CHAPTER 05 - RESULTS AND DISCUSSION

5.1 Chapter Overview

This section comprises of three parts: (a) WCM efficiency scores of selected nine manufacturing industries over a period from 2009-2020 using SBM-DEA model; (b) panel data fixed-effects model for assessing the relationships using dependent and independent variables wherein the efficiency scores obtained in part (a) formed as a dependent variable; (c) application of ANN for validating the WCM model using multi-layer perceptron and sensitivity analysis for checking the relative importance of significant determinants on WCM efficiency.

5.2 Stage 1: Working Capital Management Efficiency Values Calculated as per SBM DEA Model

Table 5.1 represents the minimum, maximum, mean, and median values of WCM efficiency from 2009-2020 in Indian manufacturing industries obtained through SBM DEA model. Considering the space constraint, the specific WCM efficiency values for each selected firm year is not highlighted. However, the minimum, maximum, mean, and median values highlight better results for comparing or ranking the firms in terms of their WCM efficiency and works towards better propositioning for higher WCM efficiency for all the manufacturing industries.

Table 5.1: Minimum, Maximum, Mean, and Median Values of Working Capital Management Efficiency

Industry	Efficiency	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Metals	Minimum	0.004	0.002	0.001	0.001	0.003	0.005	0.005	0.005	0.221	0.034	0.007	0.007
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Mean	0.488	0.388	0.293	0.351	0.442	0.333	0.595	0.523	0.533	0.374	0.514	0.490
	Median	0.437	0.346	0.250	0.290	0.379	0.272	0.564	0.488	0.493	0.339	0.476	0.438
Textiles	Minimum	0.003	0.048	0.001	0.002	0.004	0.004	0.005	0.011	0.004	0.003	0.008	0.006
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Mean	0.426	0.292	0.274	0.289	0.470	0.480	0.476	0.584	0.383	0.592	0.551	0.523
	Median	0.377	0.222	0.214	0.227	0.426	0.453	0.421	0.550	0.308	0.564	0.510	0.481
	Minimum	0.003	0.005	0.004	0.002	0.004	0.001	0.004	0.124	0.006	0.002	0.006	0.334
Transport Equipment	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Mean	0.533	0.544	0.456	0.473	0.456	0.274	0.410	0.453	0.520	0.444	0.590	0.609
	Median	0.472	0.500	0.413	0.423	0.393	0.154	0.348	0.392	0.461	0.401	0.543	0.567
	Minimum	0.319	0.011	0.001	0.001	0.002	0.002	0.002	0.005	0.003	0.002	0.002	0.008
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Construction Materials	Mean	0.595	0.504	0.462	0.464	0.494	0.423	0.461	0.633	0.532	0.528	0.538	0.669
	Median	0.516	0.405	0.358	0.385	0.420	0.352	0.350	0.602	0.451	0.485	0.526	0.618
	Minimum	0.003	0.002	0.005	0.005	0.004	0.001	0.004	0.004	0.139	0.003	0.006	0.005
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chemicals & Chemical	Mean	0.213	0.152	0.400	0.510	0.408	0.139	0.508	0.512	0.526	0.455	0.527	0.435
Products	Median	0.188	0.091	0.370	0.479	0.377	0.119	0.477	0.482	0.490	0.421	0.496	0.402
Consumer Goods	Minimum	0.002	0.005	0.003	0.079	0.004	0.004	0.146	0.082	0.037	0.004	0.004	0.005
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Mean	0.476	0.580	0.378	0.540	0.564	0.585	0.578	0.466	0.568	0.463	0.594	0.560

	Median	0.369	0.499	0.266	0.432	0.473	0.476	0.481	0.346	0.447	0.344	0.517	0.484
	Minimum	0.003	0.003	0.002	0.008	0.002	0.002	0.296	0.001	0.015	0.005	0.092	0.008
Food & Agro-Based Products	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Mean	0.306	0.306	0.325	0.296	0.401	0.354	0.529	0.196	0.374	0.354	0.383	0.251
	Median	0.249	0.249	0.244	0.235	0.314	0.231	0.449	0.102	0.286	0.285	0.317	0.134
Machinery	Minimum	0.050	0.001	0.004	0.017	0.004	0.001	0.002	0.004	0.004	0.002	0.005	0.005
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Mean	0.425	0.415	0.376	0.291	0.444	0.437	0.455	0.553	0.553	0.317	0.619	0.656
	Median	0.350	0.365	0.330	0.212	0.424	0.396	0.386	0.533	0.530	0.262	0.577	0.622
Miscellaneous Manufacturing	Minimum	0.164	0.001	0.003	0.003	0.050	0.006	0.224	0.002	0.005	0.005	0.001	0.006
	Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Mean	0.562	0.247	0.496	0.542	0.587	0.661	0.638	0.477	0.722	0.722	0.200	0.643
	Median	0.446	0.110	0.440	0.513	0.523	0.622	0.604	0.436	0.715	0.715	0.138	0.620
Average Min		0.002	0.001	0.001	0.001	0.002	0.001	0.002	0.001	0.003	0.002	0.001	0.005
Average Max		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Average Mean		0.447	0.381	0.384	0.418	0.474	0.410	0.517	0.489	0.523	0.472	0.502	0.537
Average Median		0.377	0.346	0.330	0.385	0.420	0.352	0.449	0.482	0.461	0.401	0.510	0.484

Source: MATLAB

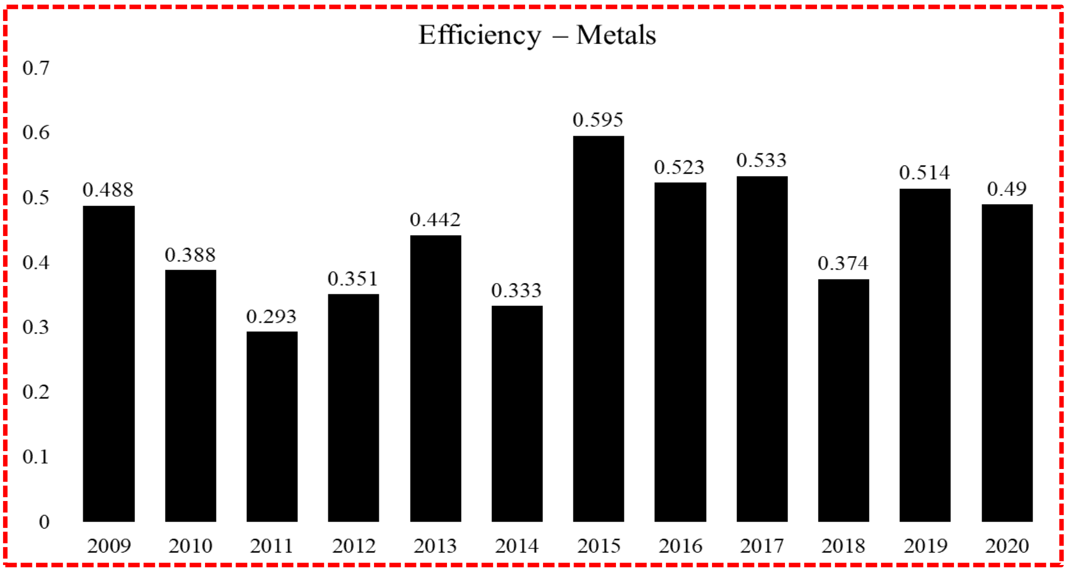

Figure 5.1: Mean Efficiency for Metals Industry

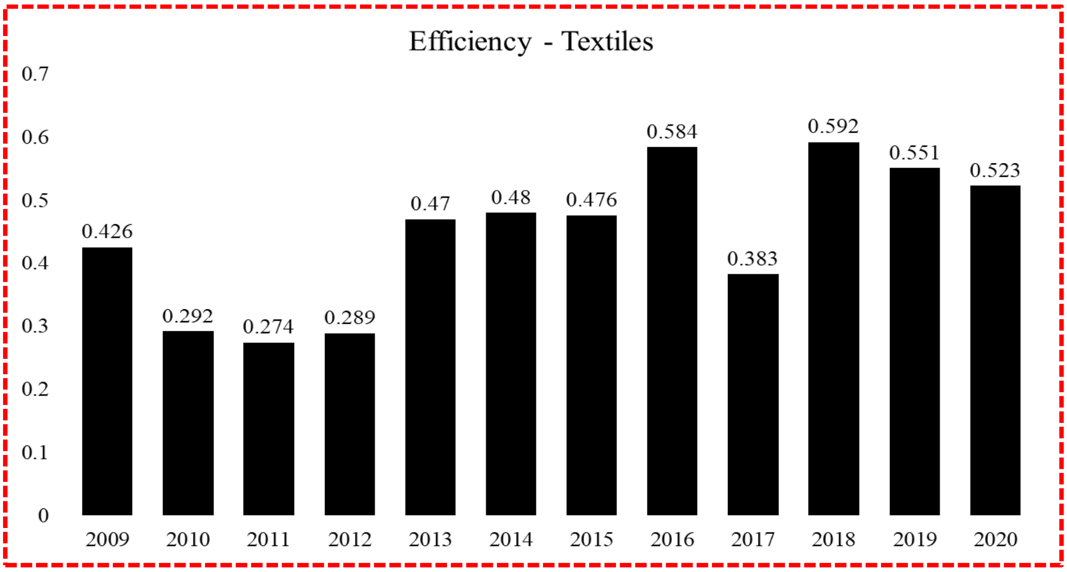

Figure 5.2: Mean Efficiency for Textiles Industry

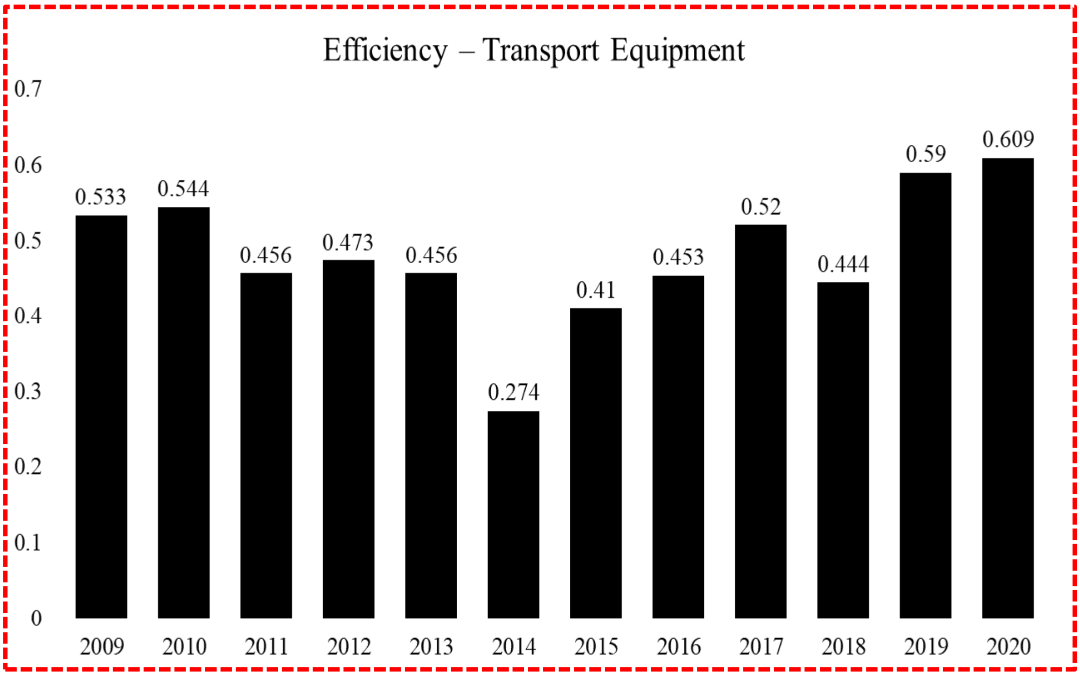

Figure 5.3: Mean Efficiency for Transport Equipment Industry

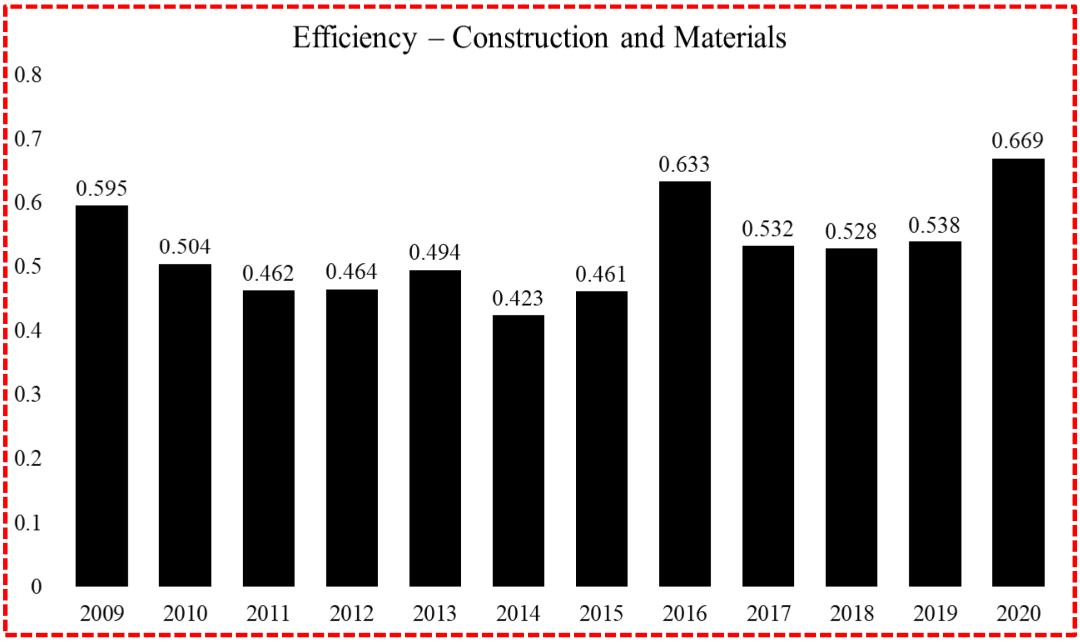

Figure 5.4: Mean Efficiency for Construction and Materials Industry

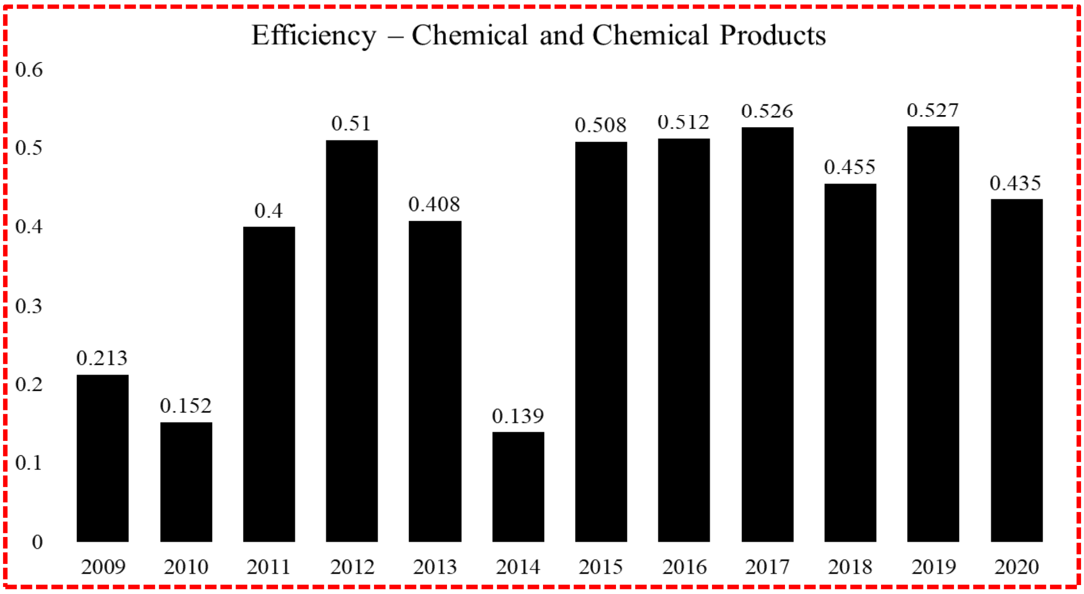

Figure 5.5: Mean Efficiency for Chemical and Chemical Products Industry

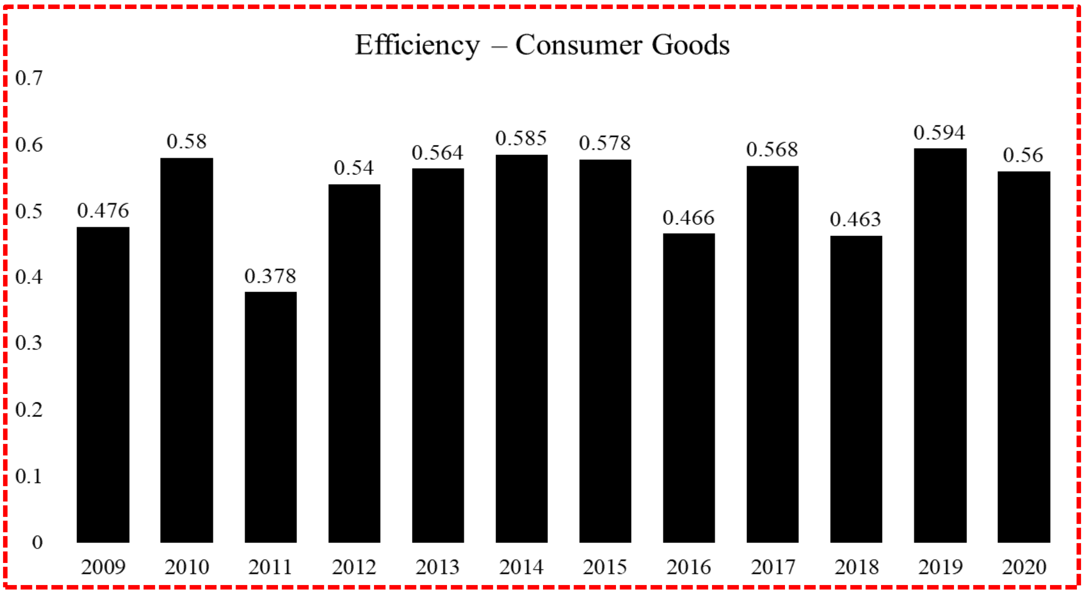

Figure 5.6: Mean Efficiency for Consumer Goods Industry

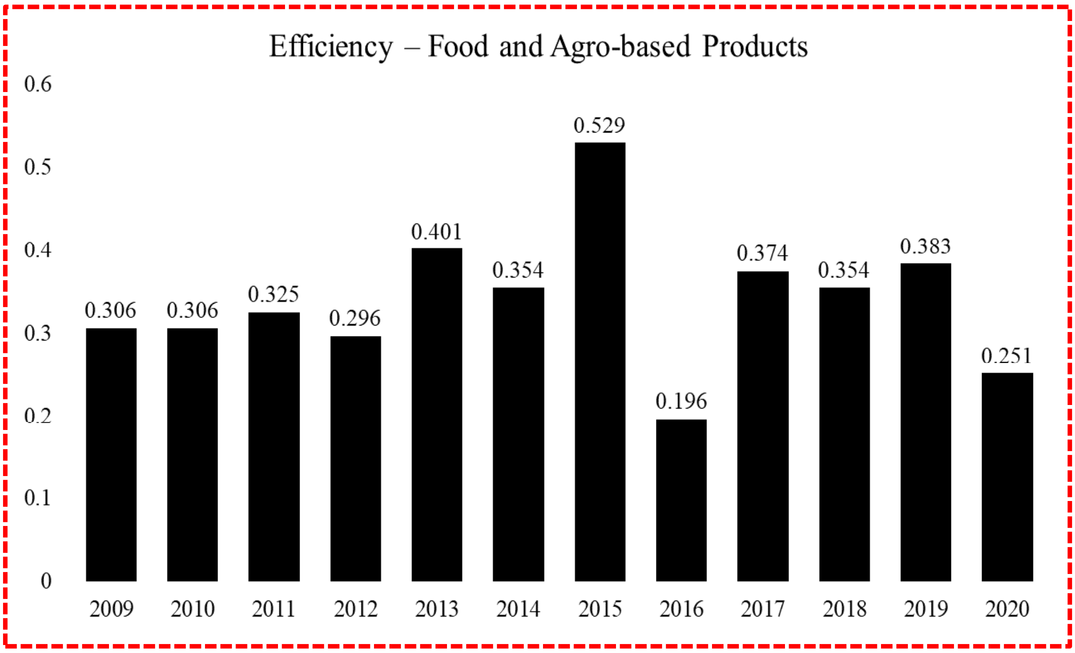

Figure 5.7: Mean Efficiency for Food and Agro-based Products Industry

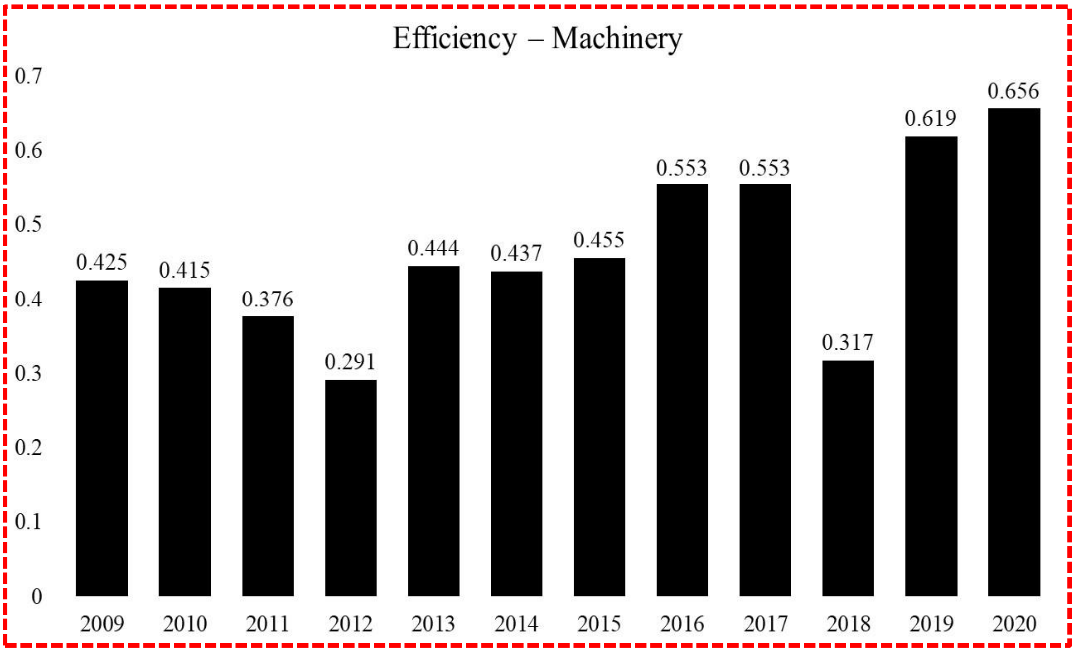

Figure 5.8: Mean Efficiency for Machinery Industry

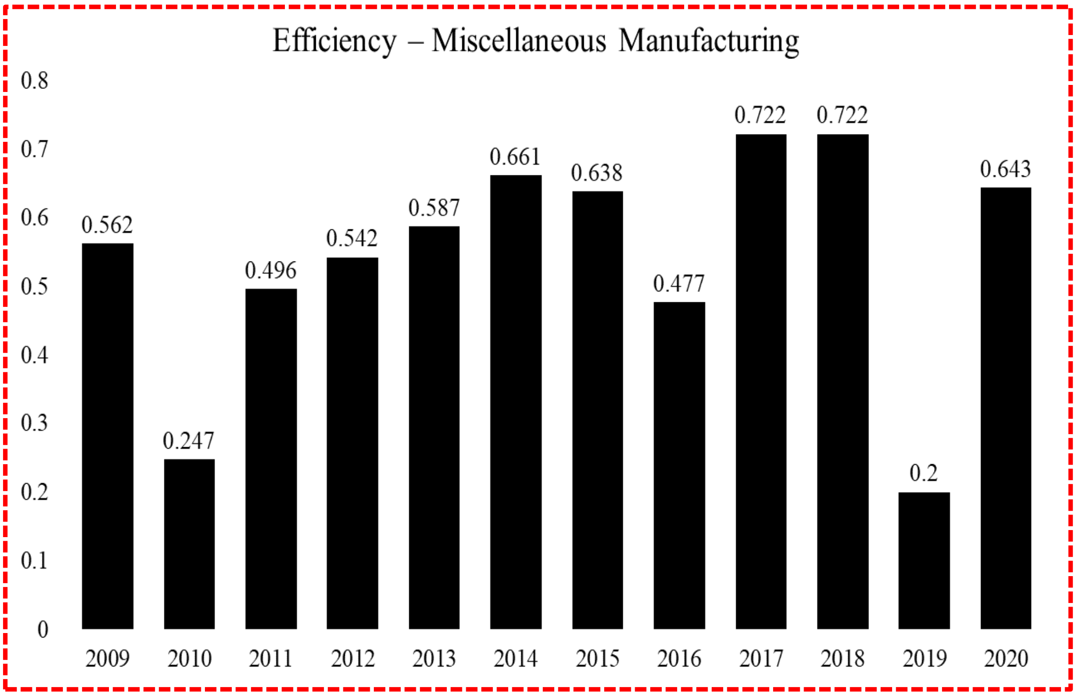

Figure 5.9: Mean Efficiency for Miscellaneous Manufacturing Industry

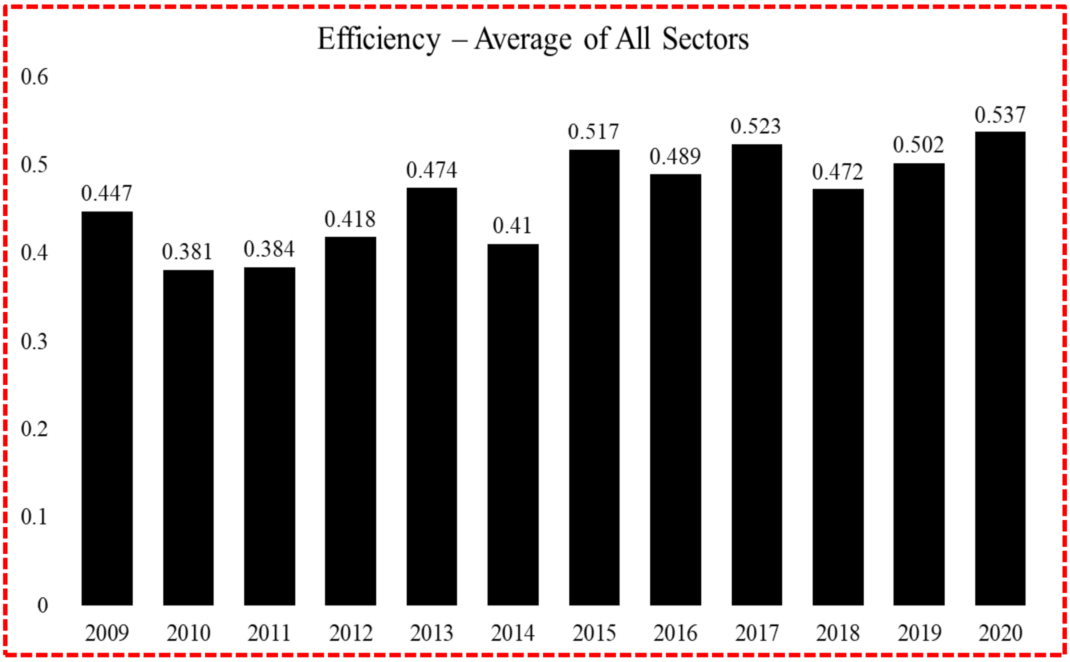

Figure 5.10: Mean Efficiency for Overall Manufacturing Sector

As per Figures 6-15 and Table 5.1, the high variability in the efficiency values across the industries highlights the consideration given to differing working capital throughout the firms. Additionally, the maximum values underlining efficient firms is 1 and in comparison, minimum values across selected nine industries range around 0.001-0.334 highlighting a huge lag among the inefficient firms to achieve WCM efficiency. Taking specific industry, mean efficiency values are consistent around 40-45 per cent except chemicals & chemical products and machinery industry. This stability in efficiency values for all industries across the selected time-period reflects less attention is paid towards efficient WCM. Chemicals & chemical products have varied mean efficiency scores from 0.152 to 0.527 but at the same time, it reflects an upsurge in efficient WCM in 2015. Moreover, machinery varies in terms of WCM efficiency from 0.291 to 0.656. Construction materials are performing best by operating at around 60-65 percent WCM efficiency. This industry has achieved the highest mean efficiency value of 0.669 in the year 2020. However, since other industries have not shown year wise improvement in mean efficiency values, this requires industry specific formulation of working capital policies and assignment of specific task force or experts responsible for efficient WCM. Further, the variation among the industry wise mean and median efficiency values detects inconsistency in efficiently managing the working capital in some industries. The industry-wise and whole manufacturing sectors' mean WCM efficiency values are greater than the median WCM efficiency values indicating positively skewed values and specifies fewer firms to be efficient in managing the working capital. The mean and median values 0.330 to 0.537 calls for huge improvement in WCM and requires more focused operations to survive the cutthroat competition in emerging markets, such as India.

5.3 Stage 2: Panel Data Fixed Effects Analysis

Table 5.2 presents panel data fixed-effects regression analysis results by examining the effect of selected determinants i.e. CFLOW, TFA, SIZ, AGE, PRD, LEV, CEF, IC, SC, HC, GRT, GDP, and INT on the WCM efficiency (values as calculated by SBM DEA model) of Indian manufacturing industries.

Table 5.2: Industry-Wise Analysis of the Association of Selected Determinants on WCM Efficiency

Independent variables	Metals and metal products	Textiles	Transport equipment	Construction materials	Chemicals & chemical products	Consumer goods	Food and agro based products	Machinery	Miscellaneous manufacturing
CFLOW	0.841*	0.538	0.736*	1.260*	0.342	0.775	0.306*	1.090*	0.271*
TFA	0.187*	0.027*	0.021	0.026*	-0.058	-0.176	0.157*	0.020*	0.042
SIZ	-0.113	-0.211	-0.170	-0.100	0.144	-0.190	-0.086	-0.003	-0.261
AGE	0.854	1.021	0.775	1.468	1.415	0.447	0.032	1.228	0.811
PRD	0.001*	-0.001	0.003*	0.002*	-0.001	0.001*	0.001*	0.001*	0.001
LEV	0.005*	- 0.057*	-0.183*	-0.100*	0.014	-0.021*	0.106	-0.019*	0.060
CEF	-0.018	-0.021	-0.025*	-0.085	-0.021	-0.029*	-0.103	-0.040	0.015
IC	0.025	-0.110*	-0.008	0.001*	-0.003	0.004*	-0.001	-0.015	-0.029
SC	0.218	0.113	0.315*	0.714	1.211	0.517*	0.215	0.368	0.594
HC	0.801*	1.727	0.228	0.412	0.341	0.138	1.049	0.084*	0.562
GRT	0.001	0.003	0.025*	0.025*	0.016*	0.031*	-0.004	0.036*	0.050*
GDP	0.008	-0.152	0.187*	0.074	-0.208*	-0.008	0.044	-0.100	-0.296
INT	0.572*	1.394	2.219	0.525*	-0.248	-0.084	0.737*	0.593	0.217
Adj. R-Square	0.487	0.529	0.510	0.568	0.445	0.562	0.458	0.482	0.282
Hausman test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Eviews 10

Note:

1. Fixed effects model results reported when null hypothesis for Hausman test is rejected at the .05% level.
2. * denotes significant at 0.05 level
3. The low value of Adj. R-Square for miscellaneous manufacturing is because of very less proportion of sample falling in this category. Moreover, miscellaneous manufacturing covers all those firms that could not become a part of any other industry. These miscellaneous manufacturing firms might differ severely in terms of scale, size, and operations leading to biased figures.

Adjusted R-Square values in Table 5.2 for most of the sectors falls between 0.482 to 0.568 signifying high explanatory power of the regression model used. Also, earlier studies have justified the value of adjusted R-Square of around 0.40-0.50 to be adequate enough in case of large sample size and higher number of predictors (Goel and Sharma, 2015; Laghari and Chengang, 2019; Seth, Chadha and Sharma, 2020), which the current study contains. Also, the studies have mentioned to limit the number of independent variables used in the regression model to avoid the multicollinearity issue (Li et al., 2019; Ma and Yao, 2020).

Table 5.2 underlines CFLOW, LEV, GRT, TFA, and PRD to be significant in most of the manufacturing industries wherein CFLOW, GRT, TFA, PRD have significant positive effects on WCME for most of the industries and LEV significantly influence WCM efficiency negatively. Results also highlight SIZ, AGE, CEF, IC, SC, HC, GDP AND INT to have no significant impact on the WCME for majority industries. The current study focusses on the most vital determinants influencing WCME, hence, we further undertook ANN approach for validation and sensitivity analysis of our WCM model in order to assist the firms by focusing on the key determinants and thereby minimizing the unwanted efforts for achieving WCM efficiency.

5.4 Stage 3a: Artificial Neural Networks Analysis

Analysis for ANN in which multi-layer perceptron (comprising of forward and backward propagation) was performed on two layers i.e., input and output through SPSS 20. The input layer comprised of five independent significant predictors obtained from fixed-effects analysis (CFLOW, LEV, GRT, TFA, and PRD) whereas the output layer consists of the outcome variable (WCM efficiency values obtained through SBM DEA). Moreover, for avoiding the over-fitting, we utilized a ten-fold cross validation wherein network training was done for 90 per cent of the data and remaining 10 per cent was applied for testing. Furthermore, for validating the accuracy of our model, both training and testing values' Root Mean Square of Error (RMSE) was computed, together with averages and standard deviations.

Table 5.3 highlights the mean RMSE values wherein training models' cross-validated RMSE is 0.173 and testing model is 0.149. These values indicate that the accuracy of the ANN model is acceptable. The values as per table 5.3 are relatively smaller for ANNs, averages, and standard deviations, signifying greater accuracy of the proposed model where the relative importance of the significant predictors is examined on WCM efficiency of Indian manufacturing firms. The results also denote that the model under test is worthy of trust to capture the mechanisms of predictors and output variables as presented in Figure 5.11.

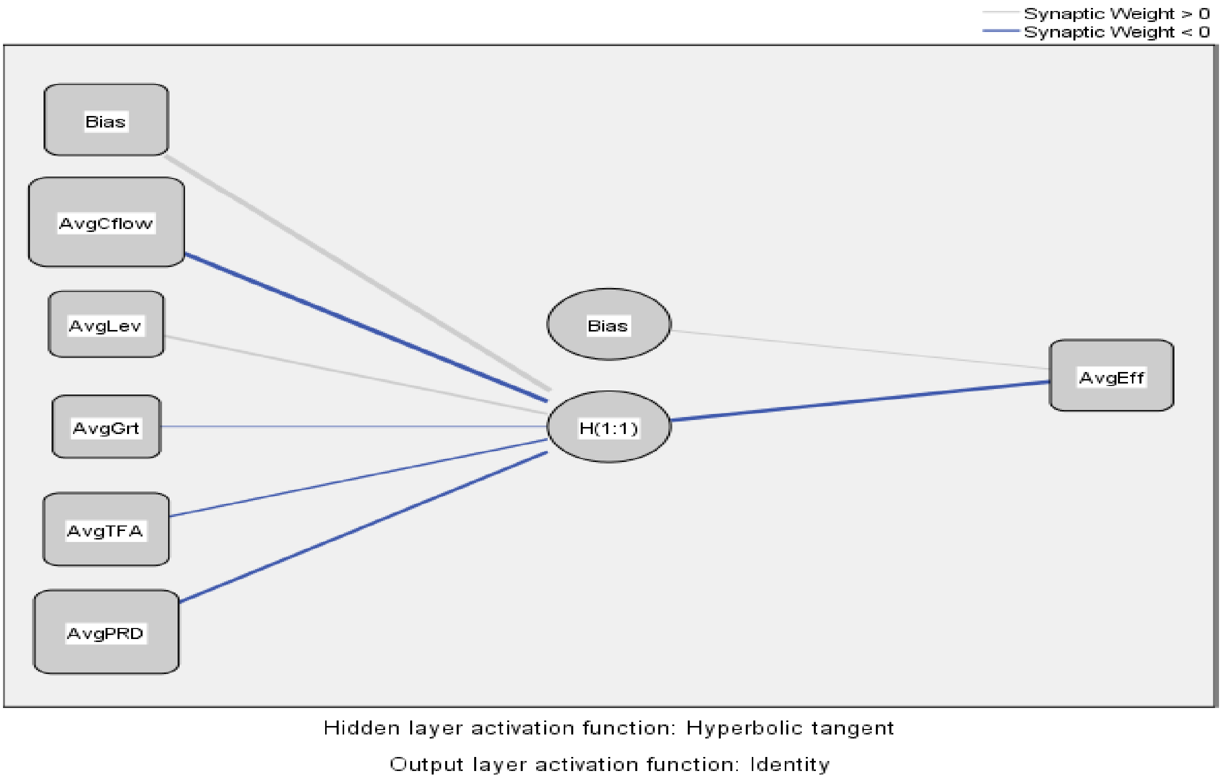

Figure 5.11: Artificial Neural Network model

Table 5.3: RMSE Values of Artificial Neural Networks Analysis

Network	RMSE (Training) (InT)	RMSE (Testing) (InT)
ANN1	0.160	0.142
ANN2	0.166	0.139
ANN3	0.171	0.130
ANN4	0.156	0.136
ANN5	0.161	0.141
ANN6	0.222	0.123
ANN7	0.163	0.167
ANN8	0.211	0.109
ANN9	0.160	0.223
ANN10	0.162	0.179
Mean	0.173	0.149
SD	0.022	0.031

Source: IBM SPSS Statistics 20

5.5 Stage 3b: Sensitivity Analysis

Finally, the current study incorporates sensitivity analysis which ascertains the average importance and normalized importance of predictors on the outcome variable. Table 5.4 presents the average importance and normalized importance of variables in which CFLOW, PRD, TFA, LEV, GRT with values 0.333, 0.278, 0.179, 0.122, 0.088 respectively were found to be vital predictors based on their order of importance.

Table 5.4: Sensitivity Analysis: Average and Normalized Importance

Significant Predictors	Average Importance	Normalized Importance (%)
CFLOW	.333	100
PRD	.278	83.5
TFA	.179	53.9
LEV	.122	36.5
GRT	.088	26.3

Source: IBM SPSS Statistics 20

CFLOW was found to be the most vital predictor with 100 per cent of normalized importance followed by PRD (83.5 per cent), TFA (53.9 per cent), LEV (36.5 per cent), and GRT (26.3 per cent).

CFLOW was found to have a positive influence on WCM efficiency for majority industries as firms with high cash flows have enough internal funds available for working capital investments rather than preferring costly external sources of funds. These firms benefit from a lower cost of capital due to lesser risk premium and less likelihood of getting default on payments as suggested by pecking order theory (Myers and Majiuf, 1984). Since these firms have enough liquidity and the ability to create funds internally, they require less investment in working capital and adopt aggressive working capital policies (Altaf and Ahmad, 2019). Additionally, these firms hold a strong position against the suppliers and enjoy relaxations in the form of larger payables period, less cost on raw materials, timely delivery of goods, and discounts on early payments, which collectively reduces CCC in firms and hence, makes firms with high cash flows to manage the working capital efficiently (Laghari and Chengang, 2019). Consistent with the results, Hill, Kelly and Highfield (2010) found firms with larger cash flows or higher capacity to generate internal resources operate with conservative working capital. Contrastingly, Baños-Caballero et al. (2010) indicated that with the rise in firms' capacity to generate internal funds, firms go for more current assets' investment and as a result, CCC also increases, negatively impacting WCM efficiency.

Consistent with results of Seth *et al.* (2020), it was found that firms with high PRD had higher WCM efficiency, and this might be because such firms can achieve higher sales against incurred wages, leading to higher productivity. Such firms have better cash levels and are in a better bargaining position with suppliers availing larger credit period. Further, less investment is required for working capital and surplus funds can be used for other investment purposes. Such firms rely less on costly external financing due to higher liquidity levels available in firms that reduce financial burden. Moreover, these firms use internal financing sources for managing short-term expenses (Chaney, 2016). Thus, firms are better able to manage their working capital efficiently with shorter cash conversion cycle (CCC). Bellouma (2011) and Habib and Huang (2018) also found a similar positive influence of PRD on WCM efficiency.

TFA influence WCM efficiency positively, similar to the study by Goel and Sharma (2016), stating that larger investments in fixed assets provide better infrastructure facilities and greater capabilities for efficient functioning of firms. Such firms are quite diverse and require more liquid investments, so they focus even on the smallest aspects followed by the larger ones such as vendor selection, partner bank, capital market investments, growth, profitability, and sales. Due to this efficient management along with ample machinery, large storing capacities, and lower probability to default, firms with large TFA enjoy larger payable period from its suppliers and firms can better manage the receivables from its customers by providing early payment discounts. Additionally, these firms would be capable to invest adequate amount in inventories and selling them without keeping them idle for long even in case of uncertain customers' demand. These results are supported by Wesley *et al.* (2013) and Nazir and Afza (2009) in context of Nairobi and Pakistan.

LEV is found to have negatively affecting the efficient management of working capital. In the world of limited choices, high levered firms might face difficulty in WCM due to limited financing capacity and cash flow issues. Leverage attaches an interest to be borne by firms for which more funds need to be earned or internal funds are to be exhausted. Furthermore, suppliers might not feel comfortable with high levered firms as they might default on paying dues. So, such risk bearing by suppliers might be compensated by high raw material costs or shorter payables period, which enhances the CCC leading to inefficiency in WCM. Consistently, studies done by Goel and Sharma (2015), Tahir and Anuar (2016), and Akinlo (2012) in India, Pakistan, and Nigeria found negative impact on the WCM efficiency from leverage. Hence, manufacturing firms specifically needs adequate attention to working capital components such as early payment from receivables, appropriate cash levels, discounts from suppliers, and extended payables period for efficient functioning.

In line to Kieschnick, Laplante and Moussawi (2006) and Boțoc and Anton (2017), GRT is significant positive to WCM efficiency. Firms' with high GRT signifies growing sales year after year. Directly, this high GRT reflects more internal funds with firm, greater capability to diversify or invest, fulfill customers' huge orders in short time span, easy availability of cheaper financing sources. Indirectly, high growth firms have a better goodwill among suppliers, shareholders, competitors, and customers (Goel and Sharma, 2016). So, it becomes relatively easy for high growth firms to utilize cheaper internal funds for working capital investments. Also, due to high liquidity position these firms provide heavy discounts on early payments by customers and further enhances the customer demands. Suppliers, due to very low default probability, provide raw materials on credit along with higher payables period. This makes the high growth firms manage working capital efficiently along with shorter CCC.

The current chapter investigates the WCM efficiency using DEA approach. Further, it offers prevailing levels of WCM efficiency in Indian manufacturing sector and performs identification of the relationship of selected determinants that impact the WCM efficiency. The results of efficiency of the chosen sectors highlighted firms to be operating at 40 -50 percent WCM efficiency and indicated huge variation among minimum and maximum efficiency scores. WCM efficiency trend implied that firms vary with time which might be due to several factors. Furthermore, the results suggested that efficiency levels are impacted by factors that are not only firm specific but could be affected by factors that are outside firm's control. Additionally, the chapter also developed a prediction model wherein a sensitivity analysis was performed in order to obtain variable wise importance of the significant variables.