSDV with its return stands robust. As LSDV fits the data better than the pooled (OLS) model, it can be understood from the statistical outcome of the F-statistic that showed a decrease from 996.35to 784.84 ($p<.0001$); SSE (sum of squares due to error or residual) showed a decrease from 5.178to 1.520; and R^2showed an increase from 0.93 to 0.98. By including group dummies, this model loses 10 degrees of freedom (from 216 to 210). The parameter estimates individual regressors that are slightly different from those in the pooled OLS. For instance, the coefficient of fuel consumed changed from negative -0.4728 to positive 0.5881 but its statistical significance remained almost unchanged ($p<0.0001$).

Further, the question arises as to which estimation is the most valid. If the analysis is done based on the outcome of the LSDV, it seems to be more robust in estimation than others. At the same time, it is imperative to find out the significant fixed effect of LSDV. Therefore, F-test has been conducted. The F-test reveals that the null hypothesis of this F-test is that all dummy parameters except for one are zero: $H_0: u_1 = \cdots = u_{n-1} = 0$. Thus, the outcome of the F-test conducted for fixed effect is 784.84. This figure looks large enough to reject the null hypothesis. It also indicates that the fixed effect model is appropriate to deal with the data. Further, to refine the result better random effect model has been constructed. This is to solve the doubt whether differences across industries in any way influence the dependent variable "Gross Industrial Value Added".

The random effects model is: $Y_{it} = \beta X_{it} + \alpha + u_{it} + \varepsilon_{it}$

u_{it}= between entity error

ε_{it}= Within entity error

The outcome of random effect estimation is surprising as it seemingly suits the data better in relation to the pooled OLS model. Therefore, the significant test was conducted using Breusch and Pagan Lagrangian Multiplier Test. The test resulted in a larger Chi-squared (1)150.48 and proved to reject the null hypothesis in favor of the random group effect model ($p <0.0001$) which also indicates that the random effect model is more statistically viable to deal with the data.

These results further create a dilemma as both models demonstrate validation. Therefore, the decision, of which model is better than the other, becomes challenging. However, the Hausman specification test was performed to find out the most significant estimation. The Hausman Specification test resulted in 50.80, which is statistically significant at 0.01 significance as the P-value is ($p<0.0001$). Moreover, the data succeeds in meeting the asymptotic assumptions. Here, the chi-squares score is large enough to reject the null hypothesis;

H_0: The Random effect model rather than the fixed effect model is appropriate

H_1: The Random effect model is not appropriate.

Thus, it is concluded that the fixed effect model is analytically better than its Random effect counterpart.

In addition, a production function framework has been worked out. Where labour, Capital, and Energy are taken as inputs, and the industrial net output is taken as output.

Symbolically it can be written as QN=f(K, L, E,t)

Hence growth equation follows as:

$$\Delta InQN_t = \bar{Y}_{K,t}\,\Delta InK_t + \bar{Y}_{L,t}\,\Delta InL_i + \bar{Y}_{E,t}\,\Delta InE_t + \Delta InA_t$$

$\bar{Y}_{K,t}, \bar{Y}_{L,t}, and\ \bar{Y}_{E,t}\ are\ income\ shares, \Delta InA_t\ denotes\ Total\ Factor\ Productivity\ growth$

.

Consequently, the energy demand function has been estimated as a function of output and real energy prices. Moreover, the price elasticity of energy demand in the manufacturing sector is worked out.

Extending the energy demand equation as:

$$\mathrm{In}(\mathrm{E_t}) = \alpha + \beta\ \mathrm{In}(\mathrm{Q_t}) + \gamma\ \mathrm{In}\{\left(\frac{\mathrm{P_E}}{\mathrm{P_Q}})_t\right\}\theta\ \mathrm{In}\{\left(\frac{\mathrm{K}}{\mathrm{Q})_t}\right\} + \mathrm{u_t} \ldots (1)$$

In addition, the translog-Production equation has been utilized

$$\begin{aligned}In(QN) = {} & \alpha + \beta_L InL + \beta_K InK + \beta_E InE + 0.5 * \beta_{LL}(InL)^2 + 0.5 * \beta_{KK}(InK)^2 + 0.5 \\ & * \beta_{EE}(InE)^2 + \beta_{LE}(InL * InE) + \beta_{KE}(InK * InE) + \beta_t t + 0.5 * \beta_{tt} t^2 \\ & + \beta_{Lt}(InL * t) + \beta_{Kt}(InK * t) + \beta_{Et}(InE * t) \ldots \ldots (2)\end{aligned}$$

In line with the production function framework income share equation has been estimated.

$$S_L = \left[\frac{In(QN)}{\partial InL}\right] = \beta_L + \beta_{LL}(InL) + \beta_{LK}(InK) + \beta_{LE}(InE) + \beta_{Lt}(t) \dots . (3)$$

$$S_L = \left[\frac{In(QN)}{\partial InE}\right] = \beta_E + \beta_{LE}(InL) + \beta_{KE}(InK) + \beta_{EE}(InE) + \beta_{Et}(t) \dots . (4)$$

4.7 Descriptive analysis

Firstly, descriptive statistics (Table 1) of the panel data have been explored to obtain the summary of statistics. Here, the total number of observations is 220 from 11 industries for 21 years time periods. The overall mean of industrial gross value-added is (12.70854) while the standard deviation is (1.363902). Similarly, the mean and standard deviation of fuel consumption, fixed capital, and Labor are given below. There are three types of statistical outcomes, such as overall, between, and within. "Overall" statistics are the ordinary statistics that are based on the 220 observations. Whereas, the "between" statistics are calculated based on summary data of 11 industries regardless of the period, while the "within" statistics by summary statistics of 20 years but without regarding the industries.

Table-4.1 Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
GVA	Overall	12.70854	1.363902	10.02076	16.5013	N = 220
	Between		1.170181	11.1546	15.45267	n = 11
	Within		0.780835	10.69235	13.99423	T = 20
FC	Overall	11.33093	1.518107	8.138039	15.0677	N = 220
	Between		1.410913	9.414552	14.137	n = 11
	Within		0.697624	9.305213	12.63327	T = 20
FK	Overall	13.38327	1.407375	10.38921	1.73E+01	N = 220
	Between		1.246564	11.7261	1.61E+01	n = 11
	Within		0.749398	11.91037	14.86239	T = 20
L	Overall	13.19902	1.254213	11.12548	1.66E+01	N = 220
	Between		1.28111	11.48588	16.18302	n = 11
	Within		0.272394	12.6297	13.87001	T = 20

Source: Author's Calculation

Table-4.2 Correlation Matrix

	IGVA	Fuel consumed	Fixed capital	Labour
Gross I-Value added	1.00			
Fuel consumed	0.85	1.00		
Fixed capital	0.95	0.94	1.00	
Labour	0.73	0.79	0.73	1.00

Source: Author's Calculation

The above table-4.2 on the correlation matrix shows a high positive correlation (0.85) between fuel consumption and industrial gross value added. From such an integrated correlation, the magnitude of income share to industrial gross value added can be identified.

4.8 Analysis through Pooled Linear Regression Model

The pooled OLS is a pooled linear regression without fixed or random effects. It assumes there is no difference in intercepts and slopes across all the groups and periods.

$$y_{it} = \alpha + X_{it}\beta + \varepsilon_{it}\ (u_i = 0)$$

$$Gross\ Industrial\ Value\ Added_i = \beta_0 + \beta_1 fuelconsumed_i + \beta_2 fixed\ capital_i + \beta_3 labour_i + \varepsilon_i$$

$$\beta_0\ is\ the\ intercept$$

$$\beta_1 = is\ the\ slope\ (coefficient\ or\ parameter\ estimate) of\ fuelconsumed$$

$$\beta_2 = is\ the\ slope\ of\ fixed\ capital$$

$$\beta_3 = is\ the\ slope\ of\ labour\ used$$

$$\varepsilon_i = is\ the\ error\ term$$

The pooled OLS model fits the data well at the 0.05 significance level (F=996.35) and P<0.0001). R^2 of 0.93 denotes that this model accounts for 99 percent of the total variance in the gross value-added in the industries.

The regression equation is,

GrossValueAdded=-0.7307-0.4728*fuel+1.255*fixedcapital+0.3306*labour

The p-values given below are the results of t-tests for individual parameters.

In the case of zero fuel consumption, zero fixed capital, and zero labour in each industry is expected to have a -0.7307 amount of change in gross value-added ($p<0.0001$). For, one unit increase in fuel consumed, the gross value-added is expected to change by -0.4728, holding all other variables constant ($p<0.0001$). Whenever fixed capital increases by one-unit, gross value-added increases by 1.255units, holding all the other variables constant ($p<0.0001$).

Although pooled OLS model fits well with a given data, but we need to consider Y-intercept same for all the industries. This creates room for adopting fixed effects models. On the other hand, the question arises about the disturbance term. What if it varies across industries and time series? Hence, to solve such queries, an attempt is made to conduct fixed and random effects.

4.9 Analysis through Fixed Effect Model

The LSDV (fixed effect) model is-

$$\begin{aligned} Gross\ Industrial\ Value\ Added_i &= \beta_0 + \beta_1 fuelconsumed_i + \beta_2 fixed\ capital_i + \beta_3 labor_i + u_1 d_1 + u_2 d_2 \\ &+ u_3 d_3 + u_4 d_4 + u_5 d_5 + u_6 d_6 + \cdots + u_{11} d_{11} + \varepsilon_i \end{aligned}$$

In the above-specified model, eleven groups (industry) dummies have been introduced. The eleventh dummy has been dropped to avoid perfect multi-collinearity. The dummy variables and regressors are allowed to be correlated in a fixed effect model. $u_1 - u_{11}$are respective parameter estimates of group dummy variables $d_1 - d_{11}$.

This LSDV fits the data better than the pooled OLS model. The F statistic shows a decrease from 996.35 to 784.84 ($p<0.0001$); SSE (sum of squares due to error or residual) shows a decrease from 5.1784 to 1.520; and R^2 shows an increase from 0.93 to 0.98. By including group dummies, this model loses 10 degrees of freedom (from 216 to 206). The parameter estimates that individual regressors are slightly different from those in the pooled OLS. For instance, the coefficient of fuel consumed changed from negative -0.47287 to positive 0.5881 but its statistical significance remained almost unchanged ($p<0.0001$). This fixed effect model shows that each Industry has its intercept but the slopes of regressors are the same for all Industries (i.e., fuel consumed, fixed capital, labor). Now, an attempt has been made to derive industry-specific intercepts that interpret the dummy coefficients *u1-u11* and report regression equations in LSDV.

The parameter estimates of d_{11} (dropped dummy) is obtained in the LSDV intercept (-2.6169), which is the baseline intercept (reference point). Each of $u_1 - u_{11}$represents the deviation of its group-specific intercept from the baseline intercept (-2.6169) of Industry11. For instance, u_1= 0.2364means that the intercept of the basic metal industry is 0.2364, which is greater than the baseline intercept (-2.6169). Hence, the intercept of the basic metal industry can be derived as -2.3805= -2.6169+ 0.2364. Similarly, when the intercepts of each group are analyzed, it is observed that the intercept is deviating from that of the baseline intercept.

Further, a comparison has been made to find out the advantage and disadvantages of choosing between Pooled OLS, LSDV, LSDV1, LSDV2; and to understand the outcome of using group dummies and individual intercept for each group, also to check the significance of adding dummies in the model during the later stage.

Table- 4.3 Comparing Pooled OLS; LSDV, LSDV1, and LSDV2 (Fixed Effect Model)

	Pooled OLS		LSDV		LSDV1		LSDV2	
Fuel consumed	-.47287 (.0526)	(p<.001)	.58814 (.0680)	(p<.001)	.5881 (.0680)	(p<.001)	0.5997	(p<.001)
Fixed capital	1.2553 (.5090)	(p<.001)	.29315 (.0740)	(p<.001)	0.2931 (.0740)	(p<.001)	0.4542	(p<.001)
Labour	.22338 (.0316)	(p<.001)	.52091 (.1348)	(p<.001)	0.5209 (.1348)	(p<.001)	-.0228	(p<.048)
Overall intercept (baseline intercept)	-.73070 (.1386)	(p<.001)	-2.6169 (.6415)	(p<.001)	Suppress ed		.01435	(p<.088)
Basic Metal (deviation from the baseline)	-		.2364 (.1253)	(p<.001)	-	-	-.2748 (.0232)	(p<.001)
Beverages (deviation from the baseline)	-		.9288 (.1824)	(p<.001)	-	-	.1785 (.0233)	(p<.001)
Chemical Products (deviation from the baseline)	-		.4759 (.1281)	(p<.001)	-	-	-.0481 (.0214)	(p<.005)
Coke& refinery products (deviation from the baseline)	-		1.188 (.2298)	(p<.001)	-	-	.2479 (.0383)	(p<.001)
Fabricated metal products (deviation from the baseline)	-		.6980 (.1135)	(p<.001)	-	-	.2370 (.0236)	(p<.001)
Machinery and equipment (deviation from the baseline)			.9194 (.1098)	(p<.001)			.4832 (.0327)	(p<.001)

Textiles (deviation from the baseline)			0.1366 (.0761)	(p<.074)	-	-	-0.1642 (0.0239)	(p<.001)
Nonmetallic mineral product (deviation from the baseline)			0.1838 (.1141)	(p<.001)	-	-	-0.2768 (0.0270)	(p<.001)
Paper& paper product (deviation from the baseline)			0.3975 (.1602)	(p<.109)	-	-	-0.2613 (0.0211)	(p<.001)
Pharmaceuticals Medicinal (deviation from the baseline)			0.9073 (.1337)	(p<.001)	-	-	0.3618 (0.0248)	(p<.001)
F-test	996.35	(p<.001)	784.84	(p<.000)	65574.67	(p<.001)	787.28	(p<.001)
Degrees of freedom (error)	216		206		206			
SSE (Sum of squares error)	5.1784		1.5206		1.5206			
Root MSE	0.15484		.08592		0.8592		0.0892	
R2	0.9326		0.9802		0.9998			
Adjusted R2	0.9317		0.9790		0.9998			
N	220		220		220		220	

Source: Author's Calculation

Estimating LSDV1includes all dummies but suppresses the intercept (i.e., intercept to be zero). Its functional form is,

$$Gross\ Value\ Added_i = \beta_1 fuel_i + \beta_2 fixedcapital_i + \beta_3 labour_i + \mu_1 d_1 + \mu_2 d_2 + \mu_3 d_3 + \mu_4 d_4 + \mu_5 d_5 + \cdots \mu_{11} d_{11} + \varepsilon_i$$

Estimating LSDV1, it is noticed, that all parameter estimates of regressors are more or less the same as those in LSDV. The coefficients of eleven industrial group dummies represent their group intercepts. In which, it need not calculate the individual group intercepts. This is advantageous in LSDV1; however, the resulting outcome denotes an inflated R^2 (0.9998>0.9808) and F (very large 65574.67). Unsurprisingly, getting an R^2 of 0.9998 may not be similar. The reason behind it is that the X matrix does not permit it because of the suppressed intercept, which has a column vector of 1 and produces incorrect sums of squares of the model (Uyar and Erdem, 1990). However, the sum of squares of errors (SSE) and their standard errors of parameter estimates are correct and the same in any LSDV.

Estimating LSDV2 includes the intercept and all dummies but with a restriction that the sum of parameters of all dummies is equal to zero. The functional form of LSDV2 is,

$$\text{Gross Value Added}_i = \beta_0+\beta_1\text{fuel}_i + \beta_2\text{fixed capital}_i + \beta_3 \text{ labour}_i + \mu_1 d_1 + \mu_2 d_2 + \mu_3 d_3 + \mu_4 d_4 + \mu_5 d_5 + \cdots \mu_{11} d_{11} + \varepsilon_i$$

$$\textit{Subject to}: \mu_1 d_1 + \mu_2 d_2 + \mu_3 d_3 + \mu_4 d_4 + \mu_5 d_5 + \cdots \mu_{11} d_{11} = 0$$

All the above results, end up fitting the same model and giving the same parameter estimates of predictors and their standard errors. Approaches like LSDV and LSDV2 give accurate R^2 while LSDV1 gives inflated R^2 but unfitting SSE and MSE. The actual difference between the above approaches rests on the outcome of the intercept and dummy coefficients. The LSDV reveals the dummy coefficient and the extent to which the actual intercept of the group deviates from the overall baseline intercept. The null hypothesis of the t-test is that the deviation from the reference group is zero. Whereas the LSDV2 approach denotes that its actual parameter is far from the average group effect (Suits 1984:178), therefore, in this case, the null hypothesis is that the deviation of a group intercept from the averaged intercept is zero. In summarizing the above three approaches, it can be said that LSDV is the model that fits the best. It is because of constructing the LSDV model, the analysis seems to be less cumbersome.

Table-4.4 Comparison of OLS, LSDV, and Within Effect Models

	OLS	LSDV	.xtreg	.areg
Fuel consumed	-.47287** (.0526)	.58814** (.0680)	.5881** (.0680)	.5881** (.0680)
Fixed capital	1.2553** (.5090)	.29315** (.0740)	.2931** (.0740)	.2931** (.0740)
Labour	.22338** (.0316)	.52091** (.1348)	.5209** (.1348)	.5209** (.1348)
Overall intercept (deviation from the baseline) (baseline intercept)	-.73070** (.1386)	-2.6169** (.6415)	-2.0648 (.5207)	-2.0648** (.5207)
Basic Metal (deviation from the baseline) (dummy)	-	.2364** (.1253)	-	-
Beverages (deviation from the baseline) (dummy)	-	.9288** (.1824)	-	-
Chemical Products (deviation from the baseline) (dummy)	-	.4759** (.1281)	-	-
Coke& refinery product (deviation from the baseline) (dummy)	-	1.188** (.2298)	-	-

Fabricated metal product (deviation from the baseline) (dummy)	-	.6980** (.1135)	-	-
Machinery and equipment (deviation from the baseline) (dummy)	-	.9194** (.1098)	-	-
Textiles (deviation from the baseline) (dummy)	-	.1366** (.0761)	-	-
Nonmetallic mineral product (deviation from the baseline) (dummy)	-	.1838*** (.1141)	-	-
Paper& paper product (deviation from the baseline) (dummy)	-	.3975** (.1602)	-	-
Pharmaceuticals Medicinal (deviation from the baseline)	-	.9073** (.1337)	-	-
F-test	996.35	784.84	1068.54	1068.54
Degrees of freedom (error)	216	206		568
SSM (Model)			*23.663*	*1.5206*
SSE (Sum of squares error)	5.1784	1.5206	*.5206*	*.3178*
Root MSE(SEE)	.15484	.08592	.0859	0.0859
R2	0.9326	0.9802	*0.9396*	0.98
Adjusted R2	0.9317	0.9790	*0.9358*	0.97
F-test (fixed effect)	-	-	**49.55**	**49.55**
N	220	220	220	220

Standard errors in parenthesis; Statistics hidden in macros are italicized; Statistical significance: * <.05, **<.01, **<10

Source: Author's Calculation

The above table-4.4 brings the output of pooled OLS and four other fixed estimations (i.e., LSDV .xtreg, .areg & the within effect model), their results are almost the same, however, there is a bit of change in standard error and R^2. Now the question arises as to which estimation is the best. When we go with the outcome of the LSDV it seems to be better in estimation than others. However, it is imperative to find out the significance of fixed effect LSDV for which the F-test has been conducted. The F-test reveals that the null hypothesis of this F-test is that all dummy parameters except for one are zero: H0:$u_1 = \cdots = u_{n-1} = 0$

The F-test conducted for fixed effect is 49.55 looks large enough to reject the null hypothesis which indicates that the fixed effect model is appropriate to deal with the data. However, an attempt has been made to use random effect estimation. Unlike the fixed effects model, the random effect estimation assumes the variation across the industry to be random and uncorrelated with the predictor. In that case, it permits time-invariant variables to play a vital role as explanatory variables.

4.10 Analysis through Random Effect Model

The random effects model is:

$$Y_{it} = \beta X_{it} + \alpha + u_{it} + \varepsilon_{it}$$

u_{it}= Between entity error

ε_{it}= Within entity error

The random effect model is worked out to solve the doubt, of whether differences across industries in any way influence the dependent variable "Industrial Gross Value-Added".

Table-4.5 Comparison of OLS and Various Random Effect Estimations

	OLS	Random Effect	.xtmixed	.xtregmle
Fuel consumed	-.47287** (.0526)	.3575** (.0728)	.5649** (.0672)	.5649** (.0681)
Fixed capital	1.2553** (.5090)	.6386** (.0675)	.3633** (.0700)	.3633** (.0755)
Labor	.22338** (.0316)	.0515** (.0731)	.3654** (.1176)	.3654** (.1313)
Overall intercept	-.73070** (.1386)	-.2482** (.2909)	-1.467** (.465)	-1.467** (.516)
F, Wald, LR test	996.35	2483.83	3239.05	-
SEE	5.1784	.0859	.0856	.0856
$\hat{\sigma}_{\mu}$	-	.0883	.3268	.3268
Θ	-	.7874	-	-
R2	0.9326	0.9321	-	-
Adjusted R2	0.9317	-	-	-
LR Test	-	-	194.15	593.70

Standard errors in parenthesis; Statistical significance: * <.05, **<.01

Source: Author's Calculation

This random effect estimation also is seemingly fitting the data better in relation to the pooled OLS model. Whereas, the F statistic shows an increase from 996.35 to 2483.83($p<0.0001$); SSE (sum of squares due to error or residual) has changed from 5.1784 to 0.0859; and R^2 shows a reduction from 0.9326 to 0.9321. However, overall, the model fits the data better. Hence, Breusch and Pagan Lagrangian multiplier test was used to check the significance of the random variable.

4.11 Breusch and Pagan Lagrangian Multiplier Test

Breusch and Pagan Lagrangian Multiplier Test for random effects result with a larger Chi-squared (1)150.48, appears strong enough to reject the null hypothesis in favor of the random group effect model ($p < 0.001$) which further indicates that the random effect model is appropriate to deal with the data.

4.12 Hausman Specification Test

Since the outcome results of fixed and random effects are significant, there emerges a decision making as to which model is better than the other. The Hausman specification test is worked out to find out the most significant estimation. The Hausman test checks if the individual effects are not-correlated with other regressors in the model. In case, the individual effects are correlated with any other regressor, the random effect model violates a Gauss-Markov assumption and is no longer Best Linear Unbiased Estimate (BLUE). It is because individual effects are parts of the error term in a random effect model. Therefore, if the null hypothesis is rejected, a fixed effect model is favored over the random effect model. In a fixed effect model, individual effects are parts of the intercept and the correlation between the intercept and regressors does not violate any Gauss-Markov assumption; a fixed effect model is still BLUE.

Table-4.6 Hausman Specification Test

	(b)	(B)	(b-B)	Sqrt (diag (V_b-V_B))
	Random	Fixed	Difference	S.E.
Fuel consumed	.3575825	.5881467	-.2305642	.0261428
Fixed capital	.6386944	.2931516	.3455428	-
Labour	.0515636	.5209128	-.4693493	-
	chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)			
Chi-squared	50.80 **	(p<.001)		

Source: Author's Calculation

The Hausman Specification test returns 50.80, which is statistically significant at 0.01 significance as the P-value is ($p<0.001$). Moreover, the data succeeds to meet the asymptotic assumptions. Here, the chi-squares score is large enough to reject the null hypothesis;

H_0: The Random effect model rather than the fixed effect model is appropriate

H_1: The Random effect model is not appropriate.

We may now conclude that the Fixed effect model is better than its Random counterpart.

Table-4.7 Comparison of Pooled OLS, Fixed Effect, and Random Effect Models Results

	OLS	Fixed Effect	Random Effect
Fuel consumed	-.47287** (.0526)	.58814** (.0680)	.3575** (.0728)
Fixed capital	1.2553** (.5090)	.29315** (.0740)	.6386** (.0675)
Labour	.22338** (.0316)	.52091** (.1348)	.0515** (.0731)
Overall intercept	-.73070** (.1386)	-2.6169** (.6415)	-.2482** (.2909)
F, Wald, LR test	996.35	784.84	2483.83
SEE	5.1784	1.5206	.0859
$\hat{\sigma}_{\mu}$	-	-	.0883
Θ	-	-	.7874
R2	0.9326	0.9802	0.9321
Adjusted R2	0.9317	0.9790	-

Standard errors in parenthesis; Statistical significance: * <.05, **<.01

Source: Author's Calculation

For another set of explanatory and dependent variables such as capital, the real price of energy, and the capital-output ratio, the following fixed & random effect model results have been presented below.

Table-4.8 Fixed and Random Model effects for the Indian Manufacturing sector for variables such as Gross output, Real price of energy, and capital-output ratio.

Explanatory Variables	Manufacturing Sector	
	Fixed Effect Model	Random Effect Model
Gross output	0.458 (12.13)	00.459 (12.39)
The real price of energy	-0.426 (-4.37)	--0.452 (-4.61)
Capital output ratio	0.177 (3.42)	0.183 (3.54)
R-square	0.472	0.476
Number of Observations	220	220

Standard errors in parenthesis.

Source: Authors' calculation

The results from the table-8 show that all the other variables remain constant, each additional increase in the real price of energy was associated with a fall in fuel consumption by 0.426 amount.

Estimation of the Trans-log Production function

$$In(QN) = \alpha + \beta_L InL + \beta_K InK + \beta_E InE + 0.5 * \beta_{LL}(InL)^2 + 0.5 * \beta_{KK}(InK)^2 + 0.5 * \beta_{EE}(InE)^2 + \beta_{LE}(InL * InE) + \beta_{KE}(InK * InE) + \beta_t t + 0.5 * \beta_{tt} t^2 + \beta_{Lt}(InL * t) + \beta_{Kt}(InK * t) + \beta_{Et}(InE * t) \dots\dots (2.2)$$

In line with the production function framework income share equation has been estimated.

$$S_L = \left[\frac{In(QN)}{\partial InL}\right] = \beta_L + \beta_{LL}(InL) + \beta_{LK}(InK) + \beta_{LE}(InE) + \beta_{Lt}(t) \dots . (3.2)$$

$$S_L = \left[\frac{In(QN)}{\partial InE}\right] = \beta_E + \beta_{LE}(InL) + \beta_{KE}(InK) + \beta_{EE}(InE) + \beta_{Et}(t) \dots . (4.2)$$

Table-4.9 Estimation based on Trans-log production function for panel data on 11 broad manufacturing Industries

Parameters	Indian Manufacturing Sector
α	-0.523 (5.32)
β_L	0.302 (17.32)
β_K	0.552(27.31)
β_E	0.138 (7.93)
β_{Lk}	-0.018 (-2.95)
β_{LE}	-0.039 (-8.05)
β_{KE}	-0.009 (-1.50)
β_{LL}	0.058 (8.65)
β_{KK}	0.235 (6.11)
β_{EE}	0.049 (8.83)
β_{Lt}	-0.0018 (-2.39)
β_{Kt}	0.0007 (0.85)
β_{Et}	0.0011 (1.53)
β_t	0.025 (2.55)
β_{tt}	-0.0009 (-1.78)
R-Squared For Eqution-2.2 For Eqution-3.2 For Eqution-4.2	 0.62 0.42 0.41

Source: Author’s Calculation

The estimated results validate the economic theory that energy demand in manufacturing rises with an expansion in output and falls with a rise in real energy prices.

Table: 4.10 **Estimated result of Allen Partial Elasticity of Substitution**

Indian Manufacturing Sector	AES_{LL}	AES_{KK}	AES_{EE}	AES_{LK}	AES_{LE}	AES_{KE}
On panel data of 11 industries	-4.59	-1.03	-9.11 (-1.4)	1.38	2.60	1.33
Textiles & textiles products, leather and footwear	-1.04	-0.50	-6.43 (-0.72)	0.63	0.25	1.21
Pulp, paper, paper products, printing and publishing	-1.86	-1.03	-7.58 (-1.17)	0.85	1.85	1.12
Coke, Refined petroleum and nuclear fuel products	-12.1	-0.41	-11.95 (-1.75)	0.62	3.42	1.91
Chemicals and chemical products	-13.30	-0.46	-14.85 (-1.87)	1.19	-0.80	2.41
Other Non-Metallic Mineral products like cement etc.	-8.57	-1.43	-2.43 (-0.61)	2.75	1.52	0.58
Basic Metals and Fabricated Metal products	-3.76	-0.60	-4.31 (-1.18)	-0.02	2.85	1.18

Source: Author’s Calculation

Note: parentheses indicate the price elasticity demand for energy

The energy demand model estimates reveal that the price elasticity of energy demand for manufacturing is about (-) 0.4. which means a one percent change in energy price will lead to a 0.4 percent decline in the fuel demand in the manufacturing sector. However, the estimated trans-log production functions of the price elasticity of energy demand are found to be (-) 1.4. which validates the hypothesis that an increase in the real fuel price, causes lower demand for fuel. i.e., one percent increase in the energy price will lead to a 1.4 percent reduction in fuel consumption overall for the reported eleven industries. The negative relationship between energy prices and demand for energy being conformed.

4.13 Conclusion

The above investigation of eleven groups of manufacturing industries revealed that there is a positive relationship between fuel consumption and gross industrial value-added and an inverse relationship between real energy price and fuel demand. The results have been obtained by conducting various models. Such as the fixed & random models and Allen Partial Elasticity of Substitution, the fixed effect model fits the data better, and result outcomes are significant and effective to the economic theories. The slope coefficient of the fuel consumed under the fixed effect model indicates that a per unit increase in fuel consumption leads to an increase in industrial gross value-added by 0.58814 at a 1% level of significance with the R^2 of 0.9802. The slope coefficient of fixed capital drives the industrial gross value-added to change by 0.29315 for every one-unit change in fixed capital. Similarly, the coefficient of labor influences the industrial gross value-added by 0.52091 for every unit change in labor. The statistical representation of the slope coefficient of fuel consumption is large enough to impact the industrial gross value-added. Hence, there has been a substantial influence of energy on industrial gross value added.

On the other hand, the energy demand model estimates reveal that the price elasticity of energy demand for manufacturing is about (-) 0.4. which means a one percent change in energy price will lead to a 0.4 percent decline in fuel demand in the manufacturing sector. However, the estimated trans-log production functions of the price elasticity of energy demand are found to be (-) 1.4. Similarly, here a one percent increase in the energy price will lead to a 1.4 percent reduction in fuel consumption overall for the reported eleven industries.

Based on the aforementioned empirical findings, an interesting functional link between inputs and outputs is clearly understood. It has been determined that there is a positive relationship between energy consumption and industrial gross value added, that a decrease in the real price of energy increases energy demand, and that energy plays a significant input role in industrial output. But without looking into how energy influences industrial gross value added in a disaggregated way, the understanding from this chapter is incomplete. Because of this, the fifth chapter empirically analyses the connections between energy use and gross industrial value added by breaking down different energy sources using models like Correction of Vector Error.

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