

Multi-Period Efficiency Evaluation of Indian Construction Sector



विद्यारत्नम् महद्वनम्

Thesis submitted in partial fulfilment
for the Award of Degree of
Doctor of Philosophy

By

VIKAS

**RAJIV GANDHI INSTITUTE OF PETROLEUM TECHNOLOGY
JAIS, INDIA – 229304**

PM1611

2021

CERTIFICATE

It is certified that the work contained in the thesis titled "*Multi-Period Efficiency Evaluation of Indian Construction Sector*" by "*Vikas*" has been carried out under our supervision and that this work has not been submitted elsewhere for a degree.

It is further certified that the student has fulfilled all the requirements of Comprehensive, Candidacy, and SOTA/Open seminar.

Supervisor
(**Dr. Rohit Bansal**)

DECLARATION BY THE CANDIDATE

I, "*Vikas*", certify that the work embodied in this thesis is my own bona fide work and carried out by me under the supervision of "*Dr. Rohit Bansal*" from "*July 2016*" to "*November 2021*" at the "*Department of Management Studies*", Rajiv Gandhi Institute of Petroleum Technology, Jais (India). The matter embodied in this thesis has not been submitted for the award of any other degree. I declare that I have faithfully acknowledged and given credits to the research workers wherever their works have been cited in my work in this thesis. I further declare that I have not wilfully copied any other's work, paragraphs, text, data, results, etc., reported in journals, books, magazines, reports dissertations, theses, etc., or available at websites and have not included them in this thesis and have not cited as my own work.

Vikas

Date:
Place: Jais

Roll No: PM1611

CERTIFICATE BY THE SUPERVISOR

It is certified that the above statement made by the student is correct to the best of our knowledge.

(Dr. Rohit Bansal)

(Supervisor)

(Dr. Jaya Srivastava)

Head of Department

(DoMS)

CERTIFICATE

CERTIFIED that the work contained in the thesis titled “**Multi-Period Efficiency Evaluation of Indian Construction Sector**” by Mr. **Vikas** has been carried out under my supervision. It is also certified that he fulfilled the mandatory requirement of TWO quality publications that arose out of his thesis work.

It is further certified that the two publications (copies enclosed) of the aforesaid Mr. **Vikas** have been published in the Journals indexed by –

- (a) SCOPUS
- (b) ABDC – B list
- (c) SCI Extended

Supervisor

(Dr. Rohit Bansal)

Convenor, DPGC

(Dr. Saroj Mishra)

COPYRIGHT TRANSFER CERTIFICATE

Title of the Thesis: Multi-Period Efficiency Evaluation of Indian Construction Sector

Name of the Student: Vikas

Copyright Transfer

The undersigned hereby assigns to the Rajiv Gandhi Institute of Petroleum Technology Jais all rights under copyright that may exist in and for the above thesis submitted for the award of the "Doctor of Philosophy ".

Date:

Vikas

Place: Jais

Roll No: PM-1611

Note: However, the author may reproduce or authorize others to reproduce material extracted verbatim from the thesis or derivative of the thesis for the author's personal use provided that the source and the Institute's copyright notice are indicated.

Dedicated To

*My Beloved
Parents, Teachers and
Friends*

For their endless love, support, and encouragement

Acknowledgments

First and foremost, I would want to express my heartfelt gratitude to Dr. Rohit Bansal, my Doctoral Supervisor, for his insightful direction and support, as well as his continued encouragement, patience, and great confidence in me throughout my research journey. As I go through my studies and daily life, his vast knowledge and experience serve as a source of an inspiration. I am very grateful for the helpful discussions and suggestions that I have received from him during the thesis preparation process. Every discussion has improved the quality of my work and helped me to become a more effective researcher overall. His guidance also taught me the fundamentals of the workplace. This, I think, will allow me to be a better person in the future, both professionally and personally.

My parents and relatives also deserve the most gratitude from my side as this journey would have been very tough had they not provided emotional support to me throughout it. My parents, Sri Ashok Kumar Verma and Smt. Chanchal Verma work as my constant source of strength and faith in myself which propelled me to overcome all hurdles. My heartiest gratitude to elder brother Mr. Vivek Abhishek and my sister Ms. Suruchi Kumari for their continued love and support throughout. A special thanks to my fiancé, Ms. Jyoti Tandon for the encouragement, support, endurance and care during the Ph.D journey.

I would like to take this opportunity to extend my deepest gratitude to external collaborators in my work. The support and constructive criticism of Prof. A.S.K. Sinha (Director, Rajiv Gandhi Institute of Petroleum Technology, Jais), Dr. Ashu Khanna, (Associate Professor Accounting & Finance, Department of Management Studies, Indian Institute of Technology, Roorkee), Prof. Pankaj Sinha, (Professor, Finance, Faculty of

Management Studies, Delhi University, Delhi) in making my work more elegant and structured highly appreciated. Thank you all for your time, faith and support.

I would like to express my gratitude to the faculty members of the Department of Management Studies for their help and support during my research work. I also like to acknowledge the role of University Grant Commission (UGC), New Delhi for providing me Junior Research Fellowship (JRF) and financial support for research activities. I also like to acknowledge the role of RGIPT, Jais for computer lab, library and hostel facilities I needed to perform my research successfully. A special note of thanks is also owed to various research and administrative staff members who ensured that I was never deprived off my peace during my stay at RGIPT.

Finally, I consider myself very lucky to be a member of business analytics lab, research groups and the memories, experiences, and knowledge I have acquired from this place will stay with me lifelong. I would want to express my gratitude to all members of the business analytics lab for creating and maintaining the nice environment. For this, my lab mates Rakesh, and Rachit Jaiswal are acknowledged for making this workspace lively and productive.

Vikas

Table of Contents

Acknowledgments	i
Table of Contents	iii
List of Figures	v
List of Tables	vii
Abbreviations/Notations	ix
Preface	xiii
CHAPTER 1 – Introduction	1
CHAPTER 2 – Literature Review	7
CHAPTER 3 – Research Methodology	75
3.1. Ratio Approach	77
3.2. Frontier approach	78
3.3. Deterministic Approach	79
3.4. Non-Parametric Techniques	80
3.5. DEA Approach	81
3.6. Malmquist Productivity Index (MPI)	85
3.7. Super-Efficiency DEA Models	85
CHAPTER 4 – Result Analysis	89
4.1. Technical Efficiency and Pure Technical Efficiency	91
4.2. Scale efficiency	98
4.3 Performance of the Companies over five years	104

4.4. Future Projections	123
4.5. Malmquist Productivity Index	125
4.6. Comparison using Super-Efficiency DEA Models	129
CHAPTER 5 – Conclusion	135
CHAPTER 6 – Research Implications and Future Scope	141
References	146

List of Figures

Figure 3. 1: Methodological Framework	77
Figure 3. 2: Super Efficiency DEA Models.....	87
Figure 4. 1: Efficiency levels of AGI Infra Ltd. from 2016-2020.....	109
Figure 4. 2: Efficiency levels of Ahluwalia Contracts India Ltd. from 2016-2020.....	109
Figure 4. 3: Efficiency levels of Ajmera Realty and Infra India Ltd. from 2016-2020	109
Figure 4. 4: Efficiency levels of AMJ Ltd. from 2016-2020.....	110
Figure 4. 5: Efficiency levels of Anant Ltd. from 2016-2020	110
Figure 4. 6: Efficiency levels of Arvind Smartspaces Ltd. from 2016-2020	110
Figure 4. 7: Efficiency levels of Ashoka Buildcon Ltd. from 2016-2020.....	111
Figure 4. 8: Efficiency levels of Brigade Enterprises Ltd. from 2016-2020	111
Figure 4. 9: Efficiency levels of Capacite Ltd. from 2016-2020.....	111
Figure 4. 10: Efficiency levels of Cera Sanitaryware Ltd. from 2016-2020	112
Figure 4. 11: Efficiency levels of Dilip Buildcon Ltd. from 2016-2020.....	112
Figure 4. 12: Efficiency levels of Engineers India Ltd. from 2016-2020.....	112
Figure 4. 13: Efficiency levels of GeeCee Ventures Ltd. from 2016-2020.....	113
Figure 4. 14: Efficiency levels of Godrej Properties Ltd. from 2016-2020	113
Figure 4. 15: Efficiency levels of GPT Infra Projects Ltd. from 2016-2020.....	113
Figure 4. 16: Efficiency levels of IRB Infrastructure Developers Ltd. from 2016-2020	114
Figure 4. 17: Efficiency levels of IRCON International Ltd. from 2016-2020.....	114
Figure 4. 18: Efficiency levels of J Kumar Infraprojects Ltd. from 2016-2020.....	114
Figure 4. 19: Efficiency levels of Kajaria Ceramics Ltd. from 2016-2020.....	115
Figure 4. 20: Efficiency levels of Karda Construction Ltd. from 2016-2020	115

Figure 4. 21: Efficiency levels of KEC International Ltd. from 2016-2020.....	115
Figure 4. 22: Efficiency levels of KNR Constructions Ltd. from 2016-2020.....	116
Figure 4. 23: Efficiency levels of Kolte-Patil Developers Ltd. from 2016-2020	116
Figure 4. 24: Efficiency levels of Larsen & Toubro Ltd. from 2016-2020	116
Figure 4. 25: Efficiency levels of Man Industries Ltd. from 2016-2020	117
Figure 4. 26: Efficiency levels of Marathon Nextgen Realty Ltd. from 2016-2020....	117
Figure 4. 27: Efficiency levels of NBCC India Ltd. from 2016-2020	117
Figure 4. 28: Efficiency levels of NCC Ltd. from 2016-2020	118
Figure 4. 29: Efficiency levels of Nila Infrastructures Ltd. from 2016-2020.....	118
Figure 4. 30: Efficiency levels of Oberoi Realty Ltd. from 2016-2020.....	118
Figure 4. 31: Efficiency levels of Phoenix Mills Ltd. from 2016-2020.....	119
Figure 4. 32: Efficiency levels of PNC Infratech Ltd. from 2016-2020	119
Figure 4. 33: Efficiency levels of Prestige Estates Projects Ltd. from 2016-2020	119
Figure 4. 34: Efficiency levels of PSP Projects Ltd. from 2016-2020.....	120
Figure 4. 35: Efficiency levels of Puravankara Ltd. from 2016-2020	120
Figure 4. 36: Efficiency levels of Rail Vikas Nigam Ltd. from 2016-2020	120
Figure 4. 37: Efficiency levels of Reliance Industrial Infrastructure Ltd. from 2016- 2020.....	121
Figure 4. 38: Efficiency levels of RITES Ltd. from 2016-2020	121
Figure 4. 39: Efficiency levels of RPP Infra Projects Ltd. from 2016-2020	121
Figure 4. 40: Efficiency levels of Sobha Ltd. from 2016-2020	122
Figure 4. 41: Efficiency levels of Suntech Realty Ltd. from 2016-2020	122
Figure 4. 42: Efficiency levels of Vascom Engineers Ltd. from 2016-2020	122

List of Tables

Table 4. 1: Summary of Efficiency Scores for the year 2016.....	91
Table 4. 2: Summary of Efficiency Scores for the year 2017.....	93
Table 4. 3: Summary of Efficiency Scores for the year 2018.....	94
Table 4. 4: Summary of Efficiency Scores for the year 2019.....	95
Table 4. 5: Summary of Efficiency Scores for the year 2020.....	97
Table 4. 6: Scale Efficiency Scores and Returns to Scale for the year 2016.....	98
Table 4. 7: Scale Efficiency Scores and Returns to Scale for the year 2017.....	99
Table 4. 8: Scale Efficiency Scores and Returns to Scale for the year 2018.....	100
Table 4. 9: Scale Efficiency Scores and Returns to Scale for the year 2019.....	102
Table 4. 10: Scale Efficiency Scores and Returns to Scale for the year 2020.....	103
Table 4. 11: Technical Efficiency over five years from 2016-2020.....	104
Table 4. 12: Pure Technical Efficiency over five years from 2016-2020.....	106
Table 4. 13: Scale Efficiency over five years from 2016-2020.....	107
Table 4. 14: Input and Output levels of inefficient companies for the year 2020 (in Crores).....	124
Table 4. 15: Target Input and Output levels of inefficient companies (in Crores).....	125
Table 4. 16: Annual MPIs and their components for the Indian Construction Sector (Year 2016-2020).....	126
Table 4. 17: MPI Summary of Indian Construction Sector.....	127
Table 4. 18: Super Efficiency Scores for the year 2019-20 obtained by employing different Super- Efficiency DEA Models.....	131
Table 4. 19: Descriptive Statistics for the Super Efficiency Scores for the year 2019-20.....	133

Table 4. 20: Super Efficiency Scores based on SSBM-V-NO for the year 2016 to 2020

.....133

Abbreviations/Notations

ALP – Average Labour Productivity

BCC – Banker Charnes and Cooper

BGIs – Balanced Growth Indicators

BSC – Balanced Scorecard

BVM – Business Value Model

CAGR – Compounded Annual Growth Rate

CASR – Cumulative Annual Stock Returns

CCR – Charnes Cooper and Rhodes

CE – Cost Efficiency

CRS – Constant Returns to Scale

CSFs – Critical Success Factors

DEA – Data Envelopment Analysis

DFA – Distribution Free Approach

DMUs – Decision Making Units

EFA – Econometric Frontier Approach

EMS – Efficiency Measurement System

FANP – Fuzzy Analytical Network Process

FDI – Foreign Direct Investment

GDP – Gross Domestic Product

GVA – Gross Value Added

IAV – Industrial Added Value

IEIs – Industrial Efficiency Indicators

KPI – Key Performance Indicators

LREC – Listed Real Estate Companies

MEA – Multi-directional Efficiency Analysis

MMPI – Meta-frontier Malmquist Productivity Index

MPI – Malmquist Productivity Index

MOPL – Multi-Objective Linear Programming

OECD – Organisation for Economic Co-operation and Development

OTE – Overall Technical Efficiency

PDS – Project Delivery System

PLS – Partial Least Squares

PTE – Pure Technical Efficiency

RA – Regression Analysis

REIT – Real Estate Investment Trusts

RIS – Regional Industrial Systems

RTS – Returns to Scale

SBM – Slack Based Model

SE – Scale Efficiency

SEC – Scale Efficiency Change

SFA – Stochastic Frontier Analysis

TCE – Total Cost Efficiency

TCI – Technical Change Index

TECI – Technical Efficiency Change Index

TE – Technical Efficiency

TFA – Thick Frontier Approach

TFEE – Total Factors Energy Efficiency

TFP – Total Factor Productivity

VRS – Variable Returns to Scale

Preface

Purpose – The infrastructure sector is a crucial driver for the Indian economy, propelling overall development and accelerating India’s growth. Its importance in enhancing overall effect has been well recognized in literature, and its cross-industry linkages have increased efficiency, employment, and production capacities across industries. The Indian construction industry is expected to reach a market size of \$738.5 billion by 2022 in value terms, with an estimated CAGR of 15.7%. Its share in India’s GDP stands at nearly 9% and is the second-largest employer with more than 49 million people in the sector. As opportunities in the industry continue to come to the fore, foreign direct investment has moved upwards. India is expected to become the third-largest construction market globally by 2022. The construction sector receives undivided attention and significant resource allocation from the government at both levels. Considering the crucial importance of the industry in the economy, the study attempts to assess the efficiencies of the Indian construction sector companies over the last five years. The study's objectives are – (i) to determine the efficiencies of the Indian construction sector companies regarding technical, pure technical, and scale efficiencies for the FY period 2015-16 to 2019-20. (ii) to measure the deviations in the various efficiency levels of the companies over the five years. (iii) to analyze the reasons for the changes in efficiency levels. (iv) to assign reference set to relatively less efficient companies to improve the efficiency levels.

Design/methodology/approach – A group of 42 profit-making construction sector companies listed on the national stock exchange for which the data were available for 2015-16 to 2019-20 has been considered in the study for the analysis. Data envelopment analysis, a non-parametric approach to measuring efficiency, has been used to measure the technical, pure technical, and scale efficiencies. Three variables, namely cost of

materials consumed and manufacturing expenses, employee benefit expenses, and capital investment, have been taken as input. Two variables, namely operating revenues and profit after tax (PAT), have been taken as output for efficiency analysis. To analyze the deviations in the various efficiency levels of the companies over five years, Malmquist Productivity Index (MPI) has been used. Further, the super-efficiency DEA model has been used to assign ranks to the companies and provide a reference set.

Findings – From the results obtained, it has been found that for the year ending 31st March 2020, out of the total 42 units, 15 units (36 percent) are technically efficient, whereas 23 units (55 percent) are pure technically efficient. AMJ Land Ltd., Cera Sanitaryware Ltd., Dilip Buildcon Ltd., IRB Infrastructure Developers Ltd., Kajaria Ceramics Ltd., Kec International Ltd., Man Industries Ltd., Marathon Nextgen Realty Ltd., Oberoi Realty Ltd., Phoenix Mills Ltd., PSP Projects Ltd., Rail Vikas Nigam Ltd., RITES Ltd., RPP Infra Projects Ltd., and Sunteck Realty Ltd. are found to be technically efficient as per CCR model as well as pure technically efficient as per BCC model. From MPI analysis, the mean value of TFP came out to be 1.001, which implies a slight increase in the productivity performance during the period considered in the study. Based on the super-efficiency model, ranks and reference sets have been given to companies.

Research Implications – The study results have significant inferences for the managers and policymakers of the companies operating in the construction sector. The benchmark target levels and reference set provided to the companies can help companies increase efficiency, which is beneficial not only for managers and shareholders but also for various other stakeholders.

Originality/value – In the context of the Indian economy, minimal studies have been conducted earlier to assess the efficiency of the construction sector. The study is distinctive in terms of the number of companies considered, analysis of the efficiency for

five years, and methods used to provide various insights into the companies' performance in this sector.

Keywords – Indian construction sector, technical efficiency, pure technical efficiency, scale efficiency, Data envelopment analysis, Malmquist productivity index, Super efficiency DEA, Benchmarking.

CHAPTER 1

INTRODUCTION

Chapter 1

Introduction

The infrastructure sector is a key driver for the Indian economy, propelling overall development and accelerating India's growth. Its importance in enhancing overall development has been well recognized in literature, and its cross-industry linkages have increased efficiency, employment, and production capacities across industries. The Indian construction industry is expected to reach a market size of Rs. 53.91 lakh crore by 2022 in value terms with an estimated CAGR of 15.7%¹. Its share in India's GDP stands at nearly 9% and is the second-largest employer with more than 49 million people in the sector². The construction sector consists of three main segments, namely: Real estate construction (residential and commercial construction); Infrastructure building (roads, railways, power, etc.); and Industrial construction (oil and gas refineries, pipelines, textiles, etc.).

As opportunities in the sector continue to come to the fore, foreign direct investment has been moving upwards. FDI equity inflow in the Construction industry stood at Rs. 1.75 lakh crore for the period April 2000 to December 2020, amounting to 4.60% of the total FDI inflow received across sectors. In April 2020- December 2021, FDI Equity Inflows totaling Rs. 52187.7 crore were received³. 100% FDI through the automatic route is permitted in the following construction projects: townships, residential/commercial premises, hotels, resorts, hospitals, recreational facilities, educational institutions, city, and regional-level infrastructure. Also, the FDI limit for industrial parks under the automatic entry route is 100%⁴.

As per IBEF [2020] Indian infrastructure analysis report [3]⁵, India is expected to become the third-largest construction market globally by 2022. The construction sector receives undivided attention and significant resource allocation from the government at both levels. The Government of India has introduced many progressive reforms to unlock the sector's potential and is actively striving towards stimulating construction activities in the country. Recent initiatives such as Smart Cities, Housing for All, Make in India, Atal Mission for Urban Rejuvenation and Transformation (AMRUT), open foreign direct investment (FDI) norms, colossal budget allocation, investments in the National Infrastructure Plan, the newly-announced Affordable Rental Housing Complex (ARHC) scheme, etc. highlight this concerted focus on the construction sector and on addressing the several challenges that plague this sector. A recent push towards 'Atmanirbhar Bharat,' which aims to shift the supply chains from China to India, would likely boost this segment's growth and make India self-reliant. The National Infrastructure Pipeline (NIP), launched in 2019 with 6835 projects, has been expanded to 7400 projects with thrust on three fronts, i.e., creation of institutional structures, asset monetization, and enhancement of the share of capital expenditure⁶. Roads and highways infrastructure has received its highest-ever outlay of Rs. 1,18,101 lakh crore for the Ministry of Road Transport and Highways, under Union Budget 2021. National Rail Plan for India (2030) to create a "future-ready" Railway system by 2030 has been prepared by Indian Railways. A comprehensive National Hydrogen Energy Mission 2021-22 to be launched and Rs. 3,05,984 crore outlay over five years for a revamped, reforms-based, and result-linked new power distribution sector scheme has been planned by the government⁷. To increase the share of public transport in urban areas by expanding the metro rail network and bus services, Rs. 18,000 crore for a new scheme to augment public bus transport has been mapped out. For ports, shipping, and waterways, seven projects worth Rs.2000 Cr. has

been offered in FY 2021-22 in PPP mode to augment the operations of major ports. Union budget allocations for Centrally sponsored schemes for 2020-21 are as follows: Pradhan Mantri Awas Yojna (PMAY): 27500 Cr., Pradhan Mantri Gram Sadak Yojna: 15000 Cr., Swachh Bharat Mission (Urban): 2300 Cr., Swachh Bharat Mission (Gramin): 9994.1 Cr., Urban Rejuvenation Mission (AMRUT and Smart Cities Mission):13750 Cr. ⁸

The Rajya Sabha has passed the National Bank for Financing Infrastructure and Development (NaBFID) Bill 2021[5]⁹ by voice vote on 25 March 2021, which seeks to establish the “National Bank for Financing Infrastructure and Development” to support the development of long-term non-recourse infrastructure financing in India, including the development of the bonds and derivatives markets necessary for infrastructure financing and to carry on the business of financing infrastructure and for matters connected in addition to that or incidental to that.

This study attempts to assess the efficiencies of the Indian construction sector companies using DEA (Data envelopment analysis). The research objectives described in this paper are:

- (i) To determine the efficiencies of the Indian construction sector companies w.r.t. the technical, pure technical, and scale efficiencies for the FY period 2015-16 to 2019-20. The technical efficiency (TE) is the product of two non-additive and mutually exclusive components, namely pure technical efficiency (PTE), which signifies the managerial efficiency of the company, and scale efficiency (SE), which represents the company's efficiency in terms of operation scale and recommends whether the operation scale needs to be expanded or reduced to improve the efficiency score;
- (ii) To measure the deviations in the various efficiency levels of the companies over the period of five years;

(iii) To analyze the reasons for the changes in efficiency levels: total factor productivity change, technological change and technical efficiency change;

(iv) To assign targets to relatively less efficient companies to improve the efficiency levels.

The present paper is organized into six sections. Apart from Section 1, which is the Introduction portion, Section 2 documents the literature review. Section 3 elucidates the research methodology, the DEA model's theoretical description, and the variables taken in the present study for analysis. Section 4 deals with the analysis of the obtained results and the targets to the relatively less efficient units and depicts the companies' performance over the last five years. Section 5, summarizes key findings and Section 6 enlists the research implications and future scopes of the study.

CHAPTER 2
LITERATURE REVIEW

Chapter 2

Literature Review

The importance of the Indian construction sector has been discussed in the previous section. So, it is vital to analyze the level of efficiencies of Indian construction sector companies and the factors affecting it. There exists a considerable body of literature that has examined the efficiencies of the construction sector. We have tried to analyze the work done in this area, research methodologies used, input/ output variables, the sample size of the companies, research gaps, and findings from various countries. This review also aims to explore how efficiency measurement techniques have evolved over the period of time across different countries.

Mahadevan (2002)¹⁰ employed the DEA tool to assess the productivity growth of 28 manufacturing industries (such as electrical machinery, industrial chemicals, food industries, furniture, fixtures, etc.) of Malaysia for 1981-1996. DEA tool was applied to calculate the Malmquist index of TFP growth, which was decomposed into technical change, technical efficiency change, and scale efficiency change. Results showed that the average weighted TFP growth rate was around 0.8%. Scale efficiency analysis showed that most of the industries were operating at the optimum level and were experiencing constant returns to scale. TFP growth trend throughout the period was not found to be steady and was influenced majorly due to the change in technical efficiency. Scale efficiency trend was found to be constant throughout the period. The author also did windows analysis for assessing the stability of relative efficiency scores over time with a window length of 6 years and four windows. This analysis stated that the stability of the performance growth in the industries was there. This study concluded that the DEA

analysis tool was effective in assessing the performance of the Malaysian industries. It was also observed that in the 90s trend reversed from the trend in the 80s as TFP growth was found to be influenced by the increasing gains from technical change in the 90s instead of technical efficiency. The reason for the same was the increasing gains from technical change.

Barros and Alves (2004)¹¹ also presented empirical evidence on the intra-chain comparative efficiency of a Portuguese retail company. They assessed total productivity by applying the Malmquist Index (MI) based on DEA. Data related to 47 Portuguese retail outlets were collected from one of Portugal's leading hypermarket and supermarket chains for the years 1999 and 2000. Output variables considered for this study were Sales Value and Operational results, whereas input variables considered were only controllable Inputs such as full-time equivalent employees, labor cost, cash-out points, and stock, along with other costs. Results of this study showed that the total productivity change of three stores was found to be higher than one. The majority of the stores experienced a decline, as the mean score was found to be 0.872. However, most of the stores had reflected enhanced technical efficiency (value was higher than one). Scale efficiency change had the mean value equal to one, and pure technical efficiency was introduced. The technological change index due to innovations was found to be less than one. This study also laid down various reasons for technical inefficiency such as structural rigidities, whether associated with policies or labor markets, differential incentive systems, organizational factors, dimensional factors, etc. This study firmly concluded that most of the outlets were found to be efficient, whereas their proportion was inefficient. Economies of the scale were found to be an influential factor for the efficiency of the outlet.

Bassioni et al. (2004)¹² attempted to review the application of various performance measurement frameworks such as Balance scorecards, European Foundation for Quality Management (EFQM) Excellence Model, and Key Performance Indicators (KPI) of U.K. construction firms. The results showed that the construction firms had a lesser KPI rate than the Balanced Scorecard and EFQM (rates were given on a five-point scale with 1 as very poor and 5 as very good).

Ramirez et al. (2004)¹³ aimed to develop a benchmarking system that would form a part of the management evaluation system for evaluating and comparing the management practices in the Chilean construction industry. The methodology adopted by the authors included the use of a structured questionnaire and correlation analysis. In this study, 13 companies associated with the National Chilean Benchmarking System participated in the first application of the qualitative benchmarking system. Correlation analysis between indicators and management dimensions was done in three different stages- i) A correlation analysis using Pearson's correlation coefficient, ii) factor analysis, and iii) multivariate linear regressions. Correlation analysis of the central office showed a strong correlation between the different management, whereas the correlation between the management dimensions and the performance indicators was less than the former. Furthermore, strong negative correlations were observed with the safety indicators.

Moreover, a strong high correlation was observed between technology and deviation from the scheduled completion date. Results of correlation analysis for construction sites showed no significant correlations between management dimensions and performance indicators. Factor analysis showed differences in the focus and priority of central office management strategies compared to construction site priorities. Multivariate linear regression analysis showed a weak correlation between the performance indicators taken as dependent variables and the management dimensions taken as independent variables

performed for the central office and construction site surveys. The results of the sector trend analysis indicated that: (i) the high-rise building subsector have the highest medians for all management dimensions and its improvement opportunities included dimensions such as state of technology and purchasing and inventories control for the central office but for the construction site dimensions included were understandable goals, change management, and production system; (ii) the heavy construction subsector have the maximum feasible response for safety practices and their improvement opportunities included leadership, understandable goals, change management, and production system for both the site surveys; (iii) the low-rise housing and light industrial assembly subsector reflected the lowest standard deviations with medians of almost all dimensions being less than the sample median; and (iv) the civil works subsector showed the most significant improvement potential as one of its was found to have a minimum score in more than 60% of the dimensions evaluated in this study. This study led to the determination of a generally deficient measurement culture within the Chilean construction industry.

McCabe et al. (2005)¹⁴ adopted a three-stage methodology to establish and develop the P-DEA model framework, i.e., prequalification model using data envelopment analysis (DEA) for the construction contractors' evaluation. Data for ten contracts were collected for the period from 1998-2000, where each contract had at least 15 contractor prequalification packages. The weighted score system (the baseline model) was used to score each contract considering ten elements: financial references, letter of consent for surety, personnel resumes, CAD-7 report, etc. Two input variables, i.e., safety record (SR) and current capacity (CC), were considered, whereas, for output variables, sales history (SH), related experience (RE), and employee experience (EE) were taken into account. Based on these factors, scores were given to the contracts. The authors performed correlation analysis for variables of each contract, and it was found that they had a low

correlation with each other. Efficiency measurement system (EMS) software was used for the DEA analysis. After eliminating contracts that did not meet the bonding requirements, in stage 2, DEA analysis was done without any type of restriction imposed on the variable weights (Baseline model). Then, the relative importance of the weights assessed by the experts was converted into constraints as ratios and added to the DEA model. Finally, the analysis was done again, considering weights (DEA weight-restricted model). Comparing scores under both the scenarios, it was found that efficient DMUs decreased in number when weights were considered, i.e., DEA weight-restricted model in all the contracts.

Moreover, rankings of the contracts were also different in both models. After this, possible improvements in inputs and outputs were evaluated, which helped create the artificial contractors using P-DEA+. New values of inputs and outputs were calculated from a maximum efficiency score value by optimizing the weights. After this, a practical frontier was established based on the DEA model with both the original and the artificial contractors. As a result, it was concluded that the CPM framework could be employed effectively to prequalify contracts. Also, standard practical frontier could act as a regional performance benchmark, which would help contractors measure themselves and find possible performance targets.

To measure the relative productive efficiency and identify the factors affecting the productive efficiency of 41 construction firms in Hong Kong, Chau et al. (2005)¹⁵ employed Data Envelopment Analysis (DEA). Inputs considered by the authors were capital, labor, and two types of intermediate input: construction materials and overhead office expenses. The total value of work done (less payment to fee subcontractors to avoid double accounting) was considered as the output variable. Data related to these factors were collected from the Census and Statistics Department for 1981-2001. This study

firmly concluded that analysis of scale effect supports the U-shape average cost curve concept. The degree of subcontracting and efficiency of the industry was negatively related, although this negative impact decreased as the portion of subcontracted work was increased. It was also suggested that the growth rate was declining over the years instead of increasing productive efficiency.

Lee et al. (2005)¹⁶ strived to show the development of the CII (Construction Industry Institute) Benchmarking and Metrics (BM&M) program, its database, and the following metrics that led to the establishment of the industry norms. Data were collected through a web-based questionnaire and was segregated into different sub groups based on factors such as i) industry group type, which was buildings, heavy industrial, infrastructure, and light; ii) project nature which was an add-on, grass roots, and modernization and iii) project size in terms of the project cost. From all these groups, heavy industrial projects, which belonged to chemical manufacturing and oil refining projects, constituted the majority of the database. Along with this maximum project were those whose projects cost were less than \$15 million. This study concluded that this CII Benchmarking System helped the construction industry participants by providing them with a system for benchmarking tailored to the industry.

Vitner et al. (2006)¹⁷ adopted the DEA framework for evaluating project efficiency in a multi-project environment. Two methods, such as Earned Value Management System (EVMS) and Multidimensional Project Control System (MPCS), were considered for the project measurement. Still, the focus was given to MPCS as it also considered the EVMS measures in the DEA inputs and outputs. For clarifying the various stages of this grouping process, the example based on data collected from the typical Hi-Tech company was taken, which managed 11 projects related to hardware, software, integration, and testing elements. The input variables considered were cost, work content in hours, level of

monitoring, and level of uncertainty (levels were rated on the scale of 0-10) were selected for the analysis. In addition, outputs such as schedule performance index (SPI) and the cost performance index (CPI) of EVMS and Design yield, Operations yield, Training yield, Documentation yield, and Project management yield of MPCS were considered here. It was found that the performance of Project 8 was only satisfactory in the case of outputs, and in the case of inputs, projects 3, 9, and 10 were found to be problematic.

Using the questionnaire distribution method, Iyer and Jha (2006)¹⁸ attempted to identify and study the attributes affecting project performance and their impact. By doing a pilot survey, a list of 55 attributes was prepared. The results obtained concluded that three significant success factors, i.e., the commitment of project participants, owner's competence, and good coordination among project participation, help improve performances. In contrast, four significant failure factors, i.e., conflict among project participants, project manager's ignorance and lack of knowledge, hostile social environment, and harsh climate condition at the site, leads to retention of performance only at the current level. Furthermore, the contribution made by various factors is affected by performance ratings of the project: If it is at a high level, the owner's competence factor contributes maximum, and if ratings are low, the commitment of the project participants contributes highest in the performance.

Andersen et al. (2006)¹⁹ carried out exploratory research to analyze and understand the relationship between the project's critical success factors (grouped as X) and actual project success criteria (grouped as Y) in the Indian construction industry. The research was carried out in two stages: In stage 1, Principal Component Analysis (PCA) with varimax rotation was used for exploratory factor analysis; In stage 2, Regression analysis of X on Y was done to establish the nature and magnitude of the impact of X on Y. Data was collected from 529 students from different countries such as Norway (67%), China

(22%), France (8%) and the UK (3%). Only nine project success factors explain 62.3% of variances such as rich project communication, stakeholder endorsement, well-structured project approach, strong project committee, early stakeholder influence, etc. and three factors from Y, namely project impact, captured experience, and marginal ability to deliver explaining 59% of total variance met the defined criteria. The results indicated that these factors had complex relations with each other. Factor-rich project communication having various elements had maximum impact on the project, followed by stakeholder endorsement and a well-structured and formal project approach. However, the substantial project commitment factor explained maximum variance in the relationship, marginal ability to deliver, and early stakeholder influence. Factor-rich project communication proved to impact the project's success. The three success criteria proved to balance intention, benefits of success, and long-term contribution to the organization. It can be concluded from this study that strong project commitment and early stakeholder involvement explained marginal ability to deliver, rich project communication supported both product and personal success along with captured experience.

The data for the publicly-traded REITs listed in the National Association of Real Estate Investment Trusts (NAREIT) Handbook and the SNL REIT Quarterly for the year 1995-2003 were analyzed by Miller et al. (2006)²⁰ to measure REITs operating efficiencies and scale economies. The methodology adopted by the authors included the use of specifying the translog variable cost function with a composite error term to estimate the stochastic-frontier, panel-data model of REIT operating efficiencies. A total of 1851 observations were collected for the analysis. Input variables, specifically interest expense and the sum of operating expense, general and administrative expense, and management fees, were considered. In contrast, for output variables, total assets and total revenue were taken into

account. Analysis results showed that all coefficients were significant at 1 or 5% levels for the specifications without considering input prices. The analysis of the debt-to-asset ratio indicated that REITs were facing significantly higher costs with higher leverage. This study concluded that the economies of scale were moved to diseconomies of scale from the initial years of the examined period to the later years (given the growth in average REIT size over the examined period). The initial tests of REIT efficiency by employing DEA indicated significant inefficiencies. The study was previously done by Anderson et al., 2002 and Anderson and Springer, 2003 employed a stochastic frontier and concluded significantly lower inefficiency levels. However, this study showed even much lower inefficiency levels, and inefficiencies increased over time. This study overall suggested contradictory results while evaluating the influence of the self-management dummy variable and favored the use of revenue over assets as a measure of output in assessing the efficiency levels of the REITs.

Crawford and Vogl (2006)²¹ made an effort to measure the productivity in the construction industry by applying average labor productivity (ALP) and total factor productivity (TFP) measures and also tried to establish the relationship between the two. The authors showed the application of TFP by analyzing the data obtained from O'Mahony and Van Ark (2003)²² by employing a simple index-based growth-accounting method. Inputs considered were growth in total hours worked and increase in real non-Information and Communication Technology (ICT) capital, and the output variable considered was real value-added growth. Data were collected for the period from 1980 to 1990 for the construction industry. It was found that the strong growth in labor input and investment in fixed capital led to strong output growth during the late 1980s. When its productivity declined, the industry tried to adjust to the decline by significantly reducing the labor inputs. Not only this, the decrease in the number of total hours worked surpassed

the decline in real output. The results of this analysis showed that productivity growth was very cyclical as it increased in the initial years of upswings and then decreased in the initial years of downswings. The pace at which adjustments were made to the labor and the capital inputs depended on the variables named as employment legislation, the liquidity of assets, or expectations related to the sustainability of the demand trend. Productivity growth was found to decline during the boom of the 1980s, but then it increased significantly during the downturn in the 1990s. During this downturn, the combination of quick adjustments made to the labor inputs with the higher capital intensities led to better labor productivity. Moreover, TFP was found to have positive correlations with labor productivity.

Du ğazın and Du ğazın (2007)²³ attempted to measure the performance of 480 major manufacturing firms in Turkey with super slacks based model of data envelopment analysis. For the analysis, performances of ICI500 companies were evaluated by employing an output-oriented Super SBM model under the CRS assumption. Input factors considered in this study were net assets and the average number of employees. For output factors, gross value added, profit before taxes, and export revenues were considered in which gross value-added and profit before tax could have negative values and export revenues could have zero value. Analysis showed that only nine firms out of a total 480 were efficient as per the DEA scores. Arbel was the most efficient firm among the 500 Major Industrial Enterprises of Turkey.

To analyze the different types of efficiency named as cost efficiency, allocative efficiency, and technical efficiency of the Korean construction industry for 1996-2000 (period of economic crisis), You and Zi (2007)²⁴ employed the DEA approach and Tobit regression model. Results of this study showed that the efficiency of the Korean industry significantly dropped during the relevant period. Average Cost efficiency declined over

the years, mainly due to allocative inefficiency, whereas technical and allocative efficiency measures were relatively higher throughout the period. It was found that Korean companies suffered inefficiency as they could not optimize the cost-minimizing input mix during the crisis. Results of the Tobit regression model using the maximum likelihood method were analyzed by dividing the period into two sub-period- 1996-97 and period 2 for 1998-2000. It was observed that allocative efficiency was impacted by institutional ownership (positively related), asset size (negatively related), and leverage ratio (negatively related) in both periods. Cost efficiency was highly influenced by leverage ratio (negative), institutional ownership (positive), and asset size (negative) in both periods but receivables overdue turnover (positive) was also crucial in period 2. This study firmly concluded that efficiency measures decreased during 1996-2000. Also, agency problems prevailed between managers and owners, and agency costs had to be minimized to enhance efficiency.

Aksorn and Hadikusumo (2007)²⁵ aimed to identify the factors crucial for the safety program performance in Thai construction projects and quantitatively prioritize those critical success factors based on the respondents' perception by employing a questionnaire, T-test, and Spearman Rank Correlation method. For this analysis, a questionnaire related to 16 critical success factors (CSFs), i.e., clear and realistic goals, good communication, the delegation of authority and responsibility, sufficient resource allocation, management support, program evaluation, continuing participation of employees, personal competency, positive group norms, team work, personal attitude, effective enforcement scheme, safety equipment acquisition and maintenance, appropriate supervision and appropriate safety education and training, was prepared. Responses were collected from experts who were construction safety managers, safety engineers, and senior safety officers who have been involved in managing safety in

construction projects for at least ten years. This study concluded that among all the 16 CSFs, management support was the essential factor for safety program implementation in the Thai construction industry.

Odeck (2007)²⁶ attempted to assess the productive efficiency of the rock blasting processes in the Norwegian road construction sector by comparing the results of two models: the non-parametric DEA model and a Deterministic Frontier Analysis model (DFA) for the year 1993 for 170 units working under Public Roads Administration of Norway (PRA). The results concluded that similar distributions were between both approaches, differences in individual efficiency scores, but similar scale properties were observed. However, no general pattern was concluded between both the methods.

Watanabe and Tanaka (2007)²⁷ adopted the directional output distance function to ascertain the differences in the efficiency levels of the Chinese industry at the provincial level considering both desirable and undesirable outputs. A two-stage analysis was done. The first stage analysis aimed to assess balanced growth indicators (BGI's) and industrial efficiency indicators (IEIs) where input factors considered were capital, labor, and materials (coal consumption), and industrial products (value-added of enterprises) were the desirable output, and undesirable output was sulphur dioxide. Data for a total of 214 observations were collected for the period of 1994-2002. The second analysis aimed to identify the factors which influence the efficiency levels of each province, and for this analysis, variables were divided into four groups where the first group was linked with the government's capacity for environmental management and the number of environmental laws (Env_law) and the number of monitoring stations (Monitor) were used as the indicators. The second group considered the firm's capacity for environmental management, which was shown by the removal rate of sulphur dioxide of the provinces (Removal Rate).

In contrast, the third group comprised those variables which represent the industrial structure in each province assessed by the share of collective firms (Share_Collective), foreign firms (Share_Foreign), and heavy industries (Share_Heavy). This study concluded that both industrial output and environmental pollutants needed to be considered in analyzing the efficiency levels in China. Provinces of the central region were found to be least efficient when compared with other provinces. The analysis also concluded that the variables related to the firms' and government's capacity for environmental management were found to have mixed or insignificant effects, whereas a province's industrial structure was found to have a strong impact. Efficiency levels were at their minimum in 1999 and post 1999, they recovered.

Xue et al. (2008)²⁸ employed the DEA-based Malmquist Productivity Indices (MPIs) approach and used Input-oriented CRS DEA-based MPIs to measure the construction industry's productivity changes in China during 1997-2003. The study concluded that Chinese construction companies experienced improvements from 1997-2001, then declined in 2001-2002, and performed well in 2002-2003. However, this study only employed an input-oriented model, but further studies could be done by using an output-oriented model of DEA. Furthermore, Multi-input and multi-output DEA-based MPI approaches could be undertaken in the future to measure the performance efficiency of construction industries and its reasons.

Aksorn and Hadikusumo (2008)²⁹ aimed to identify the factors crucial for the safety program performance in Thai construction projects and quantitatively prioritize those critical success factors based on the respondents' perception. This study also aimed at classifying those factors by employing the factor analysis method.

Eilat et al. (2008)³⁰ employed an integrated Balance score card (BSC) and DEA approach to evaluate R&D projects in different stages of their life cycle for-profit and non-profit organizations. For the case study, data of 50 projects related to the R&D unit was collected so that the authors could check the capability of the extended model. The study concluded that BSC and DEA approaches were best suited for developing an integrated extended DEA model to evaluate the R&D projects. The model also helped in differentiating projects based on specific characteristics and ranking them accordingly. This model also eliminated the limitations of the BSC model.

Marti et al. (2009)³¹ employed different basic models of the DEA framework, such as the CCR model of DEA, BCC model of DEA, etc., to assess the possibilities of using the DEA approach for measuring the performance of various firms belonging to different fields. Considering the success of DEA Models in Serbia, Milan used the DEA method for comparative analysis of 30 regions; Martic and Savic (2001) considered inputs such as active fixed assets, electricity consumption, population, and Arable land. In contrast, variables such as gross domestic product, the total number of physicians, the total number of pupils in primary school, and the total number of employees in the social sector were taken as outputs. An output-oriented CCR DEA coupled with Linear Discrimination Analysis (LDA) was employed to find the efficient regions and check the DEA Results effectively. The authors also analyzed the changes to be done by the inefficient regions in outputs and inputs. It was found that results obtained by employing basic DEA and CCR models that considered exogenously fixed inputs were not that realistic. According to the study done by Martic et al., 1996, DEA models were used for assessing the efficiencies of 20 investment programs. Efficient units were recognized, and for each inefficient program, the list of peer programs was provided, and it was observed that investment program P10 was found to have appeared in all the peer groups. To compare

relative efficient units, the distribution of virtual inputs and outputs was obtained by multiplying the magnitude with their respective optimal weights. Thus, DEA methods could be used to determine the greatest relative efficiency that each investment program could achieve considering the factors and fields included in the analysis, b) get the information about the most relevant inputs and outputs for each efficient investment, c) recognizing efficient investments which formed the peer group for each inefficient one and d) to report the excess and lack of inputs and outputs respectively when investment efficiency score was less than 1. This paper firmly concluded that DEA models could be applied to various fields to assess their relative efficiency and establish their frontier.

Chang et al. (2009)³² used the BSC approach having four perspectives: financial, customer, internal process, and learning and growth perspective to develop a set of performance measures to measure the performance of the Malaysian construction industry. Based on these four perspectives, eight critical success factors (CSF1 Productivity, CSF2 Quality, CSF3 Human resources, CSF4 Knowledge, CSF5 Innovation, CSF6 Environment-friendly practice, CSF7 Industry sustainability, and CSF8 Professionalism) along with seven strategic thrusts (ST1—Integrate the construction industry value chain to enhance efficiency and increase productivity, ST2—Strengthen the construction industry image, ST3—Strive for the highest standard of quality, occupational safety and health, and environmental practices, ST4—Develop human resource capabilities and capacities in the construction industry, ST5—Innovate through R&D and adopt new construction methods, ST6—Leverage on ICT in the construction industry and ST7—Benefit from globalization and increase the export of construction products and services) which formed the basis of the strategic master plan were mapped for the year 2006. Data collected from different public sources for the base year as 2006 showed low annual increases in productivity, inadequate safety performance, low

investment in research and development, and an insufficient number of construction companies certified to quality, environmental, and occupational health standards. In addition, in the Malaysian construction industry, 50% of the workforce was unskilled. Despite all this, this industry managed to expand its operations overseas successfully and was profitable.

For better analysis of project delivery systems (PDS) in the Chinese construction industry, Chen et al. (2010)³³ utilized a robust model of DEA (SE-DEA-CCR-I model). The study concluded that DBB, DB+PM, DB/EPC, Turnkey, multi-stage DB/EPC, and EP+C were commonly used PDS in China. This was also stated that DB/EPC and Turnkey projects were not significantly different in the Chinese construction industry. The method used in this study, i.e., SE-DEA-CCR-I, provided results that were consistent with common perception, but it was unable to give owners a comprehensive guide. It did not help them in selecting the most suitable PDSs.

Sueyoshi and Goto (2009)³⁴ applied DEA- DA (Discriminant analysis) along with two rank-sum tests, i.e., Mann–Whitney rank-sum test and Kruskal–Wallis rank-sum test for bankruptcy-based performance assessment of the Japanese construction industry and the three problems associated with it, i.e., i) sample imbalance problem, ii) problem in dealing with extensive data set and iii) problem of data alignment by applying. The study concluded that DEA-DA could be used effectively to deal with the three problems. Misclassified non-default firms were classified into three different groups based on the potential of bankruptcy showed that group 1 firms (26 non-default firms with misclassified annual periods) required corporate governance so that their performance could be enhanced. Group 2 (50 non-default firms with misclassification in multiple annual periods) and group 3 (18 firms misclassified in every annual period) were found to be very close to bankruptcy. They required the construction contract from the Japanese

or local government so that they could survive. This study also concluded that Japanese capitalism was different from that of Americans.

To evaluate the total factor productivity changes in the Australian construction industry from 1990-2007, Li and Liu (2010)³⁵ also used the Malmquist index methodology. The study concluded that the construction productivity growth rate was highest in the three periods, such as 1994–1995, 1998–2000, and 2002–2003. Still, there was no stability in the construction productivity growth rate throughout the relevant period. In addition to the above, this study also concluded that productivity grew very slowly, and there was no stability and continuity. Also, increasing the technical construction levels and optimizing production deployment factors contributed to the maximum productivity. However, factors such as inputted construction scales and scopes of production activity were crucial factors that may restrict construction productivity growth. Finally, this study concluded that in the mid regions, productivity increased primarily just because of the technical progress, whereas in the eastern areas, it was majorly due to the increase in pure technical efficiency.

Mashaleh et al. (2010)³⁶ utilized the CCR model of DEA to benchmark the safety performance of 45 construction contractors. The study concluded that the DEA approach could be used for analyzing the safety performance of construction contractors. It was found that only eight contractors were efficient, with an average efficiency score of 0.32, and acted as the benchmark for the construction industry. The result of this study had been used in various programs such as the US Malcon Baldrige National Quality Award and the UK Department of Trade and Industry Business-to-Business Exchange program to promote best practices across the interested organization.

Shi et al. (2010)³⁷ adopted an extended DEA method to evaluate Chinese regional industrial energy efficiency and determine various policies based on regional energy efficiency evaluation to fix non-energy inputs and consider undesirable outputs. For this study, authors collected data for 28 provinces related to input and output factors for the period 200-2006 from China Statistical Yearbook and China Energy Statistical Yearbook. Input factors such as annual data on industrial investment in fixed assets (IFA), industrial energy consumption (IE), and industrial labor (IL) were considered. In contrast, Industrial added value (IAV) and volume of industrial waste gas from fuel-burning (WGF) were considered desirable and undesirable outputs. On comparing all the regions, the west area was found to have the lowest IEOTE score. On the other hand, in the context of IEPTE, Guangdong from the east area, Heilongjiang from the central area, and Qinghai from the west area were found to have the highest average score.

In contrast, Hebei from the east area, Shanxi from the central area, and Inner Mongolia province from the west had the lowest average scores. On comparing all the areas, the east area had the highest scores, followed by the west, and then the central area had the lowest IEPTE average score. IESE scores were calculated to assess the changes in energy input due to the changes in IAV without changing non-energy inputs. It was observed that the east area had provinces with constant returns to scale, increasing and also decreasing returns to scale. However, west and central region provinces had only increasing returns to scale. Analysis showed that the east and central areas' overall technical inefficiency was majorly due to the pure technical inefficiency; in the case of the western area, it was because of both pure technical inefficiency and scale inefficiency. Guangdong province, which always lay on the efficiency frontier of energy consumption, was considered as a benchmark. Qinghai province's inefficiency was found to be influenced only by scale inefficiency. It was also concluded that the industrial structure of provinces such as

Beijing, Shanghai, Jiangsu, and Guangdong in the east was not influenced by the consumption of a large amount of energy. On the contrary, they had constant or decreasing returns to scale. In comparison, the industrial structure of other regions was found to have increasing returns to scale.

An integrated approach based on Key performance indicators (KPI) and Data envelopment Analysis (DEA) was employed by Horta et al. (2010)³⁸ for analyzing the performance of construction industries. This study used two DEA models, i.e., the DEA organizational performance measurement model and the operations performance measurement model. Data for about 20 Portuguese contractors was collected for the year 2005 by employing the icBench web platform. By analyzing the organizational performance, it was found that only ten companies were efficient according to the standard DEA model, and those companies were also top rankers according to the KPIs average measure. The authors employed the Spearman rank-order correlation method to find the association among DEA scores and KPIs average, strongly associated. As per the restricted DEA model, only four companies were efficient. A strong association was also concluded between restricted DEA and KPIs average. Using the PDEA model, four virtual companies were created, out of which only two were efficient. From the operational performance perspective, 12 companies were efficient as per the standard DEA model, and 3 out of 12 were efficient as per the restricted DEA model. Spearman rank-order correlation was found to be more for the restricted DEA model. Only one virtual DMU had an efficient operation. A strong association was found between KPI benchmark data and original KPI data. This study led to the development of a methodology integrating both KPI and DEA scores. This study also helped the construction industries in improving their effective performance.

Mashaleh (2010)³⁹ undertook the study to employ the DEA approach for making the bid-no-bid decision. The DEA model was deployable by organizations facing the bid-no-bid problem irrespective of size, country, number, and type of factors considered in bidding. Several factors were considered for this decision, classified into two groups- positive and negative factors. Financial status, current workload, availability of other projects, public objection, the technical difficulty of the project were taken as negative factors, whereas the need for continuity in employment, the financial capability of the client, relationship with the client, availability of time for tendering, site clearance of obstructions were taken as positive bidding factors for this study. The committee then scored these factors on a scale of 1-10. For this study, the database for such 40 opportunities was considered along with positive and negative factors scores. For the DEA model, positive factors were considered outputs, and negative bidding factors were taken as inputs. Opportunities with higher values of positive factors and lower values for inputs or higher ratios of different output and input were favorable. With the help of the DEA model, every bidding opportunity was given the favourability score. Only three opportunities were found to lie on the favorable frontier with a score of 1.0. If the new bidding opportunity touched the favorable frontier, then it was accepted; otherwise, not. A new approach for the bid-no-bid decision was concluded from this study. The bid-no-bid decision was made after evaluating those opportunities in the context of favourability scores. A subjective scale was used to score the bidding factors.

Tsolas (2011)⁴⁰ also undertook a two-stage analysis by integrating BCC – DEA model and ratio analysis approach to measure the profitability and effectiveness of 16 Greek-listed construction firms. The study strongly concluded that the integrated DEA method and ratio analysis could be effectively used to compare the firms' performances. A clear relationship was observed between the performance in the operational and financial

spaces of the firm. While analyzing the drivers for efficiency and effectiveness, functional space (cost-related) factors were found to play a crucial role.

Chen and Yang (2011)⁴¹ attempted to develop and to provide the frameworks under parametric and non-parametric contexts to assess the effect of the SEC (scale efficiency change) in the decomposition of the generalized MMPI (Metafrontier Malmquist productivity index) by using distance functions with application to 41 Taiwanese and 12 mainland Chinese primary and influential banks. It was found that TGR (Technology Gap Ratio) for the banks in Taiwan was higher than that of banks in China, i.e., Taiwanese banks were operating at the better technology level. Also, the Taiwanese banks' metafrontier-based technical efficiency (TE) was more than that of the Chinese banks. Analysis of generalized MMPI and its decompositions such as TEC, TC, SEC, and PTCU showed that productivity change and growth rate were better for Taiwan banks majorly due to TC. Taiwanese banks also scored better scores for SEC, and China's scale efficiency reduced, determined by the value of scale elasticity. Taiwanese banks' productivity increased over the years due to technical advancement, SEC, and efficiency improvement. PTCU (from individual bank's point of view) and FCU (aggregate point of view) together showed that the technology adopted by the Taiwanese banks converged towards potential technology. Still, these technological catch-up dynamics were pushed by a few certain banks only. In the Chinese banks' context, productivity increased but less than the former because of technical advancement and efficiency improvement. Facts of PTCU and FCU showed that the margin of technology converging towards the potential technology was much higher in this case. The advancement rate of the used technology was low compared to the potential technology. The development and openness of the Chinese banking and financial system were found to be delayed. The technical efficiency and technological level of the primary banks were more of Taiwanese banks. Instead of

the Chinese banks showing technological advancement, the technological catch-up dynamics were adverse in recent years. However, efficiency change and technological change rates for the Chinese banks were better than that of the Taiwanese banks, but still, the productivity change was lower than the latter, which was majorly due to the SEC. Various policies for Taiwan and China had been suggested by the authors to majorly focus on scale adjustment issues such as strategies for accelerating a banking merger and financial export for Taiwanese banks, increasing market competition for Chinese banks, and also forcing them to adopt for policies that would help them in inspecting the reasons of their existing operating scales. This study evidently concluded that the SEC had the most significant impact on the productivity index. This factor could not be ignored even after the focus of productivity index measure was shifted from being group frontier-based (MPI) to meta frontier-based (MMPI).

To analyze cross-period efficiency and productivity growth of six high-tech industries, i.e., biotech, photo-electronics, communication, computer, precision equipment, and semiconductor, in Taiwan Hsin Chu Industrial Science Park for the period 2000–2006, Sun (2011) ⁴² employed DEA based window analysis and MPIs. As per the MPI, the productivity growth was divided into various components such as technical efficiency change (E), technological change (P), pure technical efficiency change (PT), scale-efficiency change (S), and total factor productivity (M) change. Window analysis was used to assess the long-term effectiveness in productivity, and the MPI was used to recognize the major source of productivity growth in the industry. The inputs factors considered were R&D expenditures, number of employees, and working capital, whereas output factors considered were the number of patents and annual sales. This study concluded that DEA-based window analysis and MPI analysis could assess the industries' efficiencies and identify the best industry. Since semi-conductor and computer industries

were two top performers, this study suggested that the owner of these industries should adopt a flexible supply chain and a robust virtual manufacturing network. Also, the government agents should try to promote the international linkages and develop a broker framework for them. However, the bio-tech industry was in the pioneering stage for the Taiwan industry, and this industry would grow if proper support were given to it from the government. From MPI analysis, it was concluded that industrial industrialists improved their managerial skills and innovative performance and technology level. It also suggested the industries build an innovative cluster and develop the cluster competence for transforming through innovations.

Zheng et al. (2011)⁴³ employed three different models based on DEA analysis: the CCR model, BCC model, and super-efficient DEA model to evaluate the performance and efficiency of 94 Listed Real Estate Companies (LRECs) of China. Registered Capital, Asset Value, Employee Number, and Operation Cost were considered as input variables, and Revenue and Profit were taken as output variables. Input-oriented CCR DEA-based model having constant returns to scale was used to calculate overall technical efficiency (OTE), and Variable returns to scale-based BCC was used to calculate pure technical efficiency (PTE) and scale efficiency (SE). Analysis showed that 12 out of 94 LRECs were found to be efficient as per the CCR model with the OTE average score of 0.78, and the BCC model result showed that the PTE average score of inefficiency was 0.84. Moreover, ten inefficient firms had PTE=1, but their SE score was less than 1, which showed that inefficiencies were primarily due to scale inefficiencies. However, SE average score was found to be 0.93. The analysis also showed that out of total LRECs, 69% of the firms were operating under increasing returns to scale, 14% were under constant returns, and 17 % of the total firms were under decreasing returns to scale. The average slack ratio of outputs was also calculated for the inefficient LRECs. It was found

that: the employees' slack was around 18.96%, followed by registered capital, which had a value of 6.54%, and asset value which had 5.57% slack.

Tmeemy et al. (2011)⁴⁴ endeavored to identify the future criteria which were necessary for the success of building projects in Malaysia from the perspective of building contractors in Kuala Lumpur by using questionnaires and factor analysis. The study concluded that the project success was a multi-dimensional concept with dimensions such as project management success (PMS), product success (PrS), and market success (MrS). PMS focused on achieving the targets in the context of the completion period and budget allotted along with the quality requirements. PrS was related to the target of the final production context of the functionality and meeting the technical requirement and customer satisfaction. Finally, MrS was concerned with the project's potential in the company's success in the long run by gaining competitive advantages, improving the company's reputation, increasing the market share, and achieving the revenue and profits target.

Comparative performance analysis of 30 publicly listed Australian construction companies was done by Balatbat et al. (2010)⁴⁵ using fundamental analysis, i.e., financial ratio analysis for the period 1998 to 2007. Analysis of market performance showed that, on average, annual share returns of these construction companies outperformed both the "All Ordinaries Index" and the "Blue-Chip Portfolio" in all the years except for 2005. This study concluded that construction companies, on average, had higher dividend yields instead of increasing share prices. Analyses of equity valuation measurements depicted that construction companies' share prices were not found to be overvalued. It was concluded that the percentage increase in its share prices over the ten years was around 370%.

In contrast, this increase was around 280% and 135% for blue-chip companies and the All Ordinaries Index, respectively. The equity valuation analysis showed that construction companies were capable enough to match their increase in share prices with higher earnings. All profitability ratios showed that the construction companies were not as profitable per operating revenue dollar as the blue-chip portfolio. This analysis showed that the market was strong and stable, and the financial performance of the construction companies was comparable with the best performers in the Australian capital market.

Tabish et al. (2011)⁴⁶ employed Questionnaire research methodology, Factor analysis, and Multivariate analysis to identify the factors which contributed to the success of public sector construction projects. A list of 36 attributes was prepared. From this study, it can be concluded that from the list of 36 attributes, four significant factors stated above are the main success factors for the public industry construction projects. The most crucial factor was awareness and compliance with norms because of the penalties for violating those norms. Pre-project planning and clarity in scope contributed maximum if the objective was shifted to compliance with anti-corruption and financial norms. When the aim was shifted to compliance with financial/audit norms, factor awareness of and observance of rules was identified as the best contributor to the success.

Wahab et al. (2011)⁴⁷ attempted to identify the factors influencing the productivity growth in major OECD countries and compared the trends of such growth in the construction industry across Europe, the US, and Japan using the Growth Accounting framework. Data for five major OECD countries such as the USA, the UK, Germany, France, and Japan were collected from the EU KLEMS database. A growth accounting framework was adopted to evaluate the contribution of the factors to productivity growth during the period 1971–2005. Capital, labor quality, and total factor productivity (TFP) were the factors considered for this analysis. This paper measured productivity as average

labor productivity (ALP) while Capital inputs were further divided into ICT capital and non-ICT capital. Analysis showed that all the countries had experienced a slowdown in the labor productivity growth except the UK. Productivity growth in construction was found to be below total industries in all countries over both sub-periods, and it further declined in the second period. It was found that the contribution of skills improvements to productivity growth in construction was low in the period 1971–89 and was below the contribution of skills improvements to total industries productivity growth in all the countries except Japan. However, in Germany, this contribution was the same in both periods. In the UK, France, and the USA, a significant improvement in labor quality was observed during 1990-2005. The gap between construction and total industries figures of these countries was found to be decline during the second sub-period depicted the enhancement in the labor quality. In terms of ICT capital, its contribution to productivity growth was found to be the maximum in only two countries: the UK and the USA. In other countries, its contribution was meager. TFP contribution to the growth in total industries was found to be the maximum in all the countries except for Germany. In the USA, the growth lead in entire sectors in the second sub-period was attributable to its more robust TFP performance. The differences in labor productivity growth between construction and whole industries were present because of the construction's poor TFP performance. This study concluded that the productivity growth in construction was lacking behind the productivity growth elsewhere in the economy, and their performance worsened in the second sub-period. This analysis revealed that productivity growth was not only influenced by the factors such as labor quality and capital, but it was also affected by the TFP.

Wei et al. (2011)⁴⁸ suggested a scientific method based on super-efficiency DEA to evaluate the investment efficiency of the real estate industry in China. The result of the

investment efficiency of real estate industry of 35 large and medium cities in China showed that out of total cities, 11 cities such as Xi'an, Wulumuqi, and Lanzhou, etc. were found to be efficient with efficiency value greater than one which stated that the efficiency of this industry was low as a whole. It was observed that the efficient cities belonged to eastern coastal areas and northwest areas, whereas cities of the middle region had values less than 0.8. It was found that the southeast coastal regions had better efficiency due to strong economic strength and a good level of resident income. Since it was observed that 24 cities along with Shenyang, Dalian, and Yinchuan were not efficient as per DEA, input redundancy and output deficiency were present. The scope improvement of the efficiency improvement was calculated. It was observed that cities might become efficient by changing their inputs according to this scope by keeping the output constant. However, change in only one most effective input would also improve efficiency. This study concluded that the difference in investment efficiency between the regions was quite significant, and the problem of input redundancy and output deficiency existed in the real estate industry of China.

Junior et al. (2012)⁴⁹ employed the DEA - BCC model in multistage along with Malmquist Index to analyze the efficiency of Brazilian firms in the construction industry between 2005 and 2008. This study concluded that efficiency improvements did not lead to growth as results indicated that companies faced internal difficulties and optimal inputs were not utilized entirely for income generation. Also, it was observed that there was no homogeneity in the performance of firms among different strata. High revenue firms seemed to have high technical efficiency but low scores of scale efficiency. Unqualified workers were the major hindrance to production efficiency. Variations in TPF were mainly due to the technological progress as analyzed by this study. It increased between 2005-06 due to various reasons such as the opening of sites in the country due to elections,

expansion of chattel mortgage, etc. This led to the election of technological innovations. On the other hand, due to the economic crisis during 2007-08, there was a high loss of technological progress, which declined TPF.

Wong et al. (2012)⁵⁰ employed DEA analysis to evaluate the performance of real estate and construction companies in Iran and their technical and cost-efficiency. The efficiency models employed included the technical and scale efficiency models, slack-based efficiency models (SBM), mix efficiency models, and cost and allocation efficiency models. Data related to 12 companies were collected for the years 2009 and 2010 from Tehran Stock Exchange. Registered capital, asset value, operation costs, and employee number were considered input variables, whereas revenue and profit were considered outputs. DEA analysis revealed that Iran's real estate and construction companies were technical, scale, and mix efficient with less cost-efficient due to higher cost of production factors and lower allocative efficiency.

The performance trends of 118 construction companies located worldwide were assessed by Horta et al. (2013)⁵¹ using the DEA - CCR model and bootstrapping to determine their efficiency levels for 1995-2003. For this purpose, the companies were classified into three regions, i.e., Europe, Asia, and North America. Construction activities were classified as follows in three different groups- buildings, heavy civil, and trade contractors. The CRS model of DEA analysis was used to measure overall technical efficiency, whose calculations suggested that the efficiency level was low during the period and relatively stable throughout the period of analysis. Bootstrapping method's estimates were within narrow confidence intervals, and these estimates were only preferred. It was also found that North American companies were the best performers. North American and European companies involved in building construction performed better in different activities, whereas heavy civil companies and trade companies were more efficient in Asia. For

comparing by pairs, the three other locations and activities, Helmert coding was used implemented in STATA software. The authors also used time dummies to control the year effect, and a total of 1062 observations were considered in the truncated regression model. The results showed that there were no significant differences in the efficiency of construction companies during the relevant years. Also, North American companies were found to be the most efficient, followed by Europe and Asia. For the different levels of activities, the results were the same as previously observed. MI result showed that Asia was the region with the most significant productivity improvement except the year 1998, mainly due to the reduction in the number of companies in that year. In Europe, the average productivity improvement was less than in Asia and declined in 1999 because of the Asian financial crisis. However, North American construction companies showed stable productivity except for a significant decline in the year 2003. These results were consistent with the hypothesis of convergence in efficiency levels across regions. North American companies' productivity remained stable over the years, but companies of Asia and Europe showed productivity improvement over the years. It was also observed that economic context had a significant impact on the performance of the companies. From this study, it could be concluded that construction companies needed to have an in-depth understanding of changing environments to develop their plans and policies accordingly.

Chang and Lee (2012)⁵² attempted to develop an integrated mathematical method of three approaches, i.e., DEA, knapsack formulation, and fuzzy set theory which would assist in choosing the best project for the organization. The authors developed the integrated model using the project prioritization model proposed by Cook and Green. For solving the combinational problem ABC algorithm (artificial bee colony), a meta-heuristic method was utilized. Three bees named employed bees, onlookers, scouts, and 25 projects were considered for the ABC algorithm. Material cost, manpower quality,

space, and Makespan penalty were assessed inputs, whereas gross profit, market share growth scale value (evaluated on the basis of 10-point scale), and technology growth scale value (for this 15-point scale was used) were used) the output variables. It was found that the first ten project problems had 17 variables and 31 constraint equations, whereas the next 15 projects had 32 variables and 61 constraints equations. Then, Deb, Puzzi and Carpinteri, and Heffmeister and sparve techniques were used to treat the constraints and performed 20 runs in both problems. It was observed that Deb could not search for better solutions but was good at searching for all the feasible solutions.

In contrast, the remaining two techniques searched only a few feasible solutions in both the problem. But the best solutions were explored by these two techniques only as they got the best objective values in both the problems. Also, the number of constraint violations of infeasible solutions was relatively less in Puzzi and Carpinteri's method than in Heffmeister and Sparve's method. Thus, the study concluded that an integration method was developed, free from the limitations of the DEA and Knapsack methods. It also showed that this method proposed was highly suited in solving project selection problems.

Nihas et al. (2013)⁵³ has used the Business Value model (BVM) to analyze the inefficiencies in India's construction industry structure and provide measures to reduce these inefficiencies. The methodology used broadly includes two steps. The first step consists of using the Construction Industry Structure (CIS) diagram, which could further help implement BVM in this industry. CIS divides Industry structure based on perceived competition and performance, which can be low or high. Since Indian industry follows the low bid traditional method, it is associated with increased perceived competition and low performance. The second step is to conclude general findings for BVM to solve similar types of problems. Its implementation has made the US, Canada, Netherlands, and

Malaysia overcome their respective challenges. BV recognized that price-based quadrants are the essential factor causing these problems, which can be overcome by taking various steps such as selecting vendors on a performance basis, increasing transparency, etc. BV also provides solutions for the problem of controlling owners by laying down a framework that maximizes the use of expertise. It can be concluded that this new BV model can help this industry to effectively deal with its inefficiencies as it will change the current system to a value-based system. It also helps in converting a win-lose environment into a win-win environment for the Indian construction Industry.

Rajaprasad et al. (2013)⁵⁴ aimed to employ Constant returns to scale (CRS) and variable returns to scale (VRS) models of data envelopment analysis (DEA) to measure the safety performance of construction segments, i.e., infrastructure and real estate in India for the year 2010-11. Therefore, it can be concluded that DEA was the best and efficient tool for analyzing safety performance. DEA also identified the set of efficient segments for each inefficient segment from which they could refer for efficiency measures. For example, the efficiency score for real estate was found to be 0.830, and for infrastructure, it was 0.864, which meant that stakeholders must concentrate on safety measures. Also, from the real estate sector, there was no efficient unit in both the models. This study also concluded that safety measures could be improved by allocating sufficient budget to safety activities. Along with this, management commitment to implement a safety system, risk assessment, legal requirements, etc., would also enhance the safety performance in India.

Amirteimoori et al. (2013)⁵⁵ aimed to propose a DEA-based production planning model without inputs so that the optimal level of output can be measured for each operational unit employed. This study was carried out by collecting the data of 11 universities in Iran. The authors first introduced the DEA model for analyzing the relative performance of the

Decision-making units (DMUs) without considering input factors. Then, they used the same method as an approach to production planning problems. Production planning problems determine the number of products produced in the next session by forecasting the demand. For this, the authors assumed that the efficiency scores of each DMU would be equal to or greater than 1. To determine the production plan, the authors also developed the Multi-Objective Linear Programming (MOPL) model. The authors undertook four output factors for this analysis: assessment score, scientific publication, external research funding obtained, and the number of students. The authors used GAMS software in this study. The linear programming model was used to assess the efficiency of the universities, and it was found that only three universities were efficient. The authors then used their proposed models for calculating the efficiency scores as well as optimal weight. From the results of this- model, the number of efficient universities increased from 3 to 5, which showed the increment in efficiency scores by using this proposed model. This study concluded that for the application of DEA, inputs were not as crucial as outputs were. Therefore, organizations should be more focused on output productions. A model was introduced which helped in solving production planning problems in centralized DMUs. This approach solved the linear planning problem, which also undertook the efficiency of those DMUs.

Tsolas (2013)⁵⁶ followed a two-stage methodology comprising the DEA and Tobit regression model to evaluate the performance of 19 construction companies listed on the Athens exchange by analyzing their efficiency in profitability and the market value generating process. DEA model results revealed that 13 firms were pure technically efficient (PTE), but out of them, only 8 were overall technically efficient (OTE) in profitability. In contrast, for stock market performance efficiency, the same four firms were PTE and OTE. Regression model results revealed that selling and the administrative

cost-to-total-revenue ratio and profit margin were the drivers of profitability with a negative relationship. Still, there was not much evidence for the systematic effects of control variables on firm valuation. This study strongly concluded that firms could improve their efficiency in both dimensions, but the primary reason for this inefficiency was the lower level of stock market performance instead of profitability.

Chiang et al. (2013)⁵⁷ aimed to analyze the efficiency of the 17 construction companies listed in the Hong Kong Stock Exchanges for 2001-2010 by employing the DEA_AR model. The Authors used the DEA_AR model with the VRS assumption named as AR-I-V model to measure the efficiency scores of the firms, and no single firm was found to be most efficient consistently in this specific time period. Also, it was observed that firms with the largest market share were not amongst the top efficient firms. This study strongly concluded that the DEA_AR model could be effectively utilized to evaluate the efficiency scores of the construction companies of Hong Kong because it had the advantage of reducing the number of zeroes and reducing the difference in weights for estimation, which helped improve the improvement the adequacy of the results of this model. However, this study also proved that it was not always right to believe that leading firms were always efficient. The three firms with the majority of the construction projects had different Returns to scale (RTS), and their marginal profit also decreased.

Two round Delphi questionnaire survey, a questionnaire survey, a semi-structured interview along with DEA were used by Seresht et al. (2014)⁵⁸ to rank construction projects' success (referred to as project efficiency here) in a post-delivery phase. From this study, it can be concluded that the DEA approach could be used to rank projects. Furthermore, the competency of project-based organizations impacted the efficiency of the project's success. Thus, on the whole, this study proposed efficiency as an overall

measure for the project's success, and this study could be used to enhance the project's success by setting the input factors.

Gandhi and Shankar et al. (2014)⁵⁹ employed Data Envelopment Analysis (DEA) along with Malmquist Productivity Index (MPI) and Bootstrapped Tobit Regression to measure the efficiency of 18 Indian retailers for the years 2008-2010. The study analyzed that 5 firms out of 18 were efficient under the CCR model of DEA, and 7 total firms were efficient under the BCC model. Moreover, 61 percent of the firms had progressed in terms of MPI during this specific period. As per the Tobit Regression number of retail outlets and mergers and acquisitions were found to have more influence on the Indian retailers' efficiency than other variables. From this study, it can be firmly concluded that Indian retailers were inefficient and had not crossed their gestation period of reaping benefits from investments made. The efficiency level for some firms was found to be very low, which showed huge scope for improvement. Standard deviations were also very high, which showed huge dispersion of the scores among the firms. The results of the DEA model employed by the authors provided the adjustments that the inefficient retailers could undertake in their scale operations, inputs and outputs. Their productivity was found to be improved from 2008-2009 but decreased from 2009-2010. It was also found that mergers and acquisitions and an increasing number of outlets acted as the driving forces for influencing their efficiency.

Amirteimoori and Yang (2014)⁶⁰ introduced a parallel-series DEA model under Constant Returns to Scale (CRS) to measure the decision process's efficiency. A two-stage analysis was done to determine the best resource split, which resulted in the optimization of the additive efficiency of the system. Data was collected for a limited company in Golestan (Iran), which had 17 plants. Each manufactory consisted of 2 production lines (Structure production line and Doors and Windows production line) for a period of six months. The

assembly line of this company used structures, doors, and windows produced by two production lines and two other outputs (concrete and corrugated plates). Inefficiency slacks were obtained using this Model, which depicted that only 8 plants were found to be efficient. It was also found that changes were to be made in first intermediate measure to ensure the overall efficiency. This study concluded the method to measure the efficiency of two-stage production processes and also helped define additive efficiency measures for such processes. This study further led to the determination of the best split of shared resources.

In an attempt to measure the dynamic cost, technical, allocative, and scale inefficiencies in the Spanish construction industry pre and post-financial crisis, i.e., from 2002-2009, Kapelko et al. (2014)⁶¹ employed the S-Z test. Data for almost 775 firms was collected for the time period 2002-2009 (divided into two parts, i.e., from 2002-2006 and 2007-2009). Three input factors: material cost, labor cost, and fixed assets, and one output were the total sales plus the change in the value of the stock. Results of this study indicated that the inefficiency of companies reduced after the crisis was due to the reduction in all the components. Many large-sized companies started operating at medium size after the crisis. CRS technical efficiency was also improved because inputs and outputs combinations turned to be less scale inefficient. For the overall time period, i.e., 2001-09, cost inefficiencies were found to be relatively higher, mainly due to technical inefficiency under CRS. Medium-size firms were classified into two different classes based on annual turnover (10-30million euros compromised first class and 30-50 million euros were class 2). For both the classes, Kernel destiny estimates were measured, which showed that overall inefficiency for both the classes was almost similar. It was found that the firm's size had no impact on the inefficiency of the Spanish construction firms. When samples from active firms and bankrupt firms were compared, overall inefficiency was higher for

firms that got bankrupt majorly due to the significant difference between CRS technical inefficiencies and scale inefficiencies for the overall time period. In the period before the crisis, the difference in the overall inefficiency was not that significant except for the difference in CRS technical inefficiency. This study concluded that medium-sized firms had 10% lower output and material costs in the period post the crisis. However, there was no change in labor cost, but the investment ratio also declined in 2007-2009. The overall efficiency of the firms increased after the crisis started because of the lower allocative inefficiencies. Class 2 of medium-sized firms had less technically and scale inefficiencies as compared to class 1. In 2007-09, class 2 had lower technical and allocative inefficiencies, but class 1 had lower technical and scale inefficiencies. Firms that got bankrupt had higher overall dynamic cost and scale inefficiency. This study also concluded that there is enough scope for improvement for the firms. Larger firms faced losses majorly due to the poor allocation of resources. Also, firms require higher flexibility in adjusting their sizes.

Liu et al. (2014)⁶² applied Partial Least Squares (PLS) path method to analyze the competitiveness of China's Regional Construction Industry by collecting data related to 29 provinces of China for the period 2005-2008. Twenty-three indicators were considered, out of which the proportion of superfine and primary production values produced by general contractors and the proportion of primary production values produced by subcontractors were taken as composite indicators, and other indicators were single indicators. These latent indicators were divided into seven categories: operation efficiency, production factors, demand conditions, auxiliary industries related, the status of the industrial organization, production efficiency, and innovation factors. Path analysis was done by using bootstrap algorithm Visual PLS software. A study of scores obtained by employing the PLS path model showed that the industry's overall competitiveness had

experienced significant changes in these four years. Out of 29 provinces, only 8 provinces were found to have increased competitiveness, whereas 11 provinces had experienced declining competitiveness, whereas 10 provinces had the same scores throughout the period. Trends of influence factors for the competitiveness showed that different provinces showed different trends, with only 3 provinces having a decreasing trend and one province named Qinghai was showing an increasing trend. By analyzing increased competitiveness, it was observed that Henan, Heilongjiang, Qinghai, Shanxi, Chongqing, Guangxi, and Hubei provinces had experienced increased competitiveness; however reason for such enhancement was different for each province. The analysis of unchanged competitiveness showed that the competitiveness of 10 provinces did not change, whereas the competitiveness of 11 provinces declined. The increased competitiveness was associated with the improved demand situation for construction products, which resulted in a continuous expansion in the overall scale of their construction industries. At the same time, for Heilongjiang and Hubei, the increment was observed due to the improvement of the market development ability in other towns. Provinces suffered declined competitiveness because of the downward trend of the construction of local infrastructure, the insufficient demand for building products, and their poor development in markets of other towns. This study concluded that the method employed in this analysis significantly synthesized latent variables and developed an integrated indicator that represented all the system's indicator variables. Along with this, it also ensured the stability of the model and helped in achieving comparative analysis across time periods.

Taylan et al. (2014)⁶³ attempted to identify the key risk assessment criteria for construction projects at King Abdulaziz University (KAU) by employing integrated hybrid methodology involving fuzzy AHP and fuzzy TOPSIS. As a result, ten risk factors were identified, which were Delay due to excessive approval procedures, Lack of

professional pre-planning studies for the project by other participants, Too tight project schedule due to loose planning practices, Schedule delays due to delays payments, Delays due to lack of coordination between project participants, Excessive delays due to late decision making by project participants, High cost due to unfair or unprofessional bidding practices, Delays due to solving legal disputes between participants, Appointment frequency of an unqualified project participant and Poor information flow between project participants (exchange of documents, reports). The analysis showed that the bureaucracy and excessive approval procedures had the highest overall RII in the KAU and was termed as the main risk category.

Widodo et al. (2014)⁶⁴ tried to assess the effect of agglomeration economies on TFP (total factor productivity) growth of 18 Indonesian manufacturing industries by employing a two-stage approach. The first stage involved the use of a Fare- Primont Productivity Index for evaluating the TFP growth at the firm level, which was followed by the assessment of every firm's TFP growth and was regressed against a set of firm and industry characteristics which included three measures of agglomeration depicting the influence of the specialization (LQ), diversity (DIV) and competition (COM). The analysis was done for the period from 2001 to 2009. This study concluded that the specialization effect had a positive and diversity had a negative impact on the Indonesian manufacturing industries' growth. In addition, geographic concentration of firms in a particular manufacturing activity enhanced the productivity growth, which was also stated by the MAR analysis of external economies, and firms located in urban areas were found to have faster productivity growth than those outside the urban areas (at the firm level), but it was not ensured at the industry sub-sector level. This study also suggested that the internal and external economies were also crucial for learning and opting for modern manufacturing technology that would increase the productivity growth of the industries.

Xue et al. (2015)⁶⁵ attempted to assess the Total Factor Productivity (TFP), which helped measure the energy consumption efficiency of the provinces of China using DEA-based MPI. 30 provinces from four regions of China, i.e., western, central-eastern, and north-eastern for this study. This study concluded that DEA-MPI based method framework was quite effective in measuring the energy efficiency of the 26 provinces of the construction sector of China. However, except Guangdong, every province taken in this study was ineffective in some years or during the whole period. Also, the central and eastern regions were performing better than the northeast and western regions.

A comparison of the efficiency and productivity levels of Chinese, Japanese, and Korean construction firms for the period 2005-2011 was made by Park et al. (2015)⁶⁶ using the DEA and DEA-based Malmquist methods and by dividing the MPIs into Technical Change Index (TCI) and Technical Efficiency Change Index (TECI). Data related to 9 construction firms in China, 12 in Japan, and 11 in Korea were collected from Osiris, Korchambiz, and Morningstar through financial and annual reports of the relevant years. Input variables considered in this study were the number of employees, total assets, capital, and selling and administrative expenses, whereas the output variable considered was total revenues. The analysis showed that the average efficiency score of the Korean firms was found to be higher than the average efficiency score of the Japanese and Chinese firms. The mean value of input variables of Korean construction firms was smaller than that of their Chinese and Japanese counterparts, but Korean construction firms had the maximum output value. MPIs values were greater than 1 in most of the years of the relevant study except for the 2006–2007 and 2009–2011 periods. China's decision-making unit (CDMU) 6 was found to have the largest increase in total productivity among all the firms in this period, whereas CDMU 2 experienced the smallest decrease in productivity among all the firms. It was also observed that the

improvement of productivity in Chinese firms was the largest. However, the productivity improvement in Korean firms was equal to the average improvement, and the Japanese firm's improvement was less. Productivity of Chinese firms increased in the initial years but then decreased. It also experienced positive shifts of TCI and TECI due to various reasons such as abundant domestic demand, technology developments, etc. The productivity of Japanese construction firms overall decreased in this whole period. The overall productivity of Korean firms improved along with TECI while TCI declined. It was found that inefficiency in the firms was majorly because of the lack of sufficient understanding of production technologies or problems with managerial communications. From this study, it could be concluded that Korean firms lay somewhere behind the firms of China and Japan in terms of technology and prices. The efficiency of Korean construction firms was higher than Chinese and Japanese firms; however, their productivity declined compared with Chinese firms. This suggested that Korean firms should focus more on enhancing their productivity rather than their efficiency.

For measuring the complexity of mega construction projects in China, He et al. (2015)⁶⁷ adopted a fuzzy analytic network process (FANP) approach. 2010 Shanghai World Expo construction project was used as the case study to analyze the mega project's complexity in China as this project had over 400 single projects. Six factors such as organizational complexity (U1), cultural complexity (U2), environmental complexity (U3), technological complexity (U4), information complexity (U5), and goal complexity (U6) were selected as significant factors. This evaluation showed that the overall complexity level of the Shanghai Expo project was found to be highly complex. It was also found the complexity of the case project could be controlled at a moderately complex level if proper strategies were planned and implemented. It was observed that the value of each of the six complexities was higher than the average level.

Moreover, cultural complexity had the maximum value followed by organizational complexity, technological complexity, and information complexity, whereas environmental complexity and goal complexity ranked last. The client adopted the program management approach to deal with the complexities. This study concluded that the research methodology proposed in this study could be applied to other megaprojects in other countries to quantify project complexity for enhancing the decision-making of construction megaprojects and maintaining their execution performance.

Bian et al. (2015)⁶⁸ employed a two-stage DEA model based on slack-based measures to assess the efficiency and decomposed elements, i.e., production efficiency and abatement efficiency of Chinese Regional Industrial Systems (RIS). Data for 30 provinces were collected, which belonged to three major areas named the eastern, central, and western regions. Efficiency analysis of the performance of the production and abatement stages showed that only 11 regional industrial systems were efficient as per the proposed model, such as Beijing, Tianjin, Shandong, Jiangsu, etc., and other regional industrial systems were inefficient. Qinghai also had the lowest efficiency among regions with lower production efficiency scores and the lowest abatement efficiency score. On the other hand, RIS was found to be efficient in both the production stage and the abatement stage. Thus, it was concluded that significant disparities existed in the efficiencies of regional industrial systems, and the inefficiencies in Chinese regional industrial systems were majorly influenced by their abatement inefficiencies. It was also shown that a higher amount of abated pollutants led to higher abatement efficiency and system efficiency.

Nazarko and Chodakowska (2015)⁶⁹ used the BCC Data envelopment analysis model and the Malmquist index to analyze the productivity of 25 European countries for the period 2006 to 2012. The tobit method was also employed to assess the relationship between variables. It was found that, on average, the construction industry contributed

more than 6% to Gross value added (GVA) and gave jobs to 3% of their citizens. On these two bases, 3 clusters were identified using the Cross-Validation method. Luxembourg was the first identified cluster having a slightly above-average contribution to GVA and the highest percentage of employment. The second cluster had 17 countries such as Belgium, Italy, France, Norway, Sweden, etc. The third cluster had 7 countries named Spain, Austria, Poland, Finland, etc., which had the highest contribution to GVA. To find the DEA and index scores (to measure productivity), the number of persons employed was treated as input, and turnover and gross operating surplus were treated as outputs. On comparing 2006 and 2012 years, it was found that labor productivity decreased. Four countries (UK, Luxembourg, Norway, Spain) were found to be both efficient and effective. In addition, 9 states showed improvement in technical efficiency change, and 18 countries showed improvement in technology change. From this study, it can be concluded that GDP per capita could measure companies' efficiency scores. Lower GDP per capita reflected lower labor productivity. Also, DEA scores reflected wide differences between productivity of the construction industry.

López et al. (2015)⁷⁰ adopted Stochastic Frontier Analysis (SFA) to measure the technical efficiency (TE) of the Spanish construction sector before and during the financial crisis. BC95 model was also used to identify the factors influencing the technical efficiency of the firms. Data related to 692 construction firms was collected from The SABI database, managed by Bureau van Dijk for 1996-2011. Capital, labor, and intermediate consumption were taken as input variables whereas value added was considered output variables. Analysis was done by dividing the period into 2 sub-periods, i.e., 1996-2007, before the Burst of the Housing Bubble (hereinafter pre-BHB); and 2007-2011, after the Burst of the Housing Bubble (hereinafter post-BHB). TE's average score of the industry was found to be 0.85 with an increasing trend between the years 1996-2003. After 2003,

it experienced a steady decline. Results revealed that Stochastic function analysis was suitable for this study to measure the TE of the Spanish construction sector. For the BC95 model, the following variables were considered explanatory: age, size, interest-expense ratio, debt-ratio, export, diversification, Public SR, Stock Market, and Mortgage Const. It was observed that in the pre-BHB period, seven out of the nine variables were found to be significant, whereas in the post-BHB period, only 5 variables were significant for the TE of the Spanish construction sector. Age and size variables were positively significant in every situation, but a higher interest–expense ratio resulted in higher inefficiency in both periods. In phase 2008-11, Debt Ratio Value was positively related, Export and diversification were negatively correlated, and the opposite for these variables was observed in the pre-crisis period. However, Public SR and Stock Market were relevant for the efficiency of the firms. The mortgage cost variable was only found to be significant (Positively) for real estate sector construction firms in recessive periods only. This study finally helped in concluding TE scores and factors responsible for such scores. This study proved the importance of promoting business concentration in this sector and promoting counter-cyclical policies to this sector of Spain.

To analyze the energy efficiency of China’s regional construction industry, Chen et al. (2015)⁷¹ employed a three-stage DEA model along with Data envelopment analysis-Discriminant Analysis (DEA – DA) model. For this analysis, energy, labor, capital, and construction machinery and equipment variables were considered as input factors, whereas energy consumption of the provinces, total output economic index, and total profit of the construction industry index was considered as the output factors along with some environmental variables within energy consumption structure, industrial development degree, organization structure, and technological level aspects. Data related to 30 provinces of China were collected from 2003-2011 from the sources such as China

Statistical Yearbook, China Construction industry Statistical Yearbook, and China Energy Statistical Yearbook. Results indicated that DEA - DA model was better than the DEA model. The results concluded that Shandong was the most stable province with the lowest values. Provinces such as Hubei, Gansu, Hubei, Anhui, Zhejiang, Henan, and Sichuan had greater fluctuations in the trends than other provinces. Eastern region's whole energy efficiency declined over the years. The energy efficiency of the construction industry in the western region fluctuated the most in this period. It was also observed that energy efficiency and the development level of the local economy had a weak relationship, whereas efficiency scores directly connected with its sustainable development. The mean energy efficiency scores of each year was found to be around 0.92 in each year. Moreover, most of the provinces experienced constant fluctuations during this period, with the highest in 2004 and then declining after 2004.

Park et al. (2015)⁷² attempted to compare the efficiency and the productivity of 9 Chinese, 12 Japanese, and 11 Korean construction firms for 2005-2011 by employing the DEA and DEA-based Malmquist methods. The analysis showed that the Korean firms' average efficiency score was higher than the average efficiency score of the Japanese firms and Chinese firms. The mean of the inputs of Korean firms was though lower than other firms, but its output produced was maximum in terms of input. However, according to this study, Chinese firms had the highest total revenues, but their total revenues to input variables rate was the lowest. By comparing the average of all the countries, it was observed that the productivity improvement in Chinese firms was highest amongst all, followed by Korean firms whose improvement was the same as average and then Japanese firms whose improvement was found to be less than the average.

Soetanto et al. (2015)⁷³ employed an output-oriented Super slack-based model (SBM), cumulative annual stock returns (CASR), and Panel regression methods to assess the

efficiency level and performance of 77 manufacturing firms listed in the Indonesian stock exchange for 2010-14. These manufacturing firms were categorized as basic, miscellaneous, and consumer goods sectors. Around 308 observations in total were recorded and considered. Input variables used for this study included salary, wages, net fixed asset, and material cost, whereas profits before tax was the output variable considered. Overall mean scores of the companies estimated using SBM efficiency and Super SBM efficiency model showed that the manufacturing industry of Indonesia was not so efficient. This study concluded that the miscellaneous sector was the most efficient as per the model, whereas the basics and consumer goods industry were not efficient on average.

Iyer and Banerjee (2016)⁷⁴ adopted the case study method to develop a model that could help in measuring and benchmarking managerial efficiency of project execution schedule performance. Grounded theory (GT), in which case data was collected which was generated by the projects followed by an inductive analysis which led to developing causal factors. The authors used an integrated approach for this study as an analytical tool. DEA framework analysis was used along with Principal Component Analysis (PCA) with some required modifications. This study concluded that the model developed had two different discriminatory features which helped in performance monitoring –i) benchmarking used as a methodology which resulted in measuring the performance and also providing grounds for performance improvement, ii) benchmarking within a peer-group of projects which performed under similar environment and similar country. Therefore, this study tried to develop a benchmarking model based on this feature only.

Hu and Liu (2016)⁷⁵ proposed a global relational two-stage DEA model, which was an integration of a relational two-stage DEA method and global benchmark technology to measure the profitability performance (effectiveness and efficiency) of the Australian

construction industry and also to identify the factors influencing it by considering the carbon emission reduction factor for achieving sustainable development. The relational two-stage DEA method involved three models (a, b, and c) with independent constraints. Model (a) was used to measure the profitability performance, which showed that during the whole period, Australian construction firms experienced improved profitability performance with the highest values scored by Western Australia (WA), the Australian Capital Territory (ACT), and the Northern Territory (NT). Using model (b), profitability efficiency was estimated, showing the increasing trend with the same 3 DMUs scoring the highest efficiency. WA and ACT were considered as the benchmarks for the construction industry in the context of profitability efficiency. Model (c) was used to measure effectiveness scores; all the DMUs were found to have the highest scores. WA outperformed in this, too, followed by Tasmania. However, NT acted as the benchmark in this context as only NT achieved 1 effectiveness score amongst all other DMUs. Profitability performance and efficiency results had lower values and showed similar movements throughout the period, whereas effectiveness reflected minor fluctuations but higher values amongst all the indicators. Construction workers, construction technologies, equipment and machinery, and construction market size were factors influencing efficiency. Overall, the study concluded that profitability performance had scope for improvement throughout the relevant period. Variation analysis exhibited that no significant gaps were present concerning profitability development among the regional sectors of the construction industry in Australia. This new method proposed and utilized in this study helped find efficiency scores and compare them at the same level of benchmark technology.

Wang et al. (2016)⁷⁶ adopted the non-radial DEA model, as with natural and managerial disposability to assess Unified efficiency under natural disposability, Unified efficiency

under managerial disposability, and Unified efficiency under natural and managerial disposability (UEN, UEM, and UENM) of industrial sector of China and also identification of investment strategies to enhance the performance of energy and environment. 5 different models with different combination of inputs and outputs were used to evaluate UEN, UEM, and UENM for 30 Chinese provinces for period 2008-2012. For this analysis, two groups of inputs, i.e., total energy consumption, labor and capital stock under natural disposability and R&D investment and IPC investment under managerial disposability; one desirable output, i.e., Industrial value-added; and four undesirable outputs, i.e., CO₂, SO₂, wastewater, and solid emissions were considered. Overall, it was indicated that Shandong and Hainan provinces were only efficient under natural and managerial disposability; the rest of the provinces had the potential to enhance their energy and environmental performance. Comparison between the regions showed that both energy conservation and technology innovation helped increase the energy and environmental performance of western China. It was also revealed that capital-labor ratio, coal consumption, and energy price factors had a negative impact, whereas economic development, natural gas consumption, and the number of R&D researchers (technological innovation) factors positively impacted the unified efficiency. It was also concluded that central China had the best investment objects in 2011-12. Coal consumption was found to be the crucial factor to negatively affect unified efficiency; however, economic development level was crucial for the improvement of unified efficiency.

Färe-Primont data envelopment analysis (DEA) method was employed by Chancellor and Lu (2016)⁷⁷ to analyze the regional and provincial productivity of the Chinese construction industry for the period 1995-2012. Analysis showed that there were regional disparities in terms of productivity. Regions such as northeast China, eastern China, and

central and southern China were found to have stronger productivity growth, whereas the northern China region was found to have the lowest growth with a decline in productivity over the period. In all the regions, the Zhejiang province of eastern China was found to have the highest productivity whereas the Shanghai province of eastern China was found to have the lowest productivity. The study contradicted the previous studies, and it was observed that TFP of the construction industry in China was low from 1997 to 2004, and it started increasing from 2006-2010. According to this study, an analysis of average construction productivity by province showed that provinces of Beijing, Shanghai and Guangdong had low productivity. In contrast, Zhejiang, Jiangsu, and Hunan provinces were found to have strong productivity. In terms of technical efficiency and average scale efficiency, it was observed that Eastern China had the highest scores. Overall, there was no significant improvement over this period with having lowest efficiency in 2004. This study revealed that the Chinese construction industry was having strong scale efficiency with a lack of gains in technical efficiency in recent years, and scale efficiency was negatively correlated with technical efficiency. Along with these findings, it was concluded that Färe-Primont DEA could be used effectively to certain the industry's productivity.

To evaluate the trends of energy productivity and total factor productivity in the Australian construction industry, Hu and Liu (2016)⁷⁸ employed Input oriented DEA Approach and the Malmquist index method. The data for this analysis were collected for the construction industries of Australian states and territories such as New South Wales (NSW), Victoria (Vic.), Queensland (Qld), Western Australia (WA), South Australia (SA), Tasmania (Tas.) and Northern Territory (NT) for the period from 1990 to 2010. Analysis of Malmquist energy productivity (MEP) changes showed that the energy productivity of the whole construction industry enhanced during this specific period, with

SA having the highest growth. Overall, all the areas showed increased growth in 2001-2001 and 1992-93 and declined in 1990-92 and 2000-01. This study concluded that the whole industry's energy productivity and total-factor productivity increased by 2.8% and 0.7% in the period due to technological advancement. However, the improvement of the two technical efficiency indexes was not proved in the Australian construction industry. The NT and NSW were the benchmarks in improving the Australian construction industry's energy productivity and total-factor productivity.

An integrated approach of Data Envelopment Analysis (DEA) and boosted Generalized Linear Mixed Models (GLMMs) was being proposed by Hamad et al. (2017)⁷⁹ for efficiency assessment of 151 commercial banks from the Middle East and North African countries and also to analyze the impact of environmental variables on their performance. Labor, physical capital (fixed assets and equity), interest expense, and deposits were used as inputs, whereas loans, net income, liquid assets, and off-balance sheet were termed as outputs, provided each factor was taken into monetary terms. 25 Environmental variables for inputs such as years, country, population, public debt, unemployment rate, etc. were selected. This study concluded that the integration of DEA models with boosted GLMMs helped predict banks' efficiency. Furthermore, when different models with different scenarios for inclusion of random effects were estimated, it was concluded that all models with the inclusion of random effects outperformed and were found to be superior to logistic regression in DEA second stage. However, the best model was the one with the inclusion of both bank and country random effect factors in addition to equity, net loans, short-term funding, and current account balance. This model acted as a good predictor of performance and did it with more percentage of accuracy and AUC compared to logistic regression in DEA's second stage. Also, 40% of the banks' data recorded was efficient as they had a target variable as 1.

Two models of DEA, i.e., inter-temporal and window benchmark techniques, were used by Hu and Liu (2017)⁸⁰ to develop a quantitative method of slack-based DEA to assess the economic efficiency of the Australian construction industry for the period 1990 to 2013. The results indicated that economic efficiency in some states decreased due to factors such as large slack ratios of resource consumption and carbon emission etc. However, skilled construction workers would help in improving its efficiency. From this study, it can be concluded that the new method of the slack-based DEA model was effective in assessing economic efficiency.

A comparative labor efficiency analysis in the European construction industry was being done by Nazarko and Chodakowska (2017)⁸¹ by employing two different frontier methods, i.e., Data envelopment analysis (DEA) and Stochastic frontier analysis (SFA). Data for 29 European countries were collected from Annual Detailed Enterprise Statistics for Construction for the year 2013 related to variables such as personnel cost, gross operating surplus, turnover, and Gross Domestic Product (GDP) per capita. Analysis showed that countries that invested the lowest labor costs in proportion to profits were Bulgaria, Czech Republic, Latvia, Hungary, and Poland as per DEA and Bulgaria, Romania, Poland, Greece, and Latvia as per SFA. Although the average efficiency score under the SFA method (1.42) was greater than the DEA method (0.59), it was said that a reliable actual score was between the scores of both the models. Furthermore, an inverse relationship was established between the labor costs related to outputs and the GDP. Results from the Tobit model were calculated, which showed that under any situation GDP variable had played a crucial role in the efficiency performance of the countries. This research concluded that mean efficiency scores were totally based on methods employed. Also, a negative relationship was found to prevail between the GDP of the country and its productivity. Simple agglomeration cluster analysis was also performed

based on the scores calculated using two methods which indicated: Bulgaria as an unequaled benchmark and Latvia, Poland, the Czech Republic, and Hungary as positively great countries. The third group consists of the remaining countries, which can further be divided into clusters: Slovakia, Estonia, Belgium, and Italy (cluster 1), Romania (cluster 2), Italy and Greece (cluster 3), and the rest (cluster 4). The analysis also indicated the highly competitive nature of new EU countries in the construction sector.

To evaluate the efficiency scores of China's construction industry from 2006-2013 under two scenarios, i.e., considering environmental regulation and without considering environmental regulation, Zhong et al. (2017)⁸² employed Data envelopment analysis (DEA) model and Malmquist index. Analysis of the efficiency evaluation of the construction industry with the consideration of environmental regulation showed that the technical efficiency of the industry was found to be relatively low but reflected the upward trend. Technical improvement and the Malmquist production index also showed an upward trend. Overall, the efficiency of the construction industry was increasing. However, the level of technical efficiency of the construction industry in the western region was found to be relatively backward. Analysis of the efficiency evaluation of the construction industry without considering environmental regulation showed that the environmental regulation affected the level of technical efficiency of the construction industry in the same way as that of environmental governance. It was also observed that the average efficiency improved over the years. Among all the eastern, central and western regions, the east region was found to have the highest efficiency, followed by the middle area and then the western area.

Kapelko (2018)⁸³ used Data Envelopment Analysis (DEA) and S-Z test to measure technical and scale inefficiencies regarding the use of individual inputs in construction firms across Spain and Portugal for the period 2002-2010. Three input variables, i.e.,

fixed assets (book value of the Fixed asset used as a proxy for capital), labor (measured by employee cost), and material (measured by the material used cost), and one output variable i.e., operating revenue were considered. Firms of both countries demonstrated considerable inefficiencies in the inputs employed, which showed the scope for improvements. The analysis showed that fixed assets contributed the maximum to these inefficiencies and were challenging to manage. Labor was found to be the most efficient input in Portugal and material input in Spain. For scale inefficiency, it was found that materials were the least efficient in both countries, which could be managed by flexibly adjusting the scale of their operations. Large firms were found to have the lowest input-specific technical inefficiencies but highest scale inefficiencies which indicated that scale inefficiency lied in scaling down of activities. It was also analyzed that constant scale to returns (CSR) inefficiencies and scale inefficiencies increased during the crisis period in both countries but medium-sized firms managed to improve their scale inefficiency during the crisis. Overall, this study helped in developing a long functional approach for such inefficiencies.

Luo et al. (2018)⁸⁴ employed the DEA analysis model along with the Distance Friction Minimization (DFM) approach to measure the efficiency of China's construction industry (CE) and to evaluate the regional differences of productive construction efficiency across three regions of China such as developed eastern region, developing midland region, underdeveloped western region. The comparison of regional construction productive efficiency showed that as per DEA, the productive efficiency of CE of China was found to be 0.66. In contrast, in the developed eastern region, it was found to be 0.907, it was 0.647 in the developing midland region, and 0.439 in the underdeveloped western region. This showed significant regional differences among the provinces and revealed a decreasing pattern as they moved from the eastern region to the western region. This study

concluded that in developed regions, construction workers were found to be more productive as they had higher salaries, but labor cost was increasing, and labor supply was decreasing in the East area. In terms of growth potential, western CE was the highest development potential for future expansion, followed by midland and eastern regions.

Hu and Liu (2018)⁸⁵ employed a relational two-stage DEA model under VRS and CRS conditions for estimating the overall performance, efficiency, and effectiveness of the construction sector of China for the years 1995-2014. 31 provinces were considered, categorized into four groups, i.e., western region, eastern region, north-eastern region, and middle land region of China. Measurement of Overall performance (OP), OP technical efficiency (OPTE), Overall scale efficiency (OSE), Construction Efficiency (CE), Pure technical efficiency (PTE-1 and PTE-2), and scale efficiency (SE-1 and SE-2) was done for all the provinces which indicated that eastern region had a better overall performance with respect to all the above measures. For measurement of the entire construction industry of China, weighted average scores of each indicator were calculated, which showed that SE-1 scores were the highest along with better scores for OSE and SE-2. The indicators for overall performance, effectiveness, OPTE, and PTE-2 increased slowly in the relevant period. Analysis of results showed that implementing policies that would also enhance management ability at the company level, policies that would help promote techniques, and policies focusing on macro development would increase the performance of China's construction industry. It can be concluded that differences between the scores of the regions were majorly due to the pure technical efficiency, which could be narrowed by promoting open markets and enterprise communication between the regions. Effectiveness indicator was mainly responsible for the ineffectiveness of the construction industry. This relational two-stage DEA model helped assess the overall performance, efficiencies, and effectiveness of the industry.

Maghsoodi and Khalilzadeh (2018)⁸⁶ aimed to identify and evaluate the critical success factors of the construction projects in Iran by using multiple criteria decision-making techniques of the Fuzzy TOPSIS method. The Fuzzy TOPSIS method showed that factors such as strategic and effective planning of the project, allocating appropriate funding, and experienced and multidisciplinary project team were the most important critical factors. However, factors such as the project employer's ongoing consultation, contact with stakeholders and people in the project, and regulations and political or economic, and social issues were found to have the least importance. On the other hand, according to the fuzzy Multi-MOORA method, the three most critical success factors found were Accurate and reliable estimates of project costs, allocating appropriate funding, and Experienced and multidisciplinary project team, whereas the least important factors were the same as the other method.

A three stage DEA model with SBM-undesirable method at first stage, Stochastic Frontier Analysis (SFA) in second stage and adjusted DEA model in final stage was employed by Zhang et al. (2018)⁸⁷ with the objective of analysing the impact of environmental regulations on the regional construction efficiency of 30 provinces and cities of China for the period 2011-2015. Inputs considered were manpower, capital, technology equipment and total energy consumption whereas output variables taken for this study were Total Profits of the Construction Industry and Gross Output Value of Construction while CO2 emissions was taken as undesirable product. Efficiency analysis showed that pure technical efficiency (PTE) had more impact than scale efficiency (SE) on technical efficiency (TE). SFA model analysis revealed that marketization was having negative correlation with the Total Assets of Construction Industry slack variables, and positively correlated with the Number of Employed Persons in the Construction Industry, the Energy Consumption of the Construction Industry and the Total Power of Machinery and

Equipment Owned slack variables whereas per capita GDP was having no significant relationship with any of the input variable. In contrast, per capita GDP had no significant relationship with any of the input variables. However, the total power of Machinery and Equipment Owned was negatively correlated with environmental regulations. Still, the Number of Employed Persons in the Construction Industry, the Total Assets of the Construction Industry, and Energy Consumption of the Construction Industry slack variables had a positive correlation. Results of stage 3 indicated that TE and PTE experienced a slow increase during 2011-13, but during 2014-15 all the efficiencies experienced a significant fall. Also, PTE was the highest amongst all the values, and technological inefficiency was the most crucial factor for performance which was highly affected by environmental variables. The underestimation of the technical efficiency of Chinese construction firms was mainly due to the low level of technology efficiency. It was interpreted that SE was overestimated, and the efficiency of China's construction industry had suffered due to the environmental variables and stochastic factors. From the regional analysis, it can be concluded that the Eastern part of China was better performing than the central and western regions.

A comparative analysis of construction sites in terms of their safety performance was done by Nahangi et al. (2019)⁸⁸ to establish a benchmark for their safety performance. The methodology followed by the authors included a DEA analysis (output-oriented) framework for assessing the safety efficiency of the sites, which had three modules, i.e., pre-processing, efficiency analysis, and identification of influential factors. Safety climate factors (SCFs) and several incidents were considered inputs and outputs of the DEA system. The sensitivity analysis technique was also undertaken to assess the impact of inputs on efficiency to analyze the significant factors. DEA framework was applied in 4 scenarios- i) considered all the inputs and outputs variables almost sophisticated ii) total

number of incidents were used as outputs iii) used the total of SCs as inputs and iv) only total of SCFs as input and total of incidents as outputs were used in this scenario (least sophisticated). 6 SCFs were management committee (MC), supervisor safety perception (SSP), co- worker safety perception (CSP), safety knowledge (SK), work pressure (WP) and role overloaded (RO). Results showed that efficiency scores calculated using the DEA model and the variability of those scores were the maximum for scenario 1 followed by 2 then 3 and were least for scenario 4 because of the number of inputs and outputs considered. Correlation between various aspects of this study was also determined. The result of the correlation between efficiency values under each scenario and inputs was evaluated. It was found that there was no significant linear relationship and direct or indirect correlation between these parameters. Sensitivity analysis was done to examine the effect of each variable on efficiency, results indicated that Work pressure (SCF-5) secured rank 1, Supervisor safety (SCF-2) got Rank2, Safety knowledge, co-worker safety perception, and management commitment (SCF-4, SCF-3, SCF-1) were on Rank 3 and Role overload (SCF-6) attained rank 4. Work pressure was found to be the most influential factor for the efficiency of the sites. The correlation between the efficiency scores and the outputs was negatively strong, i.e., efficiency was improved if the number of incidents was reduced. The correlation between SCFs and efficiency was relatively weak. It was also found that as soon as the model got non-sophisticated, correlation with the output became stronger. It was also indicated that there was a relation between the demographics and efficiency scores of the sites. It was also concluded that companies with employees more than 500 had the highest efficiency values and least variation in the scores.

To investigate the sustainable regional performance of the real estate industry operating in the 30 provinces of China from 2007 to 2013, Yang et al. (2019)⁸⁹ employed a slack-

based data envelopment analysis (DEA) approach. For this analysis, performance indicators were developed using a three-stage network logic model for the real estate industry. These three stages were identified as-land acquisition, development of houses, and housing sales. In 2020, Nguyen et al. (2020)⁹⁰ suggested an integrated approach combining Grey theory and DEA analysis that can be used effectively and efficiently for evaluating the performance of the Vietnamese construction companies.

Xian et al. (2019)⁹¹ employed DEA models with material-based principle (MBP) conditions (with different requirements related to inputs and outputs) to analyze the trade-off between environment and cost efficiency among different types of energy consumption in the construction industry of China. DEA model was used for estimating technical efficiency (TE), environmental efficiency (EE), cost efficiency (CE), and total cost-efficiency (TCE) of the construction industry. Data for 27 provinces of China's construction industry sector was collected for the period of 2011-15. For this study, CO₂ emission was taken as an environmental outcome, whereas the added value of the construction industry was taken as an economic outcome. However, seven non-energy inputs were considered, i.e., the net value of the fixed asset, labor, and construction materials, including cement, steel, glass, wood, and aluminum, along with three energy inputs: coal, oil, and electricity. Environmental and cost efficiency results showed that CE and TCE were closely related with the same results almost because total cost was close enough to the cost of polluting inputs. It was observed that carbon emissions in China's industry of construction sector compensated by some reasonable amount of cost increase could only be controlled by opting for proper optimization of energy consumption structure. Environmental and cost trade-off analysis showed the economic and social cost of the construction sector in China was reduced by adopting approaches

that led to environmental efficiency. Results also interpreted that 5 provinces were Technically Efficient, Environmentally Efficient, and Costly Efficient.

Furthermore, 10 provinces were found to have overlapped cost and efficient environment points, and they were close enough to simultaneously attain full cost and environment efficiency. The result of analyzing the average shadow cost and shadow emission of each province reflected that the construction industry needed to implement independent activities for reducing carbon emission by optimizing the energy consumption pattern and enhancing energy efficiency. This study concluded that the construction industry could produce its current output with lower CO₂ emission and at less cost by enhancing its TE and adjusting its energy consumption pattern.

In 2019, Li et al. (2019)⁹², by employing DEA analysis, pointed out that low land-use efficiency was the major reason for supply-side inefficiency in China's real estate sector. 34. In 2020, Huo et al. (2020)⁹³ attempted to assess and analyze the total-factors energy efficiency (TFEE) of 30 provinces of China's construction industry for years 2006 to 2015 by employing input-oriented DEA analysis framework with TFEE algorithm. This study on the whole, concluded that most of the provinces of China's construction industry were energy inefficient, and there was some scope for their improvement. For example, Beijing, Zhejiang, and Hainan provinces were found to have efficiency values as 1. Whereas Inner Mongolia, Sichuan, Gansu, Yunnan, and Guizhou provincial regions had high level of inefficiencies. Findings suggested that efforts related to increasing science and technical investments in this sector should be adopted to ensure common progress and sustainability development.

Sin (2019)⁹⁴ adopted a three-dimensional DEA analysis to evaluate the financial efficiency of firms considering both input and procurement capital. 76. To make a

comparison of the efficiency levels of 8 Indian real estate firms during the pre-demonetization period (2014–2016) and post-demonetization period (2016–2018), Prasad (2019)⁹⁵ employed DEA analysis. This study concluded that real estate firms performed well during the pre-demonetization when compared to the post-demonetization period. Even though in the pre-demonetization period, the number of inefficient firms was more, the efficiency scores of two inefficient firms were nearly 1 in the pre-period and the post-period; those scores were very low. Results of the analysis showed that demonetization impacted the performance of the Indian real estate firms. To enhance the firms' efficiency, they could focus on the potential improvements needed and learn from the efficient units to implement more correction actions and business insights for managers in making resources planning decisions. Also, Government policies could support this sector to perform better.

Murillo et al. (2019)⁹⁶ employed a non-parametric approach known as multidirectional efficiency analysis (MEA) for evaluating the technical efficiency of construction companies in seven European countries such as Austria (AT), Germany (GE), Hungary (HU), Italy (IT), Poland (PL), Portugal (PT) and Spain (ES) during the period 2008–2015. Data were collected for different sets, which were T, C, and S where T denoted the set of years from 2008 to 2015, the set C denoted the 7 countries, and for the set S the nine construction sectors, according to the code F from Statistical classification of economic activities in the European Country NACE Rev.2 (2008) were considered. These 9 sectors were F41.1-Development of building projects, F41.2.-Construction of residential and non-residential buildings, F42.1.-Construction of roads and railways, F42.2.-Construction of utility projects, F42.9.-Construction of other civil engineering projects, F43.1.-Demolition and site preparation, F43.2.-Electrical, plumbing, and other construction installation activities, F43.3.-Building completion and finishing and F43.9.-

Other specialized construction activities. On the whole, this study considered three big divisions of construction such as construction of buildings (F41), Civil engineering (F42), and Specialized construction activities (F43). This study concluded that the years in which the countries/sectors experienced better efficiency levels could be ranked as- first-2010, 2014, 2015, followed by 2008, 2009, third-2011, 2012, and finally fourth-2013. Countries with a lower level of efficiency with more than 50 % were Hungary and Poland only. However, countries such as Portugal and Germany had a significant proportion but less than 50%. Other countries such as Austria, Italy, and Spain were found to have a better performance in the nine sectors. Sectors were ranked based on the efficiency scores, which were as follows: other specialized construction activities (F43.9) was at the first rank followed by demolition and site preparation, electrical, plumbing and other construction installation activities, construction of utility projects, construction of roads and railways, construction of other civil engineering projects, building completion and finishing, construction of residential and non-residential buildings and development of building projects (F41.1) was at last. This showed that the specialized construction activities (F43.1, F43.2, F43.3, F43.9) were the most efficient sectors, followed by civil engineering (F42.1, F42.2, F42.9) and then the construction and development of building's projects (F41.1, F41.2). It was found that it was more relevant for efficiency to maximize the use of machinery and equipment and gross investment in tangible goods instead of opting for the standard approach of reducing personnel.

Yuan et al. (2020)⁹⁷ used super-efficiency data envelopment analysis (SE-DEA) and artificial neural network model (ANN) to assess the performance of 30 Chinese construction sectors for the years 2000 to 2017 by analyzing their overall technical efficiency (OTE), labor efficiency (LE), capital efficiency (CE) and equipment efficiency (EE). Results showed that OTE experienced a stable, increasing pattern throughout the

period except for years after 2015. It was observed that the OTE performance in the developed regions was better than in developing regions. 30 provinces were then divided into eastern, central, and western areas, which showed that OTE in the eastern region was higher and lower in the central region. LE showed that they were constantly increasing, whereas CE was stable throughout the period, and EE was significantly fluctuating. The Eastern region had the highest LE, CE, and EE. Moreover, Beijing, Shanghai and Zhejiang provinces were the best performers in all the efficiencies. In the context of analysis of reduction potential, Beijing, Shanghai, and Zhejiang had low potential for improvement as they had the highest efficiencies, whereas Shandong and Hubei had larger improvement potential. In the case of LE, Shandong, Henan, Hubei, and Sichuan had a larger scope of improvement, whereas Shandong, Henan, Hubei, and Liaoning were critical regions for CE and EE improvement. OTE was found to have a positive correlation with GDP per capita. Labor, capital, and equipment inputs and their saving targets were forecasted for 2018 (along with the years till 2022), which were then compared with the data in the Statistical yearbook form 2019 and found that the estimated values were quite close. It was exhibited that actual capital input constantly increased, whereas labor and equipment inputs fluctuated. In addition to this, it was also concluded that the spatial distribution of OTE was highly related to Chinese economic development. The labor, capital, and equipment inputs of provinces Jiangsu and Guangdong were found to be overcome. Efficiency improvement after 5 years of development was not evident in the Chinese construction sector.

Wen et al. (2020)⁹⁸ attempted to assess the efficiency of the overall energy utilization, allocation, and structure of the Chinese construction companies by combining the multiregional input-output (MIRO) model and the DEA analysis model. Results showed that developed coastal areas consumed more embodied energy due to the large

construction activities and urbanization process in those areas. It was observed that local energy use accounted for more than 60% of the total energy consumption, whereas clean energy's proportion was relatively less. The study found that the eastern provincial sector was more efficient than the central followed by the west sector. Also, most of the sectors were energy inefficient. Overall energy efficiency and allocation efficiency were positively related to high regional economic development. However, regional construction sectors were facing structural inefficiency. It was also observed that most of the regions were scale efficient but lacked technical efficiency. However, regions with a better economic output for the local construction sector enjoyed both scale and technical efficiencies. It can be strongly concluded that MRIO and DEA methods could be employed effectively to measure the efficiency of different construction firms in different regions of China.

Zhang et al. (2020)⁹⁹ employed two DEA-based difference methods i.e., the no variable-link difference (method 1) and adding variable-link difference (method 2) for measuring capacity utilization (CU) of China's construction industry by developing a CU measurement index system which considered energy consumption and undesirable output i.e., carbon dioxide emission for such measurement for the period from 2011 to 2017. Overall, CU calculated by using method 1 was found to be greater than method 2. This study also concluded that model 2 i.e., the adding variable-link difference method gave better and more accurate results. The average CU score of 0.38 reflected the underutilization of capacity basically due to an inappropriate variable input allocation, but after 2014 it improved. Moreover, inappropriate allocation of variable inputs could be overcome by adopting policies that would result in optimum allocations. This research laid down various measures to be adopted for enhancing the performance and hence its CU score.

In 2020, Wen et al. (2020)¹⁰⁰ firmly concluded that the combination of multiregional input-output (MRIO) and DEA method was significantly suitable for estimating and analysing regional disparities in the Chinese construction sector in terms of energy efficiency.

To evaluate the destocking performance of the Chinese real estate industry, Chen et al. (2020)¹⁰¹ employed DEA based Malmquist approach. Data related 62 units were collected from China Real Estate Statistical Yearbooks for the period of 2005-2015. The authors employed a three-step procedure for the analysis: Step 1 included calculating destocking efficiency in 2015 by using the traditional input-oriented BCC model and observing the redundant situation of the real estate industry before the RREI policy. Two models such as M1-Residential/Commercial real estate for sale included both areas of new residential construction and areas of real estate for sale and M2-Residential/Commercial real estate for Sale only included areas of real estate for sale were used to assess its robustness; Step 2 included employing DEA model and Malmquist model for evaluating its performance, and the last step was to analyze the impact of real estate regulations and control policies on the destocking performance. As per the DEA results using M1, only 40 units (24 central cities and 16 other regions) were inefficient, but as per M2, 42 DMUs (25 central cities and 17 other regions) were inefficient.

After reviewing the studies on construction sector efficiency, we have found several gaps and shortcomings. It is apparent from the above review that the conventional ratio approach has various drawbacks and one needs to apply better techniques for efficiency measurement. There are limited studies that have focused on the efficiency of the Indian Construction Industry, and to improve their profitability, researchers need to explore this area. In most of the previous studies on the Indian Construction Industry, researchers have analyzed on the basic level. Only a few have focused on Super efficiency models

for determining levels of efficiency, benchmarking, and defining reference sets. There seem to be no studies that have comparatively analyzed the technical and profit efficiencies of Private and Public sector Indian Construction companies. The present study aims to analyze the efficiencies of Indian construction firms for the period 2015-16 to 2019-20 using Malmquist Productivity Index and Super-Efficiency DEA Models. The combination of the Malmquist Productivity Index and Super-Efficiency DEA Models helps in evaluating not only the changes in relative productivity but also helps in determining the factors affecting the change (technical efficiency change or technological change).

CHAPTER 3
METHODOLOGY

Based on the literature review, figure 3.1 has been prepared, which depicts different approaches used in construction sector efficiency measurement.

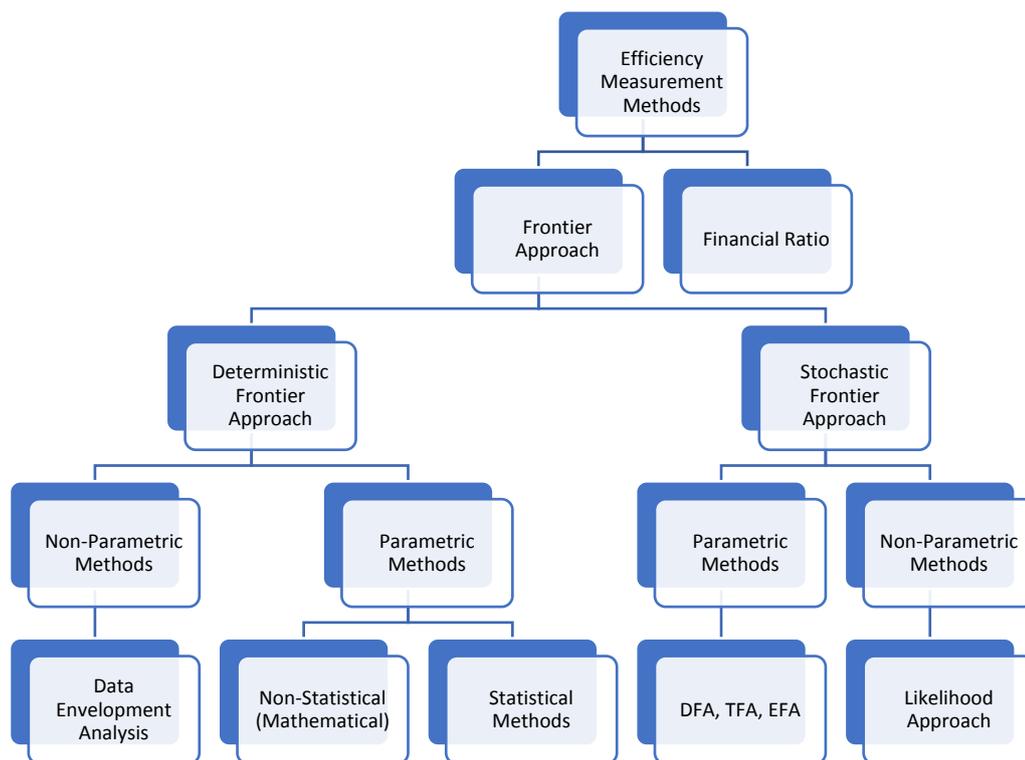


Figure 3. 1: Methodological Framework

Evolution of Different Methodologies:

3.1. Ratio Approach

Ratio analysis has always remained a vital tool for financial analysis. Ratios represent performance measures of a system as they compute the relative efficiencies of the outputs versus the inputs, and these can express many different aspects of performance (Tsolas, 2011)¹⁰². Ratio analysis is an applicable management tool usually used in a company to offer further understanding of financial results and trends over time, based on the analysis

on the business situation and to identify the strengths and weaknesses for monitoring the company's performance (Hoe, 2018)¹⁰³. The use of financial ratios in research studies is popular for the reason that they are easy to apply and understand (Mintzberg and Waters, 1989).¹⁰⁴ Financial ratios also have a very important role in making inter-firm comparisons (Langford, 1993)¹⁰⁵. Downs and Goodman (2003)¹⁰⁶ also argue that ratios are extremely significant when it comes to making yearly comparisons or determining the industry's trend. (Beyer, 2010)¹⁰⁷ suggested that quantitative measures like ratio analysis mainly drive companies' financial risk. The ratios have gained popularity because of their perceived utility in making financial decisions (Ketz et al., 1990¹⁰⁸; Needles et al., 2010¹⁰⁹).

Moreover, numerous studies have concluded that the use of statistical prediction models developed from financial ratios is increased by focusing on individual industries (Argenti, 1983; Kangari, 1988; Kangari et al., 1992)¹¹⁰. This approach, for example, has been employed by (Balatbat, 2010)¹¹¹ to make a comparative performance analysis of 30 publicly listed Australian construction companies. This has also been employed by (Kesimli and Gunay, 2011)¹¹² to examine the impact of the global economic crisis on the working capital of real estate sector in Turkey. However, while ratios are easy to compute, partly explaining their wide appeal, their interpretation is problematic, especially when two or more ratios provide conflicting signals (Feroz et al., 2003)¹¹³. They also highlighted that ratio analysis often involves subjectivity, and the analyst must pick and choose ratios to assess the overall performance of a firm. Düzakın et al. (2007)¹¹⁴ also suggested that although both the application and interpretation of ratio technique are simple, the most important drawback is the inappropriateness of making decisions based on one single ratio when there are many inputs and outputs.

3.2. Frontier approach

Michael J. Farrell (1957)¹¹⁵, greatly influenced by Koopmans (1951)'s¹¹⁶ formal definition and Debreu (1951)'s¹¹⁷ measure of technical efficiency, introduced a method to decompose the overall efficiency of a production unit into its technical and allocative components. He characterized the different ways a productive unit can be inefficient by obtaining less than the maximum output available from a determined group of inputs (technically inefficient) or by not purchasing the best package of inputs given their prices and marginal productivities (allocatively inefficient). Although his model attempted to explain the basic framework of frontier approach for measuring productive inefficiency, but the model had not utilized sufficient characteristics of error terms. Aigner et al. (1977)¹¹⁸ suggested an improvised version of the existing frontier approach and proposed a model that explains error terms better. Different techniques can be utilised to estimate the efficient frontier (Murillo-Zamorano, 2004)¹¹⁹. He suggested that frontier techniques can be classified into parametric and nonparametric methods, i.e., between techniques where the functional form of the efficient frontier is pre-defined or imposed a priori and those where no functional form is pre-established. The nonparametric approaches have a deterministic nature. With respect to parametric approaches, these can be subdivided into the deterministic frontier approach and stochastic frontier approach. A further classification of frontier models can be made according to the tools used to solve the frontier model, namely the distinction between mathematical programming and econometric approaches. Both the techniques have some advantages and disadvantages over one another.

3.3. Deterministic Approach

Deterministic frontiers fall into two categories—either non-parametric (e.g., Farrell, 1957) or parametric, and in the latter case, either non-statistical (e.g., Aigner and Chu, 1968; Timmer, 1971) or statistical (e.g., Afriat, 1972; Richmond, 1974). Stochastic

frontiers can exhibit either parametric (e.g., Aigner et al., 1977; Meeusen and van den Broek, 1977) or nonparametric (e.g., Banker and Maindiratta, 1992) specifications. Frontier models can be classified as per their ways of dealing with error terms. In the deterministic approach, efficiency level estimations are based on the distance from the individual observation to a common frontier, whereas in the stochastic approach, each firm will have an individual functional form to evaluate the inefficiency term (Aigner et al., 1977)¹²⁰. In the Deterministic frontier approach, the presence of an error term is not accepted. The inefficiency of the firm is measured as a deviation from the common frontier.

On the other hand, the stochastic approach accepts the presence of error term, and this error term has two components: (a) asymmetric half normal distributed inefficiency term and (b) symmetric normal distributed random error term (Akhigbe & McNulty, 2003¹²¹; De Borger & Kerstens, 1996¹²²). Symmetric normal distributed random error term captures the measurement error and exogenous variations which are outside the control of the firm, whereas asymmetric half normal distributed inefficiency term captures the inefficiency part of the stochastic frontier. Also, the Deterministic frontier method only gives an estimation of mean efficiency over the sample (Forsund, et al., 1980)¹²³. The deterministic frontier approach mostly includes all the sample observations and hence, this frontier approach can also be applied on a small set of data (Berger & Humphrey, 1992)¹²⁴.

3.4. Non-Parametric Techniques

Numerous research works have been carried out covering two major streams, i.e., linear programming techniques (nonparametric techniques) and econometric studies (parametric techniques) in the past. The application of these two techniques provides

different results due to their model characteristics (Resti, 1997)¹²⁵. In non-parametric approaches, Data Envelopment Analysis (DEA) is widely accepted in the research domain. Studies such as Färe et al. (1989), Chaves and Cox (1990), and Callan (1991) show that nonparametric techniques outperform parametric techniques in some situations. One significant advantage is that DEA envelopes observed input-output data without requiring a priori specification of functional forms. On the other hand, different specifications of the production function under the parametric approach provide different results, which is a serious methodological problem.

Specifically, this study has opted for employing Data envelopment Analysis as a preferred choice over regression analysis to examine the construction industry's performance. Like Regression Analysis (RA), DEA (Non-Parametric Method) does not let the user to develop a hypothesized mathematical production function. DEA easily handles the multiple inputs and outputs, and allocates more efficiently the inefficiency term (excess use of resources) compared to RA (Bowlin, et al., 1984)¹²⁶.

3.5. DEA Approach

Data Envelopment Analysis (DEA) is a “non-parametric” and “data-oriented” approach for computing the efficiency of homogeneous Decision-Making Units (DMUs). DEA suggests how to improve the efficiency level of DMUs by benchmarking a unit against the most efficient unit. DEA is a preferred way to judge efficiency since it can measure the efficiency level even in the case of multiple inputs and multiple outputs. The efficient units are assigned an efficiency score of 1. In DEA, inefficiency is defined as a distance from the benchmark frontier by using linear programming (LP).

DEA developed by Charnes, Cooper and Rhodes (1978), also known as the CCR model, is deterministic and non-parametric in nature. This nonlinear (nonconvex) model was developed on the basis of the frontier concept pioneered by Farrell (1957) to bridge the

gap between engineering and economic approaches of efficiency measurement (Charnes, et al., 1978)¹²⁷. This model was extended by Banker, Charnes and Cooper (1984)¹²⁸ to allow variable returns to scale. Data envelopment analysis is recognized in the literature as a powerful method, more suitable for performance measurement activities than traditional, econometric methods such as regression analysis and simple ratio analysis (Zhu, 2014¹²⁹; Inman et al., 2006)¹³⁰. The main advantage of DEA is that it does not require specification of the functional form of the production function (Theodoridis et al., 2006)¹³¹. They suggested that DEA calculations focus on individual observations in contrast to population averages and can simultaneously utilize multiple outputs and inputs, each being stated in different units of measurement. They also explained that DEA focuses on revealed best-practice frontiers rather than on central-tendency properties or frontier. It generates the set of “peer” units with which a unit is compared. Ruggiero (2007)¹³² demonstrated that the major advantages of the DEA approach are its nonparametric nature and its ability to handle multiple outputs and multiple inputs. The nonparametric nature of DEA allows it to concentrate on revealed best-practice frontiers rather than on the central-tendency properties of frontiers (Mahadevan, 2002)¹³³.

Furthermore, as Gong and Sickles (1992) argued, DEA is more appealing than the econometric model as inefficiency is likely to be correlated with the inputs. On the DEA down side, econometricians have argued that the approach produces biased estimates in the presence of measurement error and other statistical noise. It does not allow for statistical tests typical of the econometric approach (Mahadevan, 2002)¹³⁴. Deterministic approaches are based on cross-sectional models; however, as Ruggiero (2004)¹³⁵ argued, they can be extended to panel data models by averaging the data across time. Mahadevan (2002)¹³⁶ employed a DEA tool to assess the productivity growth of 28 manufacturing industries (such as electrical machinery, industrial chemicals, food industries, furniture,

and fixtures, etc.) of Malaysia for 1981-1996. In that study, a stable performance growth of the industries was seen, and it was concluded that the DEA analysis tool was effective in assessing the performance of the Malaysian industries.

The two commonly used models in DEA are CCR (Charnes, Cooper, and Rhodes) model and BCC (Banker, Charnes, and Cooper) model. In the CCR model, constant returns to scale (CRS) are assumed, and the scores obtained are termed as technical efficiencies (TE). A Decision-Making Unit (DMU) is considered to be Technically Efficient if, from the basket of inputs it holds, it produces the maximum of outputs possible or if, to produce a given quantity of outputs, it uses the smaller quantities possible of inputs (Atkinson and Cornwell, 1994)¹³⁷. A straight line characterizes the efficient frontier. The units whose scores are less than 1 are considered inefficient, and it is possible to increase the efficiency levels using two approaches. The two approaches are the input-oriented model and the output-oriented model. In an input-oriented model, the existing inputs can be minimized while maintaining at least the given output levels, while in the case of an output-oriented model, the outputs can be increased without increasing the existing level of inputs. In the BCC model, variable returns to scale is assumed. The variable returns to scale can either be increasing or decreasing for a decision-making unit. In the case of increasing returns to scale (IRS), the percentage increase in output is more than the percentage increase in input, while in decreasing returns to scale (DRS), the percentage increase in output is less than the percentage increase in input. By applying the BCC model, we obtain PTE scores of units. The ratio of TE to that of PTE gives the SE score of a unit. The technical efficiency can be broken into pure technical efficiency and scale technical efficiency. Pure technical efficiency reflects the way in which production unit resources are managed, while scale efficiency or scale technical efficiency determines whether the production unit operates at an optimal scale or not. The optimal scale is understood here

as the best situation that can achieve the production unit by proportionally increasing the quantity of all its factors (Yannick,et al., 2016)¹³⁸.

Mathematically, the output-oriented CCR model can be expressed as:

$$\begin{aligned} &max\theta \\ &+ \varepsilon \left(\sum_{i=1}^m S_i^- + \sum_{r=1}^s S_r^+ \right) \end{aligned} \quad (1)$$

Subject to:

$$\begin{aligned} &\sum_{j=1}^n \lambda_j x_{ij} + S_i^- \\ &= x_{i0} \end{aligned}$$

$$\sum_{j=1}^n \lambda_j y_{rj} - S_r^+ = \theta y_{r0}$$

$$\lambda_j \geq 0$$

$$i=1,2,\dots,m; r=1,2,\dots,s; j=1,2,\dots,n$$

where S_i^- is slack in the i th input of the target unit, S_r^+ is slack in the r th output of the target firm, λ_j are non-negative dual variables, θ is the simultaneous adjustment applied to all outputs of the target unit, which leads in a radial movement towards the envelopment surface. The BCC model is the dual of CCR model along with an added convexity constraint of

$$\sum_{j=1}^n \lambda_j = 1 .$$

The objective function (1) is calculated in a two-way process with maximum optimization of outputs being achieved first by ignoring the slacks. In the second stage, movement on to the efficient frontier is achieved via optimizing the slack variables. The presence of

non-Archimedean ϵ specifies the model to be a two-way process. To obtain the optimal values of $\lambda_1, \lambda_2, \dots, \lambda_n, S_i^-, S_r^+$, the above-mentioned CCR and BCC models are solved as linear programming problems. The SE scores can be obtained by taking the ratio of CCR scores to BCC scores.

A DMU is efficient if $\theta=1$ and $S_i^- = S_r^+ = 0$ for all i and r . DMU_o is weakly efficient if $\theta=1$ and $S_i^- \neq 0$ and (or) $S_r^+ \neq 0$ for some i and r . The input targets for a unit can be obtained by subtracting the input slacks from existing input levels. For determining output targets, the output slacks are to be added to the existing output levels.

3.6. Malmquist Productivity Index (MPI)

A quantity index to analyze input consumptions was being introduced by Sten Malmquist (Malmquist, et al., 1953)¹³⁹. Fare et al. (1992)¹⁴⁰ suggested a DEA-based MPI to measure the efficiency and technical changes on the basis of two measurements, namely efficiency and productivity, that was previously proposed by Farrell (1957)¹⁴¹ and Cave et al. (1982)¹⁴². The efficiency measures calculated using DEA are a reflection of the static performance and show the performance at a particular time point. Thus, to evaluate the performance over a period of time, the DEA-based Malmquist Productivity Index approach of Fare et al. (1992), which was initially introduced by Malmquist (1953), needs to be used. This model examines the change in productivity over a time period and categorizes it into technical efficiency changes and technological changes. The input and output variables taken for the MPI model are the same for the DEA model. The MPI index can be decomposed into two components, i.e., technical change (Frontier shift) and technical efficiency change (Catch up) (Das, 2017)¹⁴³. Thus, MPI can be calculated as a product of Catch up and Frontier Shift, i.e., $MPI = \text{Catch up} * \text{Frontier Shift}$.

3.7. Super-Efficiency DEA Models

In DEA model, all the efficient units are assigned the score of 1. To further ascertain the level of efficiency among the efficient units, Super-Efficiency DEA models are used. The On the basis of the radially, orientation, and slacks, there are ten different models under Super-Efficiency DEA which give different results. For comparison, the following formulations have been used:

- (i) SSBM-C-I: Slack-based super-efficiency model under the assumptions of Constant returns and Input-Orientation
- (ii) SSBM-C-O: Slack-based super-efficiency model under the assumptions of Constant returns and Output-Orientation
- (iii) SSBM-V-I: Slack-based super-efficiency model under the assumptions of Variable returns and Input-Orientation
- (iv) SSBM-V-O: Slack-based super-efficiency model under the assumptions of Variable returns and Output-Orientation
- (v) SSBM-C-NO: Slack-based super-efficiency model under the assumptions of Constant returns and Non-Orientation
- (vi) SSBM-V-NO: Slack-based super-efficiency model under the assumptions of Variable returns and Non-Orientation
- (vii) S-CCR-I: Radial-based super-efficiency CCR-Input Oriented model
- (viii) S-CCR-O: Radial-based super-efficiency CCR-Output Oriented model
- (ix) S-BCC-I: Radial-based super-efficiency BCC-Input Oriented model
- (x) S-BCC-O: Radial-based super-efficiency BCC-Output Oriented model

The pictorial classification of the Super-Efficiency DEA Models has been shown in the Figure 3.2.

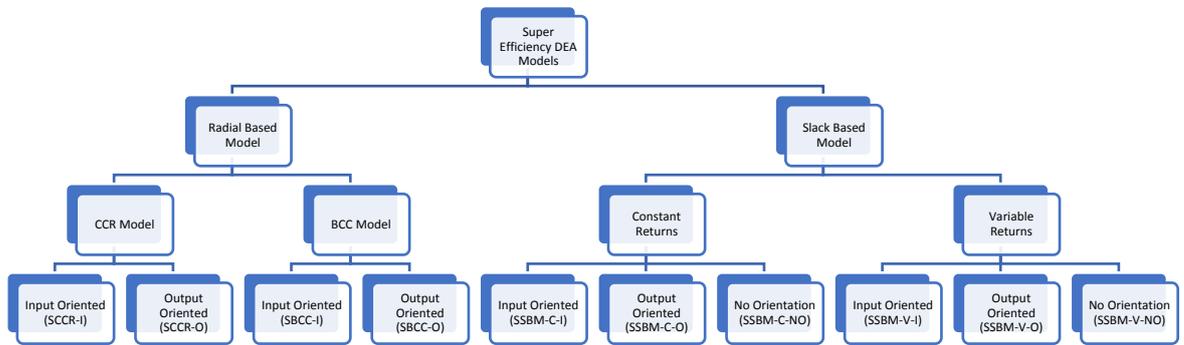


Figure 3. 2: Super-Efficiency DEA Models

CHAPTER 4

RESULT ANALYSIS

In this section, we examine the results of Technical efficiency (TE), Pure Technical efficiency (PTE) and Scale efficiency (SE) of 42 Decision-Making Units (Indian construction companies) which are profit-making for the period 2016-2020. The companies' technical efficiency (TE) scores are found using the CCR model while Pure Technical efficiency (PTE) scores are computed using the BCC model. The Scale efficiency (SE) scores are computed by dividing the TE scores with PTE scores.

4.1. Technical Efficiency and Pure Technical Efficiency

Technical efficiency (TE) scores are found using the CCR model while Pure Technical efficiency (PTE) scores are computed using the BCC model. In 2016, out of the total 42 units, 8 units (19 percent) are technically efficient, whereas 20 units (48 percent) are pure technically efficient. Dilip Buildcon Ltd., GeeCee Ventures Ltd., IRB Infrastructure Developers Ltd., Kajaria Ceramics Ltd., Marathon Nextgen Realty Ltd., PSP Projects Ltd., RPP Infra Projects Ltd. and Sunteck Realty Ltd. are found to be technically efficient as per CCR model and pure technically efficient as per BCC model. The summary statistics are presented in Table 4.1.

Table 4. 1: Summary of Efficiency Scores for the year 2016

Sl.	Decision Making Units	CCR Scores	BCC Scores	SE Scores
1	AGI Infra Ltd.	0.54	1.00	0.54
2	Ahluwalia Contracts India Ltd.	0.75	0.77	0.97
3	Ajmera Realty and Infra India Ltd.	0.56	0.57	0.98
4	AMJ Land Ltd.	0.40	1.00	0.40
5	Anant Raj Ltd.	0.61	0.68	0.89
6	Arvind SmartSpaces Ltd.	0.60	0.67	0.90
7	Ashoka Buildcon Ltd.	0.78	0.81	0.96

8	Brigade Enterprises Ltd.	0.60	0.67	0.90
9	Capacite Infra Ltd.	0.70	0.71	0.98
10	Cera Sanitaryware Ltd.	0.99	1.00	0.99
11	Dilip Buildcon Ltd.	1.00	1.00	1.00
12	Engineers India Ltd.	0.59	0.76	0.77
13	GeeCee Ventures Ltd.	1.00	1.00	1.00
14	Godrej Properties Ltd.	0.36	0.43	0.84
15	GPT Infra Projects Ltd.	0.74	0.78	0.95
16	IRB Infrastructure Developers Ltd.	1.00	1.00	1.00
17	IRCON International Ltd.	0.59	0.77	0.76
18	J Kumar Infraprojects Ltd.	0.74	0.75	0.98
19	Kajaria Ceramics Ltd.	1.00	1.00	1.00
20	Karda Construction Ltd.	0.97	1.00	0.97
21	Kec International Ltd.	0.91	1.00	0.91
22	KNR Constructions Ltd.	0.83	0.93	0.89
23	Kolte-Patil Developers Ltd.	0.37	0.40	0.93
24	Larsen & Toubro Ltd.	0.66	1.00	0.66
25	Man Industries Ltd.	0.90	0.91	0.99
26	Marathon Nextgen Realty Ltd.	1.00	1.00	1.00
27	NBCC India Ltd.	0.89	1.00	0.89
28	NCC Ltd.	0.86	1.00	0.86
29	Nila Infrastructures Ltd.	0.85	0.85	0.99
30	Oberoi Realty Ltd.	0.78	1.00	0.78
31	Phoenix Mills Ltd.	0.93	1.00	0.93
32	PNC Infratech Ltd.	0.84	0.96	0.87
33	Prestige Estates Projects Ltd.	0.71	0.90	0.78
34	PSP Projects Ltd.	1.00	1.00	1.00
35	Puravankara Ltd.	0.59	0.69	0.85
36	Rail Vikas Nigam Ltd.	0.81	1.00	0.81
37	Reliance Industrial Infrastructure Ltd.	0.46	0.48	0.95
38	RITES Ltd.	0.82	1.00	0.82
39	RPP Infra Projects Ltd.	1.00	1.00	1.00
40	Sobha Ltd.	0.59	0.66	0.89
41	Sunteck Realty Ltd.	1.00	1.00	1.00
42	Vascom Engineers Ltd.	0.54	0.55	0.99

In 2017, out of the total 42 units, 12 units (29 percent) are technically efficient, whereas 23 units (55 percent) are pure technically efficient. Cera Sanitaryware Ltd., Dilip Buildcon Ltd., GeeCee Ventures Ltd., IRB Infrastructure Developers Ltd., Kajaria Ceramics Ltd., Karda Construction Ltd., Kec International Ltd., Marathon Nextgen Realty Ltd., NBCC India Ltd., PSP Projects Ltd., RPP Infra Projects Ltd. and Sunteck

Realty Ltd. are found to be technically efficient as per CCR model and pure technically efficient as per BCC model. The summary statistics are presented in Table 4.2.

Table 4. 2: Summary of Efficiency Scores for the year 2017

Sl.	Decision Making Units	CCR Scores	BCC Scores	SE Scores
1	AGI Infra Ltd.	0.78	1.00	0.78
2	Ahluwalia Contracts India Ltd.	0.85	0.87	0.98
3	Ajmera Realty and Infra India Ltd.	0.70	0.70	0.99
4	AMJ Land Ltd.	0.31	1.00	0.31
5	Anant Raj Ltd.	0.70	0.77	0.91
6	Arvind SmartSpaces Ltd.	0.55	0.62	0.89
7	Ashoka Buildcon Ltd.	0.79	0.80	0.98
8	Brigade Enterprises Ltd.	0.73	0.79	0.92
9	Capacite Infra Ltd.	0.83	0.85	0.98
10	Cera Sanitaryware Ltd.	1.00	1.00	1.00
11	Dilip Buildcon Ltd.	1.00	1.00	1.00
12	Engineers India Ltd.	0.93	1.00	0.93
13	GeeCee Ventures Ltd.	1.00	1.00	1.00
14	Godrej Properties Ltd.	0.72	0.79	0.90
15	GPT Infra Projects Ltd.	0.88	0.88	0.99
16	IRB Infrastructure Developers Ltd.	1.00	1.00	1.00
17	IRCON International Ltd.	0.69	0.84	0.82
18	J Kumar Infraprojects Ltd.	0.71	0.71	0.99
19	Kajaria Ceramics Ltd.	1.00	1.00	1.00
20	Karda Construction Ltd.	1.00	1.00	1.00
21	Kec International Ltd.	1.00	1.00	1.00
22	KNR Constructions Ltd.	0.90	0.92	0.98
23	Kolte-Patil Developers Ltd.	0.78	0.79	0.99
24	Larsen & Toubro Ltd.	0.70	1.00	0.70
25	Man Industries Ltd.	0.77	0.78	0.99
26	Marathon Nextgen Realty Ltd.	1.00	1.00	1.00
27	NBCC India Ltd.	1.00	1.00	1.00
28	NCC Ltd.	0.90	1.00	0.90
29	Nila Infrastructures Ltd.	0.93	1.00	0.93
30	Oberoi Realty Ltd.	0.68	1.00	0.68
31	Phoenix Mills Ltd.	0.89	1.00	0.89
32	PNC Infratech Ltd.	0.74	0.78	0.95
33	Prestige Estates Projects Ltd.	0.65	1.00	0.65
34	PSP Projects Ltd.	1.00	1.00	1.00
35	Puravankara Ltd.	0.72	0.79	0.91
36	Rail Vikas Nigam Ltd.	0.87	1.00	0.87
37	Reliance Industrial Infrastructure Ltd.	0.48	0.51	0.93
38	RITES Ltd.	0.77	1.00	0.77
39	RPP Infra Projects Ltd.	1.00	1.00	1.00

40	Sobha Ltd.	0.69	0.74	0.93
41	Sunteck Realty Ltd.	1.00	1.00	1.00
42	Vascom Engineers Ltd.	0.43	0.44	0.99

In 2018, out of the total 42 units, 14 units (33 percent) are technically efficient, whereas 23 units (55 percent) are pure technically efficient. Cera Sanitaryware Ltd., Dilip Buildcon Ltd., Engineers India Ltd., GeeCee Ventures Ltd., IRB Infrastructure Developers Ltd., Kajaria Ceramics Ltd., Karda Construction Ltd., Kec International Ltd., KNR Constructions Ltd., NBCC India Ltd., PSP Projects Ltd. RITES Ltd., RPP Infra Projects Ltd. and Sunteck Realty Ltd. are found to be technically efficient as per CCR model and pure technically efficient as per BCC model. The summary statistics are presented in Table 4.3.

Table 4. 3: Summary of Efficiency Scores for the year 2018

Sl.	Decision Making Units	CCR Scores	BCC Scores	SE Scores
1	AGI Infra Ltd.	0.66	1.00	0.66
2	Ahluwalia Contracts India Ltd.	0.95	0.96	0.99
3	Ajmera Realty and Infra India Ltd.	0.81	0.82	0.99
4	AMJ Land Ltd.	0.42	1.00	0.42
5	Anant Raj Ltd.	0.58	0.75	0.76
6	Arvind SmartSpaces Ltd.	0.77	0.85	0.90
7	Ashoka Buildcon Ltd.	0.82	0.83	0.98
8	Brigade Enterprises Ltd.	0.63	0.81	0.78
9	Capacite Infra Ltd.	0.75	0.76	0.98
10	Cera Sanitaryware Ltd.	1.00	1.00	1.00
11	Dilip Buildcon Ltd.	1.00	1.00	1.00
12	Engineers India Ltd.	1.00	1.00	1.00
13	GeeCee Ventures Ltd.	1.00	1.00	1.00
14	Godrej Properties Ltd.	0.80	0.81	0.99
15	GPT Infra Projects Ltd.	0.88	1.00	0.88
16	IRB Infrastructure Developers Ltd.	1.00	1.00	1.00
17	IRCON International Ltd.	0.63	0.82	0.77
18	J Kumar Infracprojects Ltd.	0.73	0.73	0.99
19	Kajaria Ceramics Ltd.	1.00	1.00	1.00
20	Karda Construction Ltd.	1.00	1.00	1.00
21	Kec International Ltd.	1.00	1.00	1.00
22	KNR Constructions Ltd.	1.00	1.00	1.00
23	Kolte-Patil Developers Ltd.	0.84	0.90	0.94

24	Larsen & Toubro Ltd.	0.75	1.00	0.75
25	Man Industries Ltd.	0.92	0.96	0.96
26	Marathon Nextgen Realty Ltd.	0.73	1.00	0.73
27	NBCC India Ltd.	1.00	1.00	1.00
28	NCC Ltd.	0.84	0.93	0.91
29	Nila Infrastructures Ltd.	0.93	1.00	0.93
30	Oberoi Realty Ltd.	0.98	1.00	0.98
31	Phoenix Mills Ltd.	0.93	1.00	0.93
32	PNC Infratech Ltd.	0.80	0.83	0.97
33	Prestige Estates Projects Ltd.	0.70	0.86	0.81
34	PSP Projects Ltd.	1.00	1.00	1.00
35	Puravankara Ltd.	0.61	0.73	0.84
36	Rail Vikas Nigam Ltd.	0.99	1.00	0.99
37	Reliance Industrial Infrastructure Ltd.	0.53	0.64	0.83
38	RITES Ltd.	1.00	1.00	1.00
39	RPP Infra Projects Ltd.	1.00	1.00	1.00
40	Sobha Ltd.	0.74	0.80	0.93
41	Sunteck Realty Ltd.	1.00	1.00	1.00
42	Vascom Engineers Ltd.	0.50	0.53	0.95

In the year 2019, out of the total 42 units, 12 units (29 percent) are found to be technically efficient, whereas 22 units (52 percent) are pure technically efficient. Cera Sanitaryware Ltd., Dilip Buildcon Ltd., IRB Infrastructure Developers Ltd., Karda Construction Ltd., KNR Constructions Ltd., Man Industries Ltd., Marathon Nextgen Realty Ltd., NBCC India Ltd., PSP Projects Ltd., RITES Ltd., RPP Infra Projects Ltd. and Sunteck Realty Ltd. are found to be technically efficient as per CCR model and pure technically efficient as per BCC model. The summary statistics are presented in Table 4.4.

Table 4. 4: Summary of Efficiency Scores for the year 2019

Sl.	Decision Making Units	CCR Scores	BCC Scores	SE Scores
1	AGI Infra Ltd.	0.58	0.81	0.72
2	Ahluwalia Contracts India Ltd.	0.82	0.82	0.99
3	Ajmera Realty and Infra India Ltd.	0.78	0.79	0.98
4	AMJ Land Ltd.	0.49	1.00	0.49
5	Anant Raj Ltd.	0.72	0.73	0.98
6	Arvind SmartSpaces Ltd.	0.97	1.00	0.97
7	Ashoka Buildcon Ltd.	0.87	0.88	0.99
8	Brigade Enterprises Ltd.	0.83	0.87	0.94
9	Capacite Infra Ltd.	0.79	0.80	0.99
10	Cera Sanitaryware Ltd.	1.00	1.00	1.00

11	Dilip Buildcon Ltd.	1.00	1.00	1.00
12	Engineers India Ltd.	0.93	0.97	0.96
13	GeeCee Ventures Ltd.	0.87	0.88	0.99
14	Godrej Properties Ltd.	0.63	0.65	0.96
15	GPT Infra Projects Ltd.	0.88	1.00	0.88
16	IRB Infrastructure Developers Ltd.	1.00	1.00	1.00
17	IRCON International Ltd.	0.73	0.82	0.89
18	J Kumar Infraprojects Ltd.	0.77	0.79	0.97
19	Kajaria Ceramics Ltd.	0.99	1.00	0.99
20	Karda Construction Ltd.	1.00	1.00	1.00
21	Kec International Ltd.	0.98	1.00	0.98
22	KNR Constructions Ltd.	1.00	1.00	1.00
23	Kolte-Patil Developers Ltd.	0.72	0.72	0.99
24	Larsen & Toubro Ltd.	0.81	1.00	0.81
25	Man Industries Ltd.	1.00	1.00	1.00
26	Marathon Nextgen Realty Ltd.	1.00	1.00	1.00
27	NBCC India Ltd.	1.00	1.00	1.00
28	NCC Ltd.	0.94	1.00	0.94
29	Nila Infrastructures Ltd.	0.93	0.97	0.95
30	Oberoi Realty Ltd.	0.85	1.00	0.85
31	Phoenix Mills Ltd.	0.86	1.00	0.86
32	PNC Infratech Ltd.	0.83	0.85	0.97
33	Prestige Estates Projects Ltd.	0.77	0.85	0.91
34	PSP Projects Ltd.	1.00	1.00	1.00
35	Puravankara Ltd.	0.84	0.85	0.98
36	Rail Vikas Nigam Ltd.	0.99	1.00	0.99
37	Reliance Industrial Infrastructure Ltd.	0.55	0.60	0.91
38	RITES Ltd.	1.00	1.00	1.00
39	RPP Infra Projects Ltd.	1.00	1.00	1.00
40	Sobha Ltd.	0.86	0.89	0.96
41	Sunteck Realty Ltd.	1.00	1.00	1.00
42	Vascom Engineers Ltd.	0.58	0.59	0.98

In the year 2020, out of the total 42 units, 15 units (36 percent) are found to be technically efficient, whereas 23 units (55 percent) are pure technically efficient. AMJ Land Ltd., Cera Sanitaryware Ltd., Dilip Buildcon Ltd., IRB Infrastructure Developers Ltd., Kajaria Ceramics Ltd., Kec International Ltd., Man Industries Ltd., Marathon Nextgen Realty Ltd., Oberoi Realty Ltd., Phoenix Mills Ltd., PSP Projects Ltd., Rail Vikas Nigam Ltd., RITES Ltd., RPP Infra Projects Ltd. and Sunteck Realty Ltd. are found to be technically

efficient as per CCR model and pure technically efficient as per BCC model. The summary statistics are presented in Table 4.5.

Table 4. 5: Summary of Efficiency Scores for the year 2020

Sl.	Decision Making Units	CCR Scores	BCC Scores	SE Scores
1	AGI Infra Ltd.	0.95	1.00	0.95
2	Ahluwalia Contracts India Ltd.	0.82	0.83	0.98
3	Ajmera Realty and Infra India Ltd.	0.81	0.81	0.99
4	AMJ Land Ltd.	1.00	1.00	1.00
5	Anant Raj Ltd.	0.87	0.88	0.99
6	Arvind SmartSpaces Ltd.	0.79	0.81	0.98
7	Ashoka Buildcon Ltd.	0.95	1.00	0.95
8	Brigade Enterprises Ltd.	0.89	0.91	0.97
9	Capacite Infra Ltd.	0.77	0.77	0.99
10	Cera Sanitaryware Ltd.	1.00	1.00	1.00
11	Dilip Buildcon Ltd.	1.00	1.00	1.00
12	Engineers India Ltd.	0.94	0.98	0.95
13	GeeCee Ventures Ltd.	0.76	0.73	1.03
14	Godrej Properties Ltd.	0.78	0.85	0.91
15	GPT Infra Projects Ltd.	0.93	1.00	0.93
16	IRB Infrastructure Developers Ltd.	1.00	1.00	1.00
17	IRCON International Ltd.	0.84	0.93	0.90
18	J Kumar Infraprojects Ltd.	0.78	0.81	0.96
19	Kajaria Ceramics Ltd.	1.00	1.00	1.00
20	Karda Construction Ltd.	0.98	1.00	0.98
21	Kec International Ltd.	1.00	1.00	1.00
22	KNR Constructions Ltd.	0.97	0.98	0.98
23	Kolte-Patil Developers Ltd.	0.85	0.85	0.99
24	Larsen & Toubro Ltd.	0.79	1.00	0.79
25	Man Industries Ltd.	1.00	1.00	1.00
26	Marathon Nextgen Realty Ltd.	1.00	1.00	1.00
27	NBCC India Ltd.	0.91	1.00	0.91
28	NCC Ltd.	0.87	0.93	0.92
29	Nila Infrastructures Ltd.	0.95	1.00	0.95
30	Oberoi Realty Ltd.	1.00	1.00	1.00
31	Phoenix Mills Ltd.	1.00	1.00	1.00
32	PNC Infratech Ltd.	0.93	1.00	0.93
33	Prestige Estates Projects Ltd.	0.91	0.96	0.95
34	PSP Projects Ltd.	1.00	1.00	1.00
35	Puravankara Ltd.	0.84	0.84	0.99
36	Rail Vikas Nigam Ltd.	1.00	1.00	1.00
37	Reliance Industrial Infrastructure Ltd.	0.38	0.38	1.00
38	RITES Ltd.	1.00	1.00	1.00
39	RPP Infra Projects Ltd.	1.00	1.00	1.00

40	Sobha Ltd.	0.97	0.98	0.99
41	Sunteck Realty Ltd.	1.00	1.00	1.00
42	Vascom Engineers Ltd.	0.66	0.67	0.99

4.2. Scale efficiency

The product of pure technical efficiency score and scale efficiency score yields the technical efficiency score. Thus, scale efficiency scores can be found by dividing the technical efficiency score with the pure technical efficiency score. The scale efficiency score indicates whether a firm operates at the most productive scale size (score=1) or not. Tables 4.6-4.10 obtained by employing the BCC model further demarcates the returns to scale at which the companies are operating: Increasing Returns to Scale (IRS), Decreasing Returns to Scale (DRS) or Constant Returns to Scale (CRS). The companies operating at IRS should try to increase their size to reach the efficient frontier and vice versa. On the other hand, the companies operating at CRS need not be required to change their size of operations.

The results obtained for the year 2016 in Table 4.6. convey that there are 8 out of 42 companies that are scale efficient.

Table 4. 6: Scale Efficiency Scores and Returns to Scale for the year 2016

Sl.	Decision Making Units	SE Scores	RTS
1	AGI Infra Ltd.	0.54	Increasing
2	Ahluwalia Contracts India Ltd.	0.97	Decreasing
3	Ajmera Realty and Infra India Ltd.	0.98	Decreasing
4	AMJ Land Ltd.	0.40	Increasing
5	Anant Raj Ltd.	0.89	Decreasing
6	Arvind SmartSpaces Ltd.	0.90	Increasing
7	Ashoka Buildcon Ltd.	0.96	Decreasing
8	Brigade Enterprises Ltd.	0.90	Decreasing
9	Capacite Infra Ltd.	0.98	Decreasing
10	Cera Sanitaryware Ltd.	0.99	Increasing
11	Dilip Buildcon Ltd.	1.00	Constant
12	Engineers India Ltd.	0.77	Decreasing
13	GeeCee Ventures Ltd.	1.00	Constant

14	Godrej Properties Ltd.	0.84	Decreasing
15	GPT Infra Projects Ltd.	0.95	Increasing
16	IRB Infrastructure Developers Ltd.	1.00	Constant
17	IRCON International Ltd.	0.76	Decreasing
18	J Kumar Infraprojects Ltd.	0.98	Decreasing
19	Kajaria Ceramics Ltd.	1.00	Constant
20	Karda Construction Ltd.	0.97	Increasing
21	Kec International Ltd.	0.91	Decreasing
22	KNR Constructions Ltd.	0.89	Decreasing
23	Kolte-Patil Developers Ltd.	0.93	Decreasing
24	Larsen & Toubro Ltd.	0.66	Decreasing
25	Man Industries Ltd.	0.99	Increasing
26	Marathon Nextgen Realty Ltd.	1.00	Constant
27	NBCC India Ltd.	0.89	Decreasing
28	NCC Ltd.	0.86	Decreasing
29	Nila Infrastructures Ltd.	0.99	Increasing
30	Oberoi Realty Ltd.	0.78	Decreasing
31	Phoenix Mills Ltd.	0.93	Decreasing
32	PNC Infratech Ltd.	0.87	Decreasing
33	Prestige Estates Projects Ltd.	0.78	Decreasing
34	PSP Projects Ltd.	1.00	Constant
35	Puravankara Ltd.	0.85	Decreasing
36	Rail Vikas Nigam Ltd.	0.81	Decreasing
37	Reliance Industrial Infrastructure Ltd.	0.95	Increasing
38	RITES Ltd.	0.82	Decreasing
39	RPP Infra Projects Ltd.	1.00	Constant
40	Sobha Ltd.	0.89	Decreasing
41	Sunteck Realty Ltd.	1.00	Constant
42	Vascom Engineers Ltd.	0.99	Constant

The results obtained for the year 2017 in Table 4.7. convey that there are 12 out of 42 companies that are scale efficient.

Table 4. 7: Scale Efficiency Scores and Returns to Scale for the year 2017

Sl.	Decision Making Units	SE Scores	RTS
1	AGI Infra Ltd.	0.78	Increasing
2	Ahluwalia Contracts India Ltd.	0.98	Decreasing
3	Ajmera Realty and Infra India Ltd.	0.99	Constant
4	AMJ Land Ltd.	0.31	Increasing
5	Anant Raj Ltd.	0.91	Decreasing
6	Arvind SmartSpaces Ltd.	0.89	Increasing
7	Ashoka Buildcon Ltd.	0.98	Decreasing
8	Brigade Enterprises Ltd.	0.92	Decreasing

9	Capacite Infra Ltd.	0.98	Decreasing
10	Cera Sanitaryware Ltd.	1.00	Constant
11	Dilip Buildcon Ltd.	1.00	Constant
12	Engineers India Ltd.	0.93	Decreasing
13	GeeCee Ventures Ltd.	1.00	Constant
14	Godrej Properties Ltd.	0.90	Decreasing
15	GPT Infra Projects Ltd.	0.99	Increasing
16	IRB Infrastructure Developers Ltd.	1.00	Constant
17	IRCON International Ltd.	0.82	Decreasing
18	J Kumar Infraprojects Ltd.	0.99	Constant
19	Kajaria Ceramics Ltd.	1.00	Constant
20	Karda Construction Ltd.	1.00	Increasing
21	Kec International Ltd.	1.00	Constant
22	KNR Constructions Ltd.	0.98	Decreasing
23	Kolte-Patil Developers Ltd.	0.99	Constant
24	Larsen & Toubro Ltd.	0.70	Decreasing
25	Man Industries Ltd.	0.99	Increasing
26	Marathon Nextgen Realty Ltd.	1.00	Constant
27	NBCC India Ltd.	1.00	Constant
28	NCC Ltd.	0.90	Decreasing
29	Nila Infrastructures Ltd.	0.93	Increasing
30	Oberoi Realty Ltd.	0.68	Decreasing
31	Phoenix Mills Ltd.	0.89	Decreasing
32	PNC Infratech Ltd.	0.95	Decreasing
33	Prestige Estates Projects Ltd.	0.65	Decreasing
34	PSP Projects Ltd.	1.00	Constant
35	Puravankara Ltd.	0.91	Decreasing
36	Rail Vikas Nigam Ltd.	0.87	Decreasing
37	Reliance Industrial Infrastructure Ltd.	0.93	Increasing
38	RITES Ltd.	0.77	Decreasing
39	RPP Infra Projects Ltd.	1.00	Constant
40	Sobha Ltd.	0.93	Decreasing
41	Sunteck Realty Ltd.	1.00	Constant
42	Vascom Engineers Ltd.	0.99	Constant

The results obtained for the year 2018 in Table 4.8 convey that 14 out of 42 companies are scale efficient.

Table 4. 8: Scale Efficiency Scores and Returns to Scale for the year 2018

Sl.	Decision Making Units	SE Scores	RTS
1	AGI Infra Ltd.	0.66	Increasing
2	Ahluwalia Contracts India Ltd.	0.99	Decreasing
3	Ajmera Realty and Infra India Ltd.	0.99	Increasing
4	AMJ Land Ltd.	0.42	Increasing

5	Anant Raj Ltd.	0.76	Decreasing
6	Arvind SmartSpaces Ltd.	0.90	Increasing
7	Ashoka Buildcon Ltd.	0.98	Decreasing
8	Brigade Enterprises Ltd.	0.78	Decreasing
9	Capacite Infra Ltd.	0.98	Decreasing
10	Cera Sanitaryware Ltd.	1.00	Constant
11	Dilip Buildcon Ltd.	1.00	Constant
12	Engineers India Ltd.	1.00	Constant
13	GeeCee Ventures Ltd.	1.00	Constant
14	Godrej Properties Ltd.	0.99	Decreasing
15	GPT Infra Projects Ltd.	0.88	Increasing
16	IRB Infrastructure Developers Ltd.	1.00	Constant
17	IRCON International Ltd.	0.77	Decreasing
18	J Kumar Infraprojects Ltd.	0.99	Constant
19	Kajaria Ceramics Ltd.	1.00	Constant
20	Karda Construction Ltd.	1.00	Constant
21	Kec International Ltd.	1.00	Constant
22	KNR Constructions Ltd.	1.00	Constant
23	Kolte-Patil Developers Ltd.	0.94	Decreasing
24	Larsen & Toubro Ltd.	0.75	Decreasing
25	Man Industries Ltd.	0.96	Decreasing
26	Marathon Nextgen Realty Ltd.	0.73	Increasing
27	NBCC India Ltd.	1.00	Constant
28	NCC Ltd.	0.91	Decreasing
29	Nila Infrastructures Ltd.	0.93	Increasing
30	Oberoi Realty Ltd.	0.98	Decreasing
31	Phoenix Mills Ltd.	0.93	Decreasing
32	PNC Infratech Ltd.	0.97	Decreasing
33	Prestige Estates Projects Ltd.	0.81	Decreasing
34	PSP Projects Ltd.	1.00	Constant
35	Puravankara Ltd.	0.84	Decreasing
36	Rail Vikas Nigam Ltd.	0.99	Decreasing
37	Reliance Industrial Infrastructure Ltd.	0.83	Increasing
38	RITES Ltd.	1.00	Constant
39	RPP Infra Projects Ltd.	1.00	Constant
40	Sobha Ltd.	0.93	Decreasing
41	Sunteck Realty Ltd.	1.00	Constant
42	Vascom Engineers Ltd.	0.95	Decreasing

The results obtained for the year 2019 in Table 4.9. convey that there are 12 out of 42 companies that are scale efficient.

Table 4. 9: Scale Efficiency Scores and Returns to Scale for the year 2019

Sl.	Decision Making Units	SE Scores	RTS
1	AGI Infra Ltd.	0.72	Increasing
2	Ahluwalia Contracts India Ltd.	0.99	Increasing
3	Ajmera Realty and Infra India Ltd.	0.98	Constant
4	AMJ Land Ltd.	0.49	Increasing
5	Anant Raj Ltd.	0.98	Constant
6	Arvind SmartSpaces Ltd.	0.97	Increasing
7	Ashoka Buildcon Ltd.	0.99	Decreasing
8	Brigade Enterprises Ltd.	0.94	Decreasing
9	Capacite Infra Ltd.	0.99	Decreasing
10	Cera Sanitaryware Ltd.	1.00	Constant
11	Dilip Buildcon Ltd.	1.00	Constant
12	Engineers India Ltd.	0.96	Decreasing
13	GeeCee Ventures Ltd.	0.99	Constant
14	Godrej Properties Ltd.	0.96	Decreasing
15	GPT Infra Projects Ltd.	0.88	Increasing
16	IRB Infrastructure Developers Ltd.	1.00	Constant
17	IRCON International Ltd.	0.89	Decreasing
18	J Kumar Infracore Projects Ltd.	0.97	Decreasing
19	Kajaria Ceramics Ltd.	0.99	Decreasing
20	Karda Construction Ltd.	1.00	Increasing
21	Kec International Ltd.	0.98	Decreasing
22	KNR Constructions Ltd.	1.00	Constant
23	Kolte-Patil Developers Ltd.	0.99	Constant
24	Larsen & Toubro Ltd.	0.81	Decreasing
25	Man Industries Ltd.	1.00	Constant
26	Marathon Nextgen Realty Ltd.	1.00	Increasing
27	NBCC India Ltd.	1.00	Constant
28	NCC Ltd.	0.94	Decreasing
29	Nila Infrastructures Ltd.	0.95	Increasing
30	Oberoi Realty Ltd.	0.85	Decreasing
31	Phoenix Mills Ltd.	0.86	Decreasing
32	PNC Infracore Ltd.	0.97	Decreasing
33	Prestige Estates Projects Ltd.	0.91	Decreasing
34	PSP Projects Ltd.	1.00	Constant
35	Puravankara Ltd.	0.98	Decreasing
36	Rail Vikas Nigam Ltd.	0.99	Decreasing
37	Reliance Industrial Infrastructure Ltd.	0.91	Increasing
38	RITES Ltd.	1.00	Constant
39	RPP Infra Projects Ltd.	1.00	Constant
40	Sobha Ltd.	0.96	Decreasing
41	Sunteck Realty Ltd.	1.00	Constant
42	Vascom Engineers Ltd.	0.98	Constant

The results obtained for the year 2020 in Table 4.10. convey that there are 15 out of 42 companies that are scale efficient.

Table 4. 10: Scale Efficiency Scores and Returns to Scale for the year 2020

Sl.	Decision Making Units	SE Scores	RTS
1	AGI Infra Ltd.	0.95	Increasing
2	Ahluwalia Contracts India Ltd.	0.98	Decreasing
3	Ajmera Realty and Infra India Ltd.	0.99	Decreasing
4	AMJ Land Ltd.	1.00	Constant
5	Anant Raj Ltd.	0.99	Increasing
6	Arvind SmartSpaces Ltd.	0.98	Increasing
7	Ashoka Buildcon Ltd.	0.95	Decreasing
8	Brigade Enterprises Ltd.	0.97	Decreasing
9	Capacite Infra Ltd.	0.99	Increasing
10	Cera Sanitaryware Ltd.	1.00	Constant
11	Dilip Buildcon Ltd.	1.00	Constant
12	Engineers India Ltd.	0.95	Decreasing
13	GeeCee Ventures Ltd.	1.03	Constant
14	Godrej Properties Ltd.	0.91	Decreasing
15	GPT Infra Projects Ltd.	0.93	Increasing
16	IRB Infrastructure Developers Ltd.	1.00	Constant
17	IRCON International Ltd.	0.90	Decreasing
18	J Kumar Infraprojects Ltd.	0.96	Decreasing
19	Kajaria Ceramics Ltd.	1.00	Constant
20	Karda Construction Ltd.	0.98	Increasing
21	Kec International Ltd.	1.00	Constant
22	KNR Constructions Ltd.	0.98	Decreasing
23	Kolte-Patil Developers Ltd.	0.99	Decreasing
24	Larsen & Toubro Ltd.	0.79	Decreasing
25	Man Industries Ltd.	1.00	Constant
26	Marathon Nextgen Realty Ltd.	1.00	Constant
27	NBCC India Ltd.	0.91	Decreasing
28	NCC Ltd.	0.92	Decreasing
29	Nila Infrastructures Ltd.	0.95	Increasing
30	Oberoi Realty Ltd.	1.00	Constant
31	Phoenix Mills Ltd.	1.00	Constant
32	PNC Infratech Ltd.	0.93	Decreasing
33	Prestige Estates Projects Ltd.	0.95	Decreasing
34	PSP Projects Ltd.	1.00	Constant
35	Puravankara Ltd.	0.99	Decreasing
36	Rail Vikas Nigam Ltd.	1.00	Constant
37	Reliance Industrial Infrastructure Ltd.	1.00	Constant
38	RITES Ltd.	1.00	Constant
39	RPP Infra Projects Ltd.	1.00	Constant

40	Sobha Ltd.	0.99	Decreasing
41	Sunteck Realty Ltd.	1.00	Constant
42	Vascom Engineers Ltd.	0.99	Decreasing

4.3 Performance of the Companies over five years

Table 4.11. presents the technical efficiencies of the infrastructure companies throughout the study period. Geometric Mean is being calculated for the 5 years and populated in the table. 5 firms namely Dilip Buildcon Ltd., IRB Infrastructure Developers Ltd., PSP Projects Ltd., RPP Infra Projects Ltd., and Sunteck Realty Ltd. are technically efficient across the study period. 3 firms, namely Cera Sanitaryware Ltd., Kajaria Ceramics Ltd., and Karda Construction Ltd., have a GM of 0.99 and are just shy of being technically efficient in 1 or 2 years and can be considered as close to being overall technically efficient. Number of technically efficient firms for years 2016, 2017, 2018, 2019 and 2020 stands at 8 (19.04%), 12 (28.57%), 14 (33.33%), 12 (28.57%) and 15 (35.71%) respectively.

Table 4. 11: Technical Efficiency over five years from 2016-2020

Sl.	Decision Making Units	2016	2017	2018	2019	2020	G.M.
1	AGI Infra Ltd.	0.54	0.78	0.66	0.58	0.95	0.73
2	Ahluwalia Contracts India Ltd.	0.75	0.85	0.95	0.82	0.82	0.86
3	Ajmera Realty and Infra India Ltd.	0.56	0.70	0.81	0.78	0.81	0.77
4	AMJ Land Ltd.	0.40	0.31	0.42	0.49	1.00	0.54
5	Anant Raj Ltd.	0.61	0.70	0.58	0.72	0.87	0.73
6	Arvind SmartSpaces Ltd.	0.60	0.55	0.77	0.97	0.79	0.76
7	Ashoka Buildcon Ltd.	0.78	0.79	0.82	0.87	0.95	0.86
8	Brigade Enterprises Ltd.	0.60	0.73	0.63	0.83	0.89	0.77
9	Capacite Infra Ltd.	0.70	0.83	0.75	0.79	0.77	0.80
10	Cera Sanitaryware Ltd.	0.99	1.00	1.00	1.00	1.00	0.99
11	Dilip Buildcon Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
12	Engineers India Ltd.	0.59	0.93	1.00	0.93	0.94	0.88
13	GeeCee Ventures Ltd.	1.00	1.00	1.00	0.87	0.76	0.93
14	Godrej Properties Ltd.	0.36	0.72	0.80	0.63	0.78	0.68
15	GPT Infra Projects Ltd.	0.74	0.88	0.88	0.88	0.93	0.88
16	IRB Infrastructure Developers Ltd.	1.00	1.00	1.00	1.00	1.00	1.00

17	IRCON International Ltd.	0.59	0.69	0.63	0.73	0.84	0.73
18	J Kumar Infracorps Ltd.	0.74	0.71	0.73	0.77	0.78	0.78
19	Kajaria Ceramics Ltd.	1.00	1.00	1.00	0.99	1.00	0.99
20	Karda Construction Ltd.	0.97	1.00	1.00	1.00	0.98	0.99
21	Kec International Ltd.	0.91	1.00	1.00	0.98	1.00	0.98
22	KNR Constructions Ltd.	0.83	0.90	1.00	1.00	0.97	0.95
23	Kolte-Patil Developers Ltd.	0.37	0.78	0.84	0.72	0.85	0.73
24	Larsen & Toubro Ltd.	0.66	0.70	0.75	0.81	0.79	0.78
25	Man Industries Ltd.	0.90	0.77	0.92	1.00	1.00	0.93
26	Marathon Nextgen Realty Ltd.	1.00	1.00	0.73	1.00	1.00	0.95
27	NBCC India Ltd.	0.89	1.00	1.00	1.00	0.91	0.96
28	NCC Ltd.	0.86	0.90	0.84	0.94	0.87	0.90
29	Nila Infrastructures Ltd.	0.85	0.93	0.93	0.93	0.95	0.93
30	Oberoi Realty Ltd.	0.78	0.68	0.98	0.85	1.00	0.87
31	Phoenix Mills Ltd.	0.93	0.89	0.93	0.86	1.00	0.93
32	PNC Infracorps Ltd.	0.84	0.74	0.80	0.83	0.93	0.85
33	Prestige Estates Projects Ltd.	0.71	0.65	0.70	0.77	0.91	0.78
34	PSP Projects Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
35	Puravankara Ltd.	0.59	0.72	0.61	0.84	0.84	0.75
36	Rail Vikas Nigam Ltd.	0.81	0.87	0.99	0.99	1.00	0.94
37	Reliance Industrial Infrastructure Ltd.	0.46	0.48	0.53	0.55	0.38	0.54
38	RITES Ltd.	0.82	0.77	1.00	1.00	1.00	0.92
39	RPP Infracorps Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
40	Sobha Ltd.	0.59	0.69	0.74	0.86	0.97	0.80
41	Sunteck Realty Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
42	Vascom Engineers Ltd.	0.54	0.43	0.50	0.58	0.66	0.60

Table 4.12. presents the Pure Technical efficiencies and the respective geometric means of infrastructure companies throughout the study period. 17 firms, namely AMJ Land Ltd., Cera Sanitaryware Ltd., Dilip Buildcon Ltd., IRB Infrastructure Developers Ltd., Kajaria Ceramics Ltd., Karda Construction Ltd., Kec International Ltd., Larsen & Toubro Ltd., Marathon Nextgen Realty Ltd., NBCC India Ltd., Oberoi Realty Ltd., Phoenix Mills Ltd., PSP Projects Ltd., Rail Vikas Nigam Ltd., RITES Ltd., RPP Infracorps Ltd., and Sunteck Realty Ltd. are pure technically efficient across the study period.

Number of pure technically efficient firms for years 2016, 2017, 2018, 2019 and 2020 stands at 19 (45.23%), 22 (52.38%), 22 (52.38%), 22 (52.38%) and 22 (52.38%) respectively.

Table 4. 12: Pure Technical Efficiency over five years from 2016-2020

Sl.	Decision Making Units	2016	2017	2018	2019	2020	G. M
1	AGI Infra Ltd.	1.00	1.00	1.00	0.81	1.00	0.96
2	Ahluwalia Contracts India Ltd.	0.77	0.87	0.96	0.82	0.83	0.87
3	Ajmera Realty and Infra India Ltd.	0.57	0.70	0.82	0.79	0.81	0.77
4	AMJ Land Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
5	Anant Raj Ltd.	0.68	0.77	0.75	0.73	0.88	0.79
6	Arvind SmartSpaces Ltd.	0.67	0.62	0.85	1.00	0.81	0.81
7	Ashoka Buildcon Ltd.	0.81	0.80	0.83	0.88	1.00	0.88
8	Brigade Enterprises Ltd.	0.67	0.79	0.81	0.87	0.91	0.84
9	Capacite Infra Ltd.	0.71	0.85	0.76	0.80	0.77	0.81
10	Cera Sanitaryware Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
11	Dilip Buildcon Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
12	Engineers India Ltd.	0.76	1.00	1.00	0.97	0.98	0.95
13	GeeCee Ventures Ltd.	1.00	1.00	1.00	0.88	0.73	0.93
14	Godrej Properties Ltd.	0.43	0.79	0.81	0.65	0.85	0.73
15	GPT Infra Projects Ltd.	0.78	0.88	1.00	1.00	1.00	0.94
16	IRB Infrastructure Developers Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
17	IRCON International Ltd.	0.77	0.84	0.82	0.82	0.93	0.86
18	J Kumar Infraprojects Ltd.	0.75	0.71	0.73	0.79	0.81	0.79
19	Kajaria Ceramics Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
20	Karda Construction Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
21	Kec International Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
22	KNR Constructions Ltd.	0.93	0.92	1.00	1.00	0.98	0.97
23	Kolte-Patil Developers Ltd.	0.40	0.79	0.90	0.72	0.85	0.75
24	Larsen & Toubro Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
25	Man Industries Ltd.	0.91	0.78	0.96	1.00	1.00	0.93
26	Marathon Nextgen Realty Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
27	NBCC India Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
28	NCC Ltd.	1.00	1.00	0.93	1.00	0.93	0.97
29	Nila Infrastructures Ltd.	0.85	1.00	1.00	0.97	1.00	0.97
30	Oberoi Realty Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
31	Phoenix Mills Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
32	PNC Infratech Ltd.	0.96	0.78	0.83	0.85	1.00	0.90
33	Prestige Estates Projects Ltd.	0.90	1.00	0.86	0.85	0.96	0.92
34	PSP Projects Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
35	Puravankara Ltd.	0.69	0.79	0.73	0.85	0.84	0.81
36	Rail Vikas Nigam Ltd.	1.00	1.00	1.00	1.00	1.00	1.00

	Reliance Industrial Infrastructure Ltd.						
37	Reliance Industrial Infrastructure Ltd.	0.48	0.51	0.64	0.60	0.38	0.57
38	RITES Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
39	RPP Infra Projects Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
40	Sobha Ltd.	0.66	0.74	0.80	0.89	0.98	0.83
41	Sunteck Realty Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
42	Vascom Engineers Ltd.	0.55	0.44	0.53	0.59	0.67	0.61

Table 4.13. presents the Scale efficiencies and the respective geometric means of infrastructure companies throughout the study period.

6 firms, namely Dilip Buildcon Ltd., GeeCee Ventures Ltd., IRB Infrastructure Developers Ltd., PSP Projects Ltd., RPP Infra Projects Ltd., and Sunteck Realty Ltd., are scale efficient across the study period.

6 firms, namely Ajmera Realty and Infra India Ltd., Capacite Infra Ltd., Cera Sanitaryware Ltd., Kajaria Ceramics Ltd., Karda Construction Ltd., and Man Industries Ltd., have a GM of 0.99 and are just shy of being scale efficient in 1 or 2 years and can be considered as close to being overall scale efficient.

Number of scale efficient firms for years 2016, 2017, 2018, 2019 and 2020 stands at 8 (19.04%), 12 (28.57%), 14 (33.33%), 12 (28.57%) and 15 (35.71%) respectively.

Table 4. 13: Scale Efficiency over five years from 2016-2020

Sl	Decision Making Units	2016	2017	2018	2019	2020	G.M
1	AGI Infra Ltd.	0.54	0.78	0.66	0.72	0.95	0.76
2	Ahluwalia Contracts India Ltd.	0.97	0.98	0.99	0.99	0.98	0.98
3	Ajmera Realty and Infra India Ltd.	0.98	0.99	0.99	0.98	0.99	0.99
4	AMJ Land Ltd.	0.40	0.31	0.42	0.49	1.00	0.54
5	Anant Raj Ltd.	0.89	0.91	0.76	0.98	0.99	0.92
6	Arvind SmartSpaces Ltd.	0.90	0.89	0.90	0.97	0.98	0.94
7	Ashoka Buildcon Ltd.	0.96	0.98	0.98	0.99	0.95	0.98
8	Brigade Enterprises Ltd.	0.90	0.92	0.78	0.94	0.97	0.91
9	Capacite Infra Ltd.	0.98	0.98	0.98	0.99	0.99	0.99
10	Cera Sanitaryware Ltd.	0.99	1.00	1.00	1.00	1.00	0.99
11	Dilip Buildcon Ltd.	1.00	1.00	1.00	1.00	1.00	1.00

12	Engineers India Ltd.	0.77	0.93	1.00	0.96	0.95	0.93
13	GeeCee Ventures Ltd.	1.00	1.00	1.00	0.99	1.03	1.00
14	Godrej Properties Ltd.	0.84	0.90	0.99	0.96	0.91	0.93
15	GPT Infra Projects Ltd.	0.95	0.99	0.88	0.88	0.93	0.94
16	IRB Infrastructure Developers Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
17	IRCON International Ltd.	0.76	0.82	0.77	0.89	0.90	0.85
18	J Kumar Infraprojects Ltd.	0.98	0.99	0.99	0.97	0.96	0.98
19	Kajaria Ceramics Ltd.	1.00	1.00	1.00	0.99	1.00	0.99
20	Karda Construction Ltd.	0.97	1.00	1.00	1.00	0.98	0.99
21	Kec International Ltd.	0.91	1.00	1.00	0.98	1.00	0.98
22	KNR Constructions Ltd.	0.89	0.98	1.00	1.00	0.98	0.97
23	Kolte-Patil Developers Ltd.	0.93	0.99	0.94	0.99	0.99	0.97
24	Larsen & Toubro Ltd.	0.66	0.70	0.75	0.81	0.79	0.78
25	Man Industries Ltd.	0.99	0.99	0.96	1.00	1.00	0.99
26	Marathon Nextgen Realty Ltd.	1.00	1.00	0.73	1.00	1.00	0.95
27	NBCC India Ltd.	0.89	1.00	1.00	1.00	0.91	0.96
28	NCC Ltd.	0.86	0.90	0.91	0.94	0.92	0.92
29	Nila Infrastructures Ltd.	0.99	0.93	0.93	0.95	0.95	0.96
30	Oberoi Realty Ltd.	0.78	0.68	0.98	0.85	1.00	0.87
31	Phoenix Mills Ltd.	0.93	0.89	0.93	0.86	1.00	0.93
32	PNC Infratech Ltd.	0.87	0.95	0.97	0.97	0.93	0.95
33	Prestige Estates Projects Ltd.	0.78	0.65	0.81	0.91	0.95	0.84
34	PSP Projects Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
35	Puravankara Ltd.	0.85	0.91	0.84	0.98	0.99	0.93
36	Rail Vikas Nigam Ltd.	0.81	0.87	0.99	0.99	1.00	0.94
37	Reliance Industrial Infrastructure Ltd.	0.95	0.93	0.83	0.91	1.00	0.94
38	RITES Ltd.	0.82	0.77	1.00	1.00	1.00	0.92
39	RPP Infra Projects Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
40	Sobha Ltd.	0.89	0.93	0.93	0.96	0.99	0.95
41	Sunteck Realty Ltd.	1.00	1.00	1.00	1.00	1.00	1.00
42	Vascom Engineers Ltd.	0.99	0.99	0.95	0.98	0.99	0.98

The performance of all the 42 companies for the five years period, i.e., from FY 2015-16 to FY 2019-20 has been graphically represented in Figure 4.1. to Figure 4.42. respectively. The graphs represent the TE, PTE and SE scores of the companies year-wise which give a clear insight into the deviations in the efficiency levels.

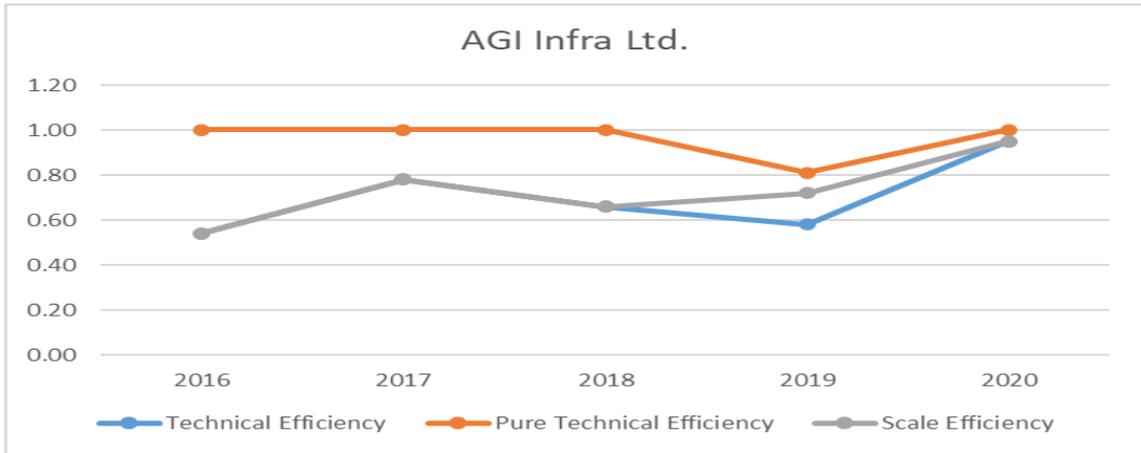


Figure 4. 1: Efficiency levels of AGI Infra Ltd. from 2016-2020

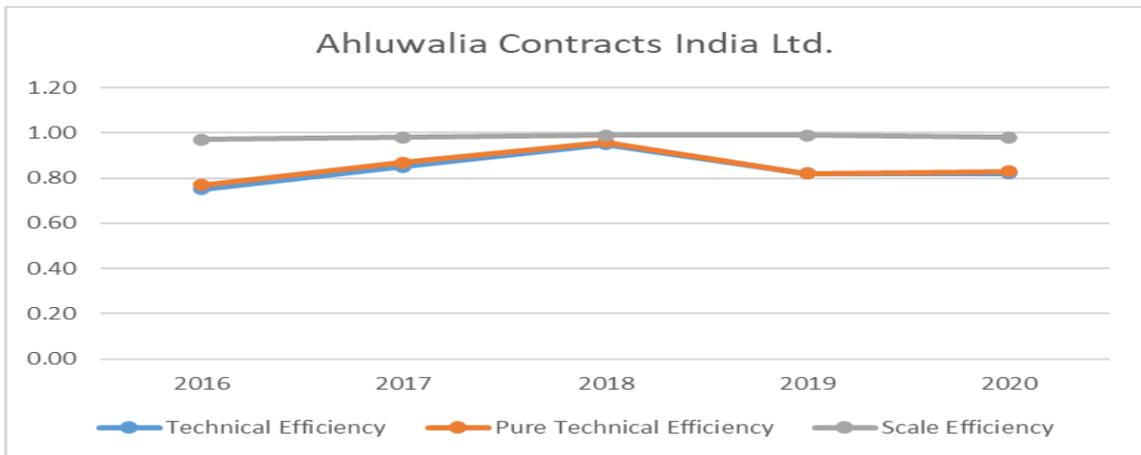


Figure 4. 2: Efficiency levels of Ahluwalia Contracts India Ltd. from 2016-2020

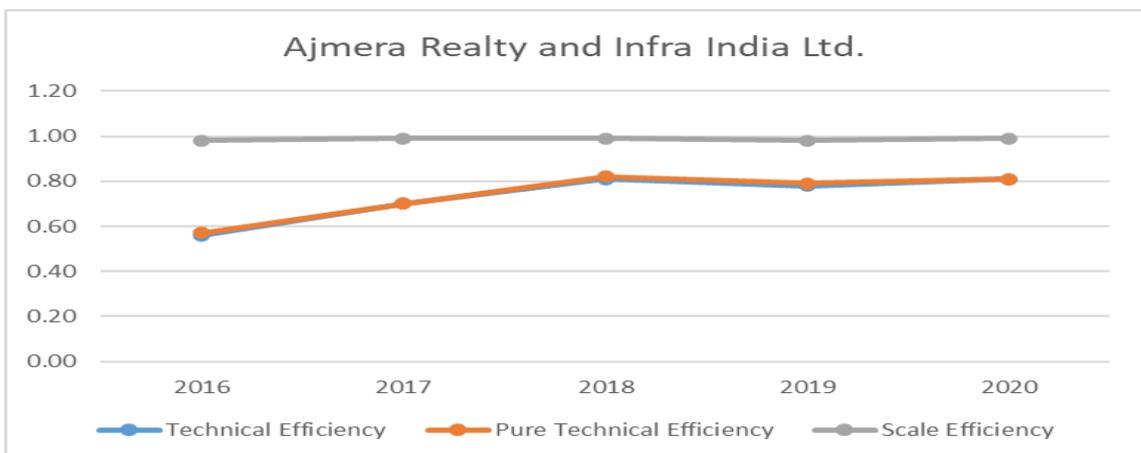


Figure 4. 3: Efficiency levels of Ajmera Realty and Infra India Ltd. from 2016-2020

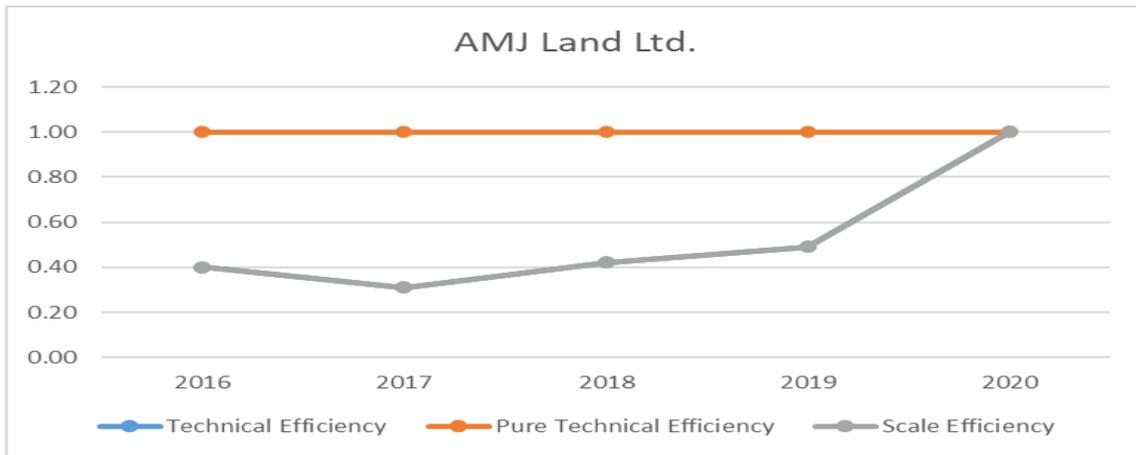


Figure 4. 4: Efficiency levels of AMJ Ltd. from 2016-2020

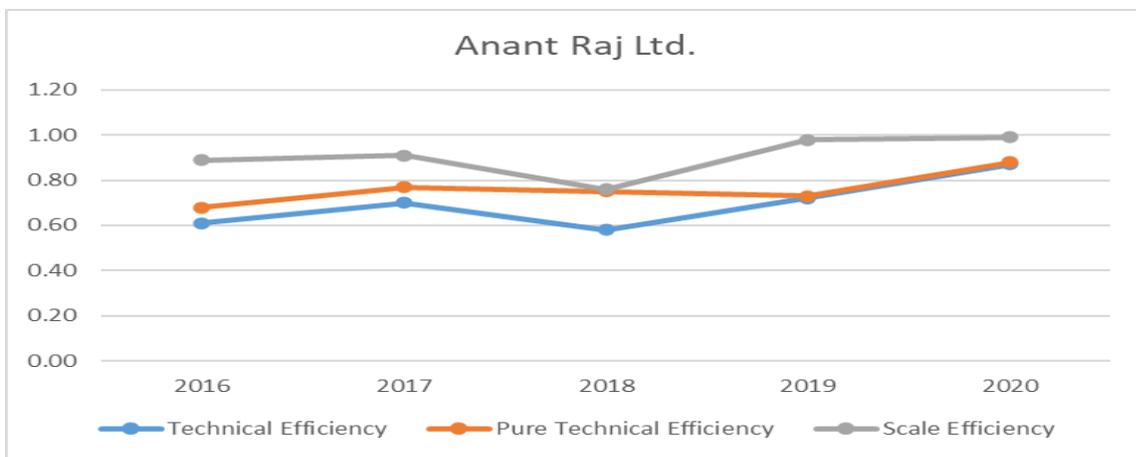


Figure 4. 5: Efficiency levels of Anant Ltd. from 2016-2020

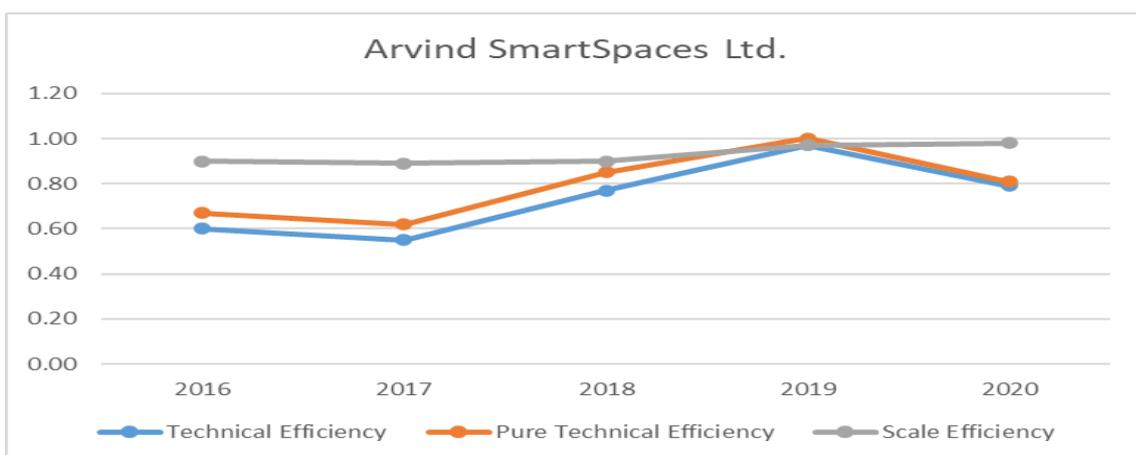


Figure 4. 6: Efficiency levels of Arvind Smartspaces Ltd. from 2016-2020

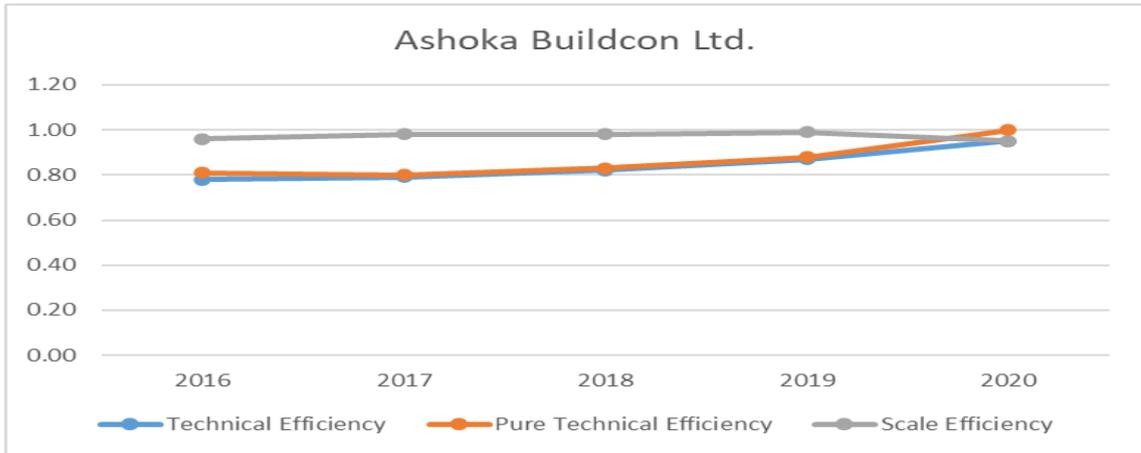


Figure 4. 7: Efficiency levels of Ashoka Buildcon Ltd. from 2016-2020

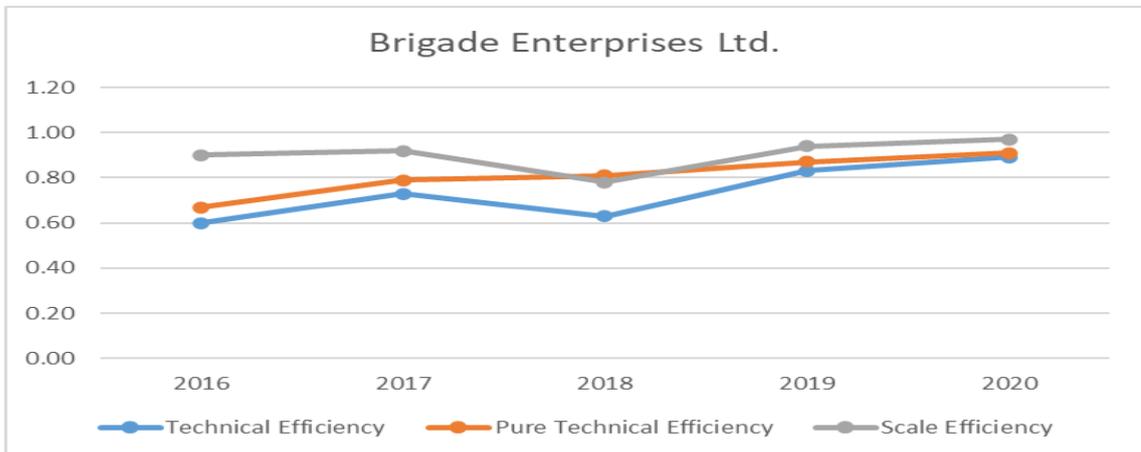


Figure 4. 8: Efficiency levels of Brigade Enterprises Ltd. from 2016-2020

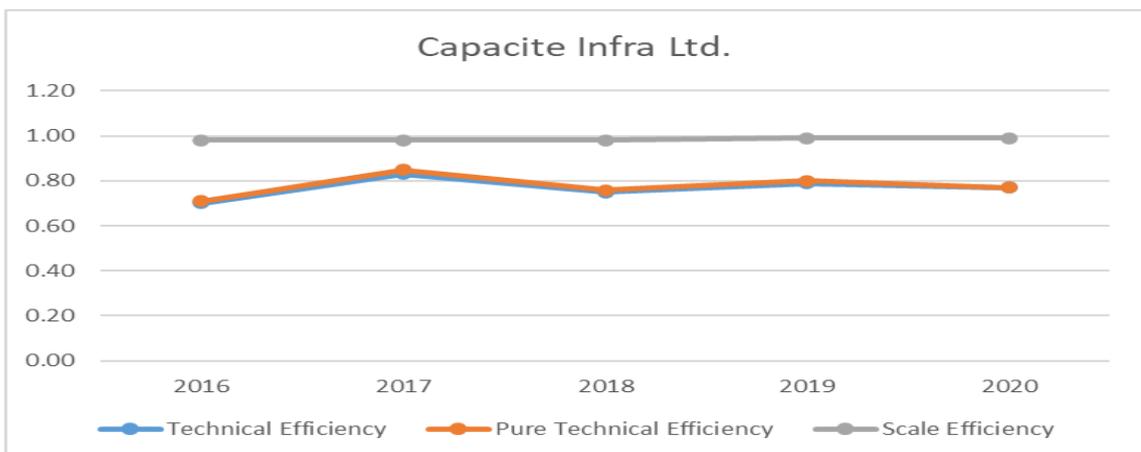


Figure 4. 9: Efficiency levels of Capacite Ltd. from 2016-2020

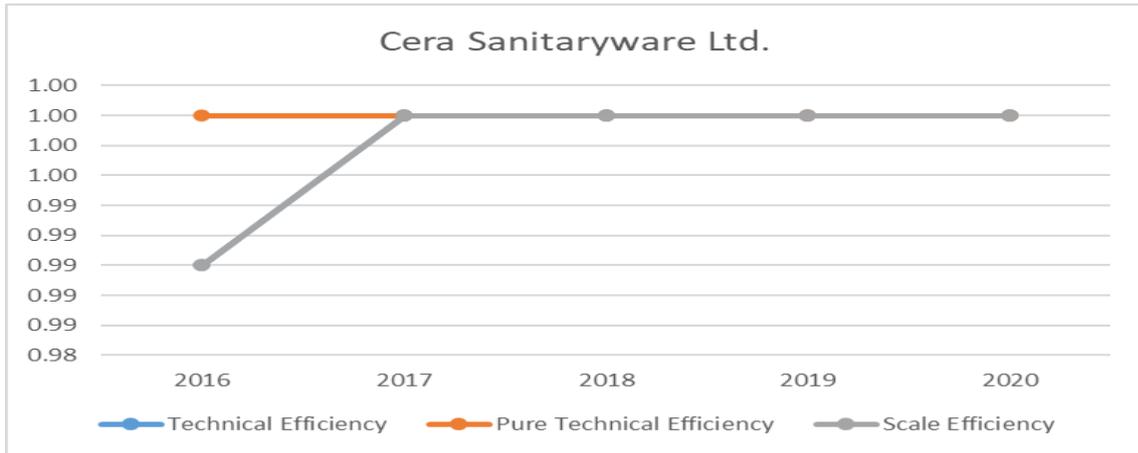


Figure 4. 10: Efficiency levels of Cera Sanitaryware Ltd. from 2016-2020

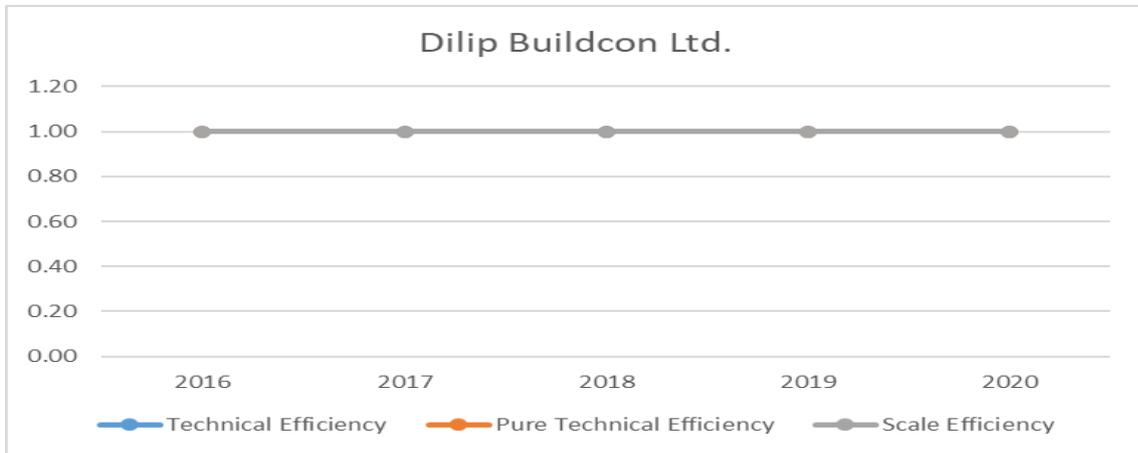


Figure 4. 11: Efficiency levels of Dilip Buildcon Ltd. from 2016-2020

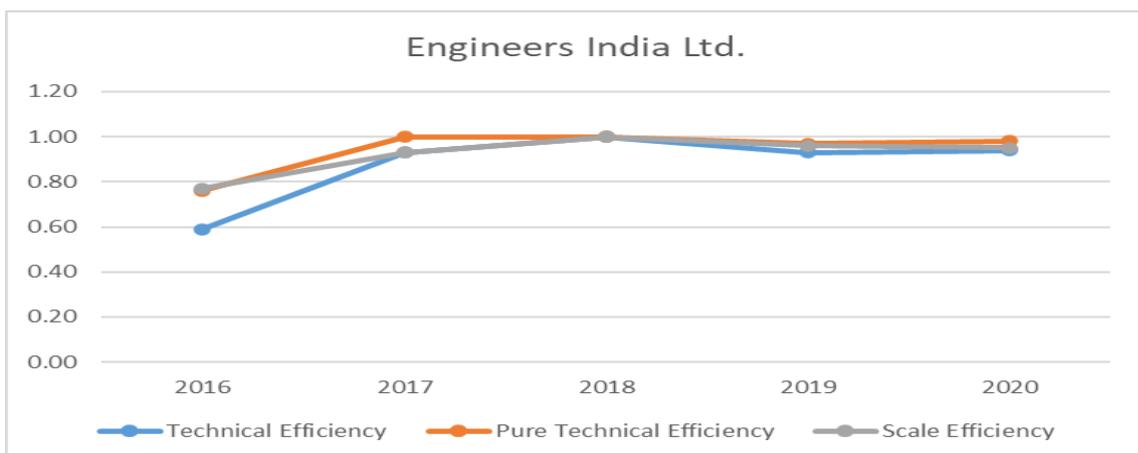


Figure 4. 12: Efficiency levels of Engineers India Ltd. from 2016-2020

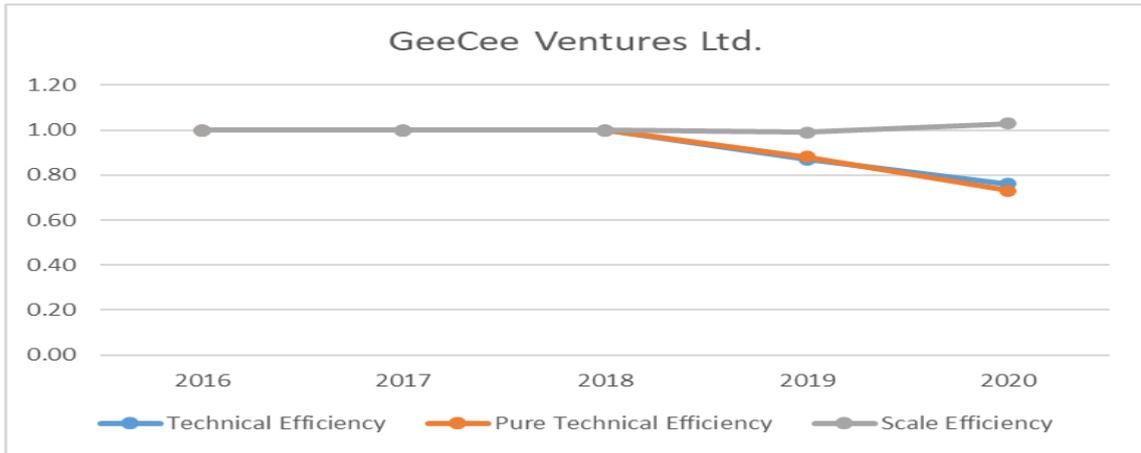


Figure 4. 13: Efficiency levels of GeeCee Ventures Ltd. from 2016-2020

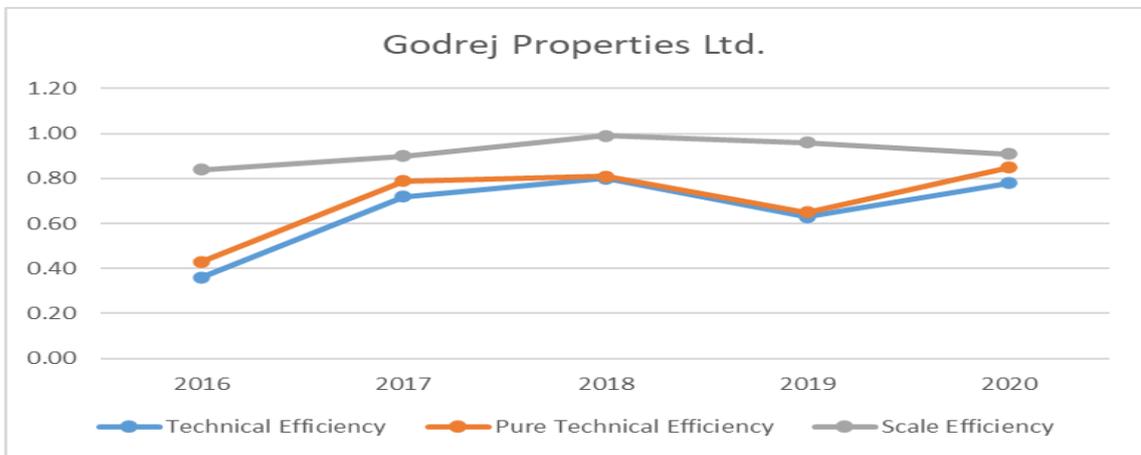


Figure 4. 14: Efficiency levels of Godrej Properties Ltd. from 2016-2020

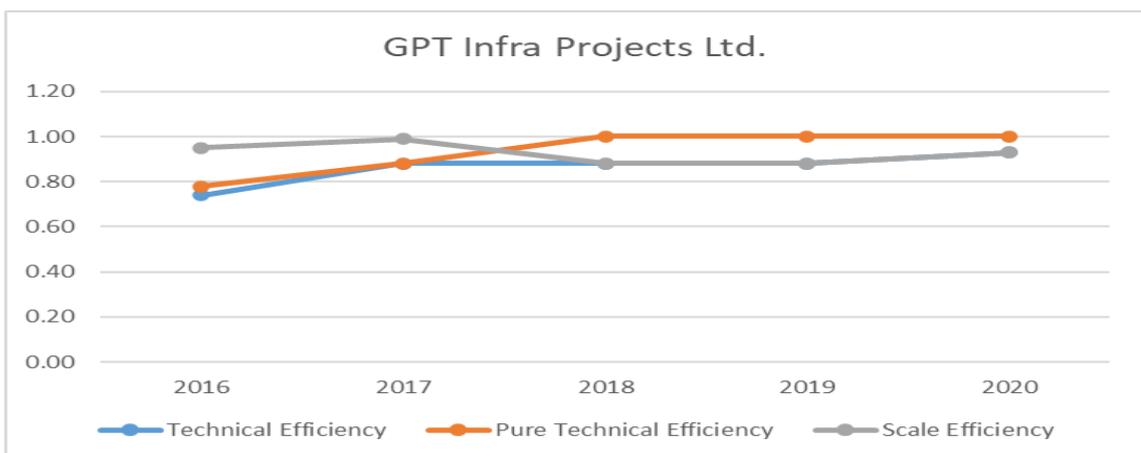


Figure 4. 15: Efficiency levels of GPT Infra Projects Ltd. from 2016-2020

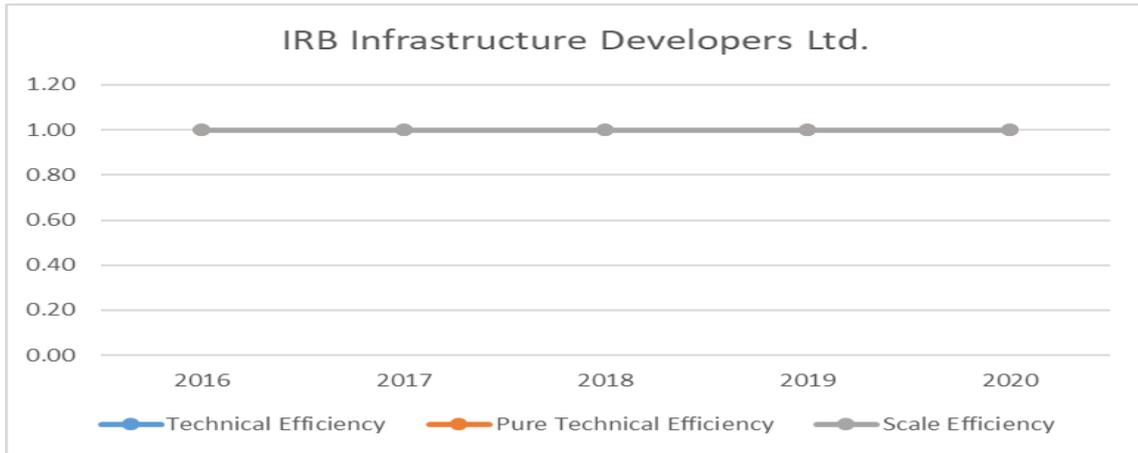


Figure 4. 16: Efficiency levels of IRB Infrastructure Developers Ltd. from 2016-2020

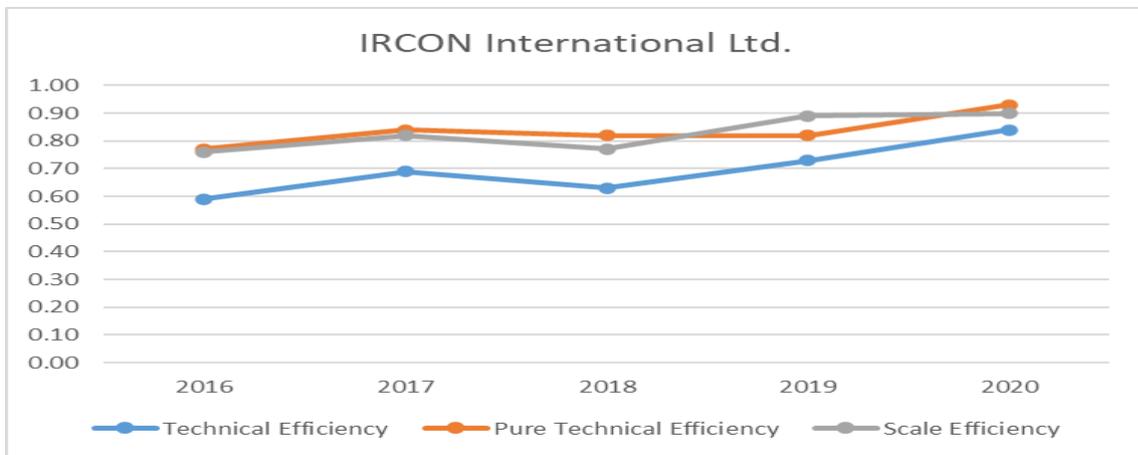


Figure 4. 17: Efficiency levels of IRCON International Ltd. from 2016-2020

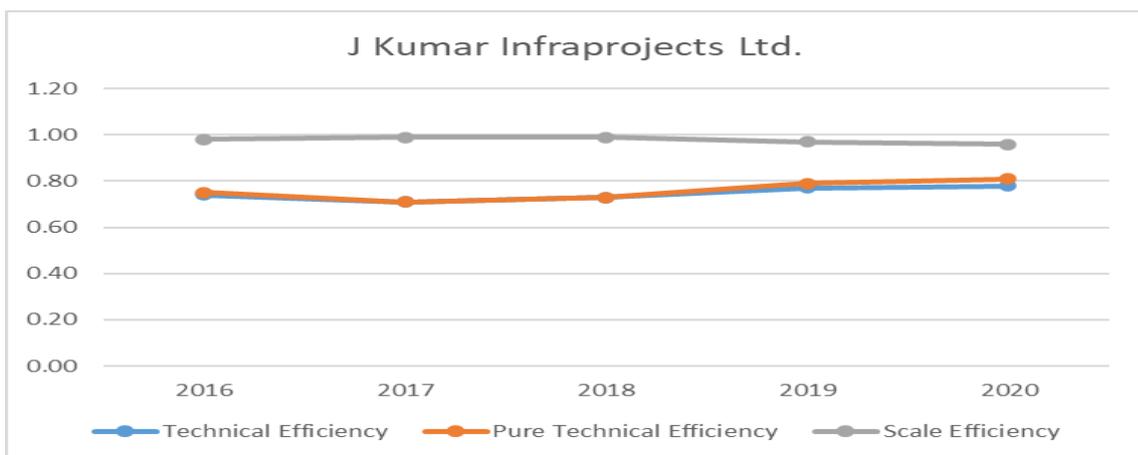


Figure 4. 18: Efficiency levels of J Kumar Infraprojects Ltd. from 2016-2020

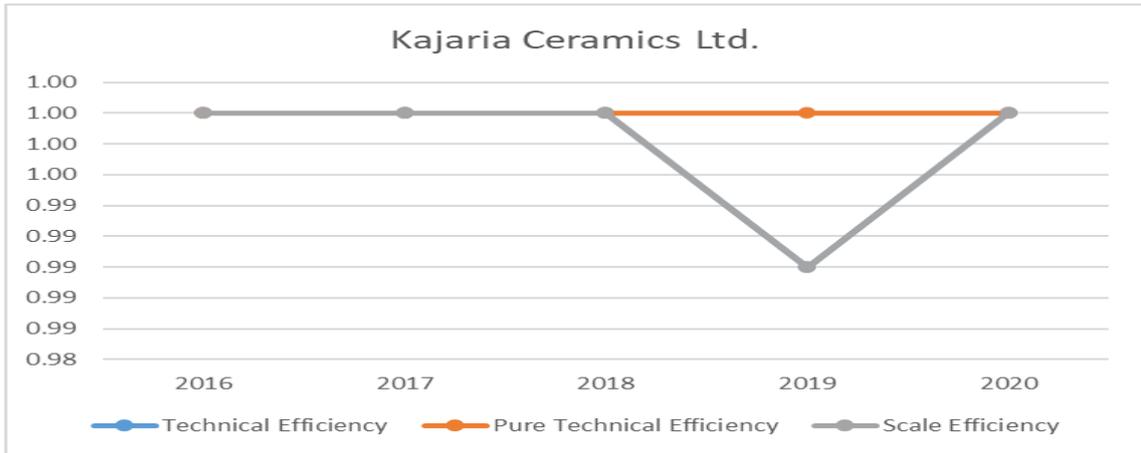


Figure 4. 19: Efficiency levels of Kajaria Ceramics Ltd. from 2016-2020

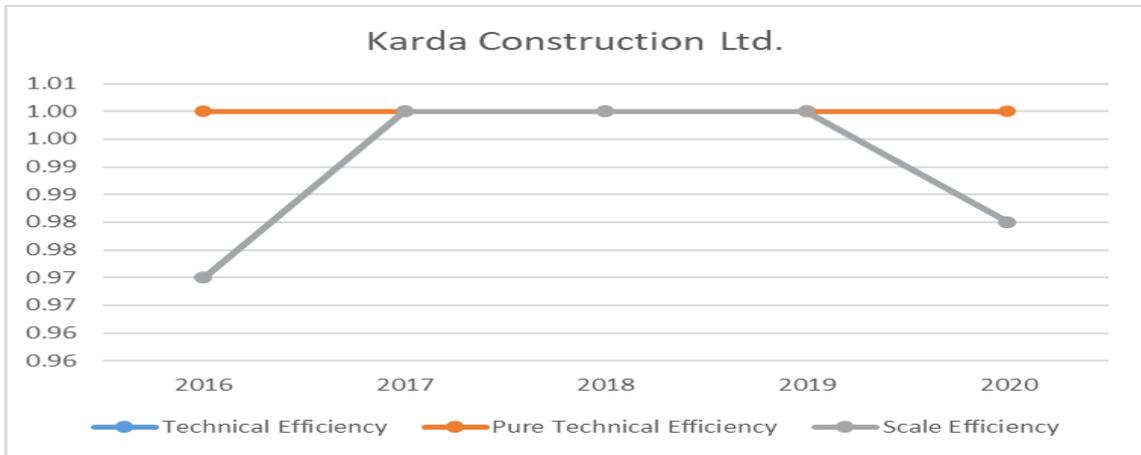


Figure 4. 20: Efficiency levels of Karda Construction Ltd. from 2016-2020

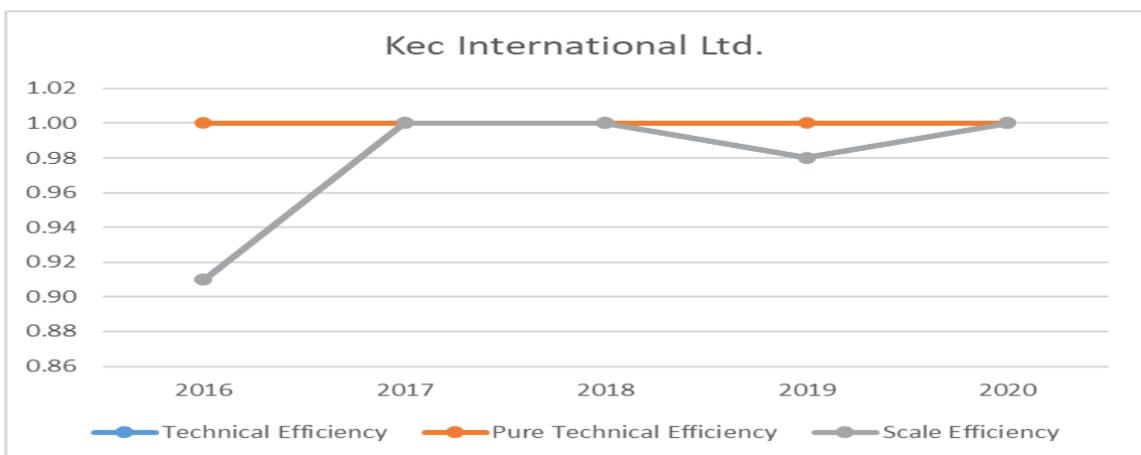


Figure 4. 21: Efficiency levels of KEC International Ltd. from 2016-2020

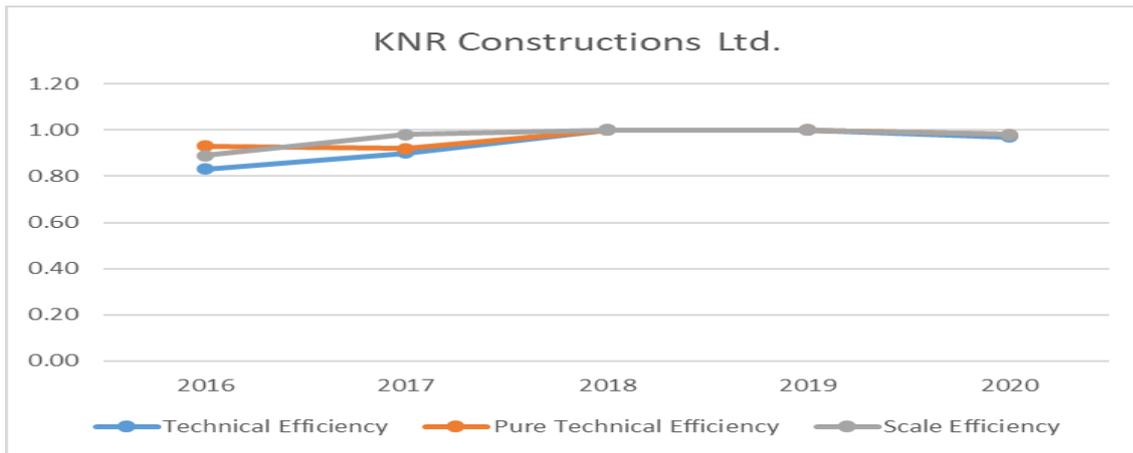


Figure 4. 22: Efficiency levels of KNR Constructions Ltd. from 2016-2020

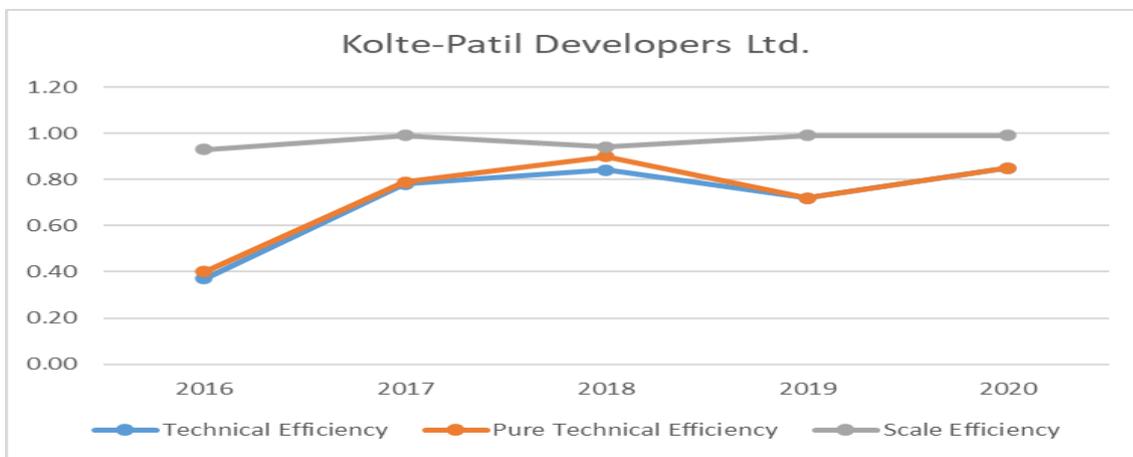


Figure 4. 23: Efficiency levels of Kolte-Patil Developers Ltd. from 2016-2020

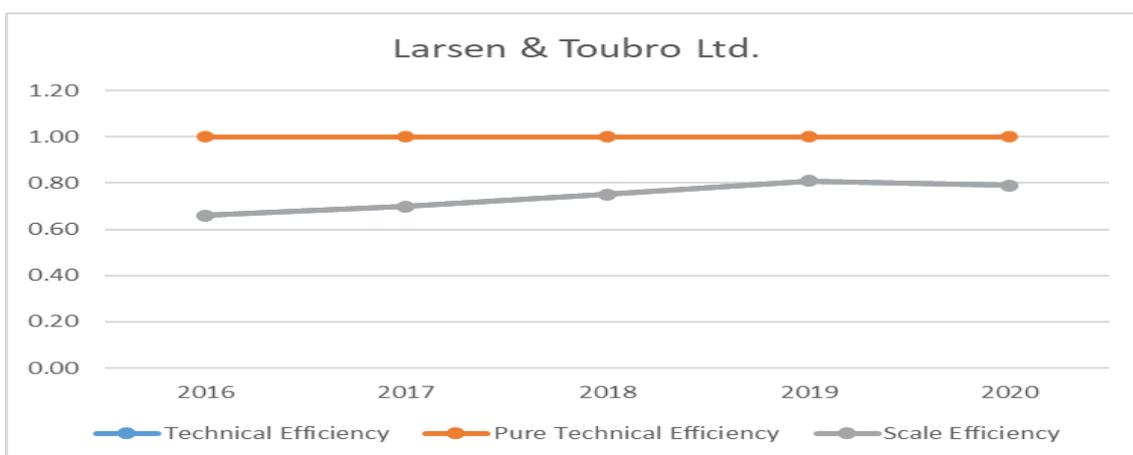


Figure 4. 24: Efficiency levels of Larsen & Toubro Ltd. from 2016-2020

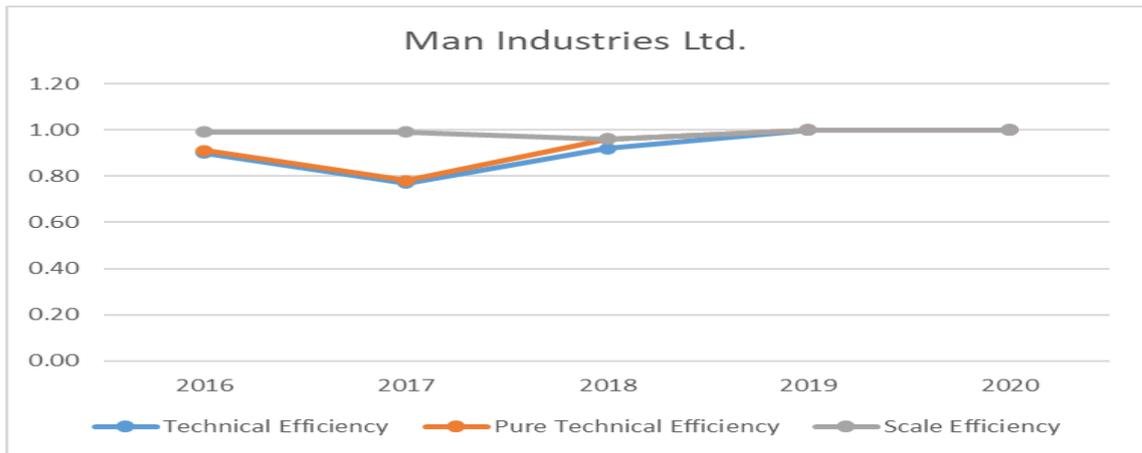


Figure 4. 25: Efficiency levels of Man Industries Ltd. from 2016-2020

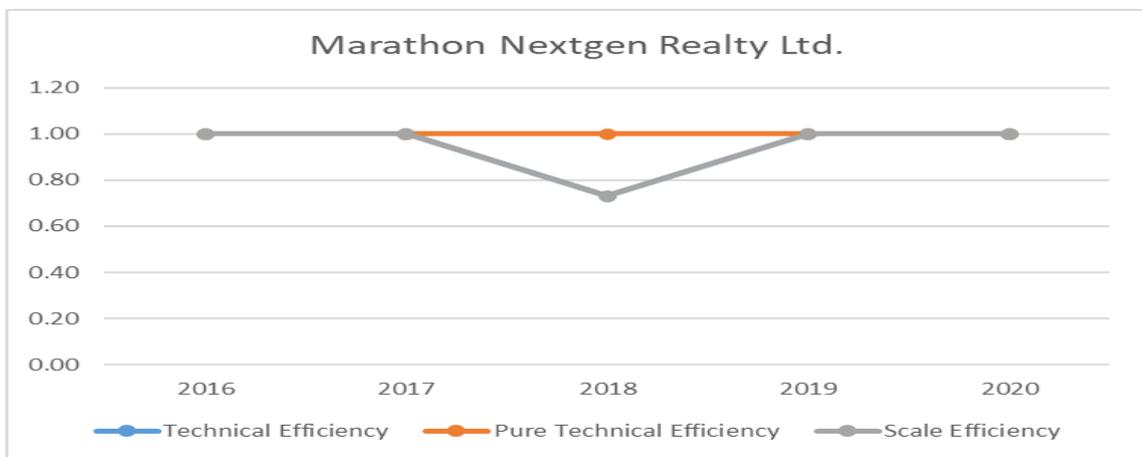


Figure 4. 26: Efficiency levels of Marathon Nextgen Realty Ltd. from 2016-2020

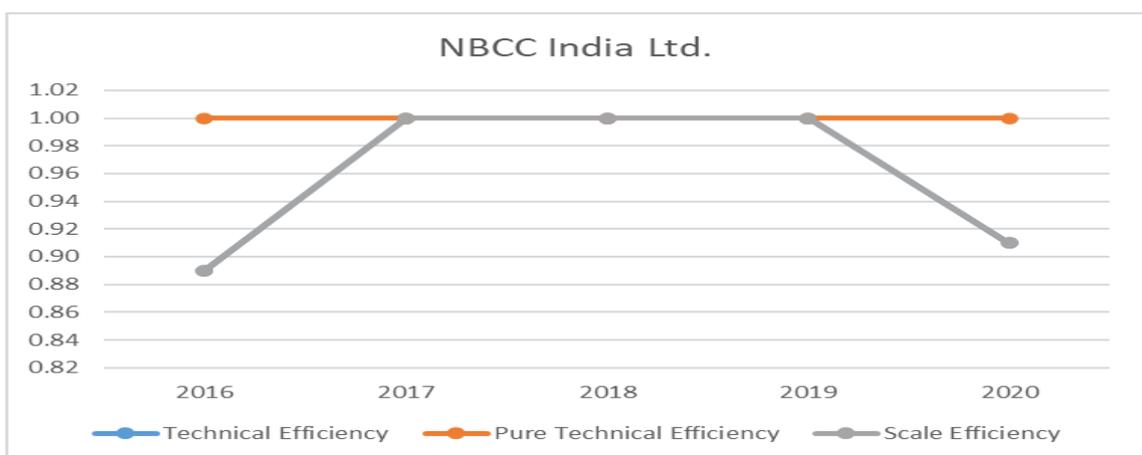


Figure 4. 27: Efficiency levels of NBCC India Ltd. from 2016-2020

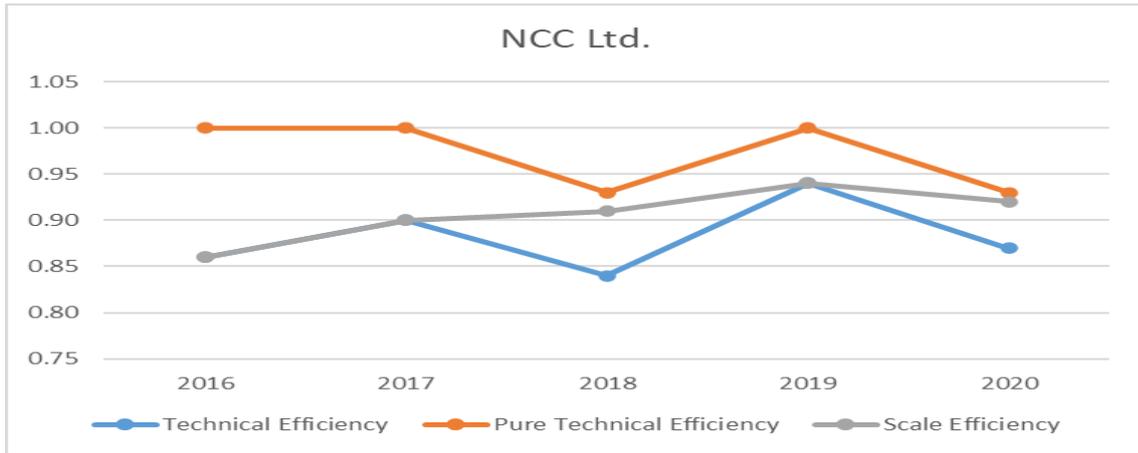


Figure 4. 28: Efficiency levels of NCC Ltd. from 2016-2020

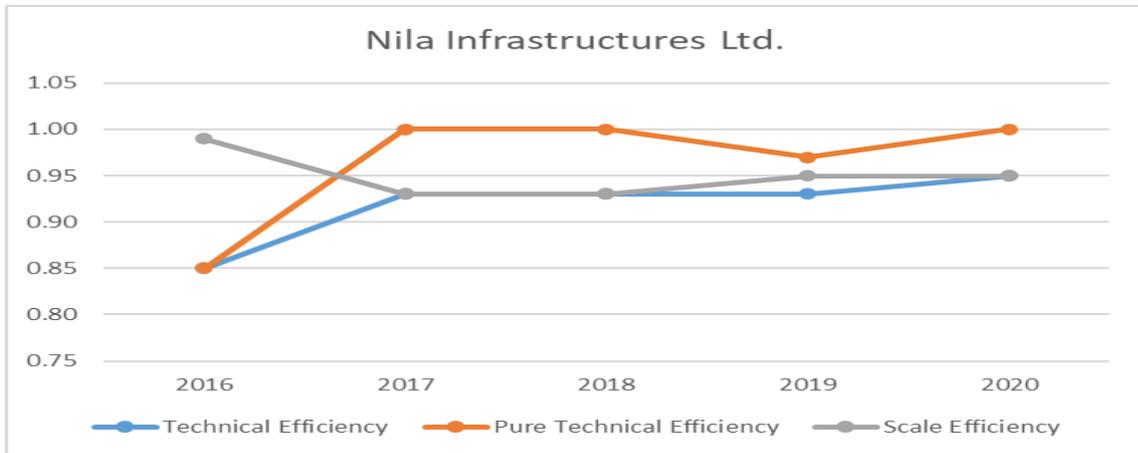


Figure 4. 29: Efficiency levels of Nila Infrastructures Ltd. from 2016-2020

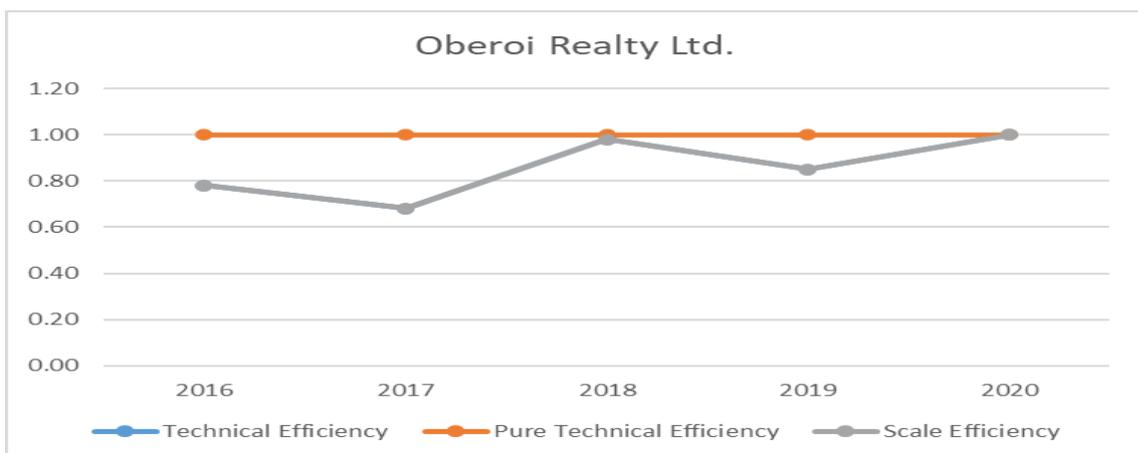


Figure 4. 30: Efficiency levels of Oberoi Realty Ltd. from 2016-2020

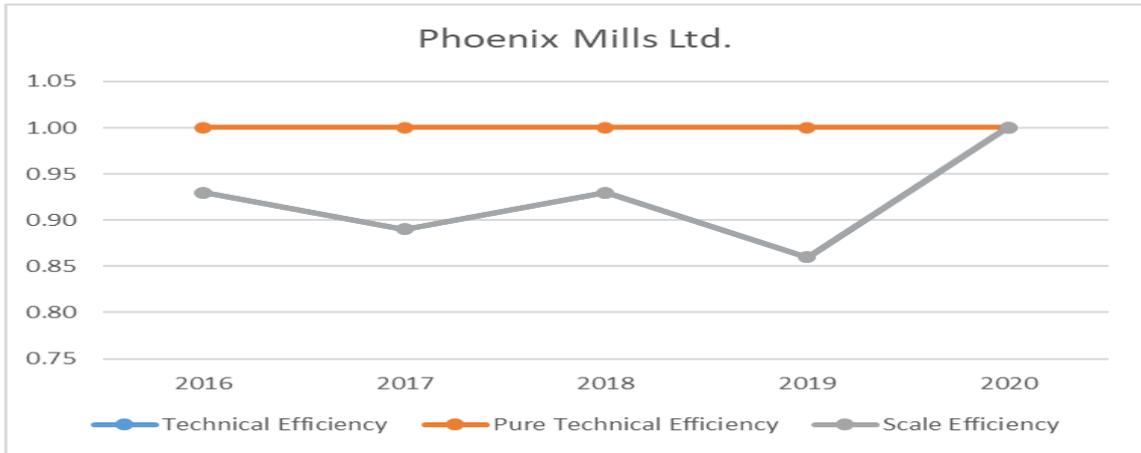


Figure 4. 31: Efficiency levels of Phoenix Mills Ltd. from 2016-2020

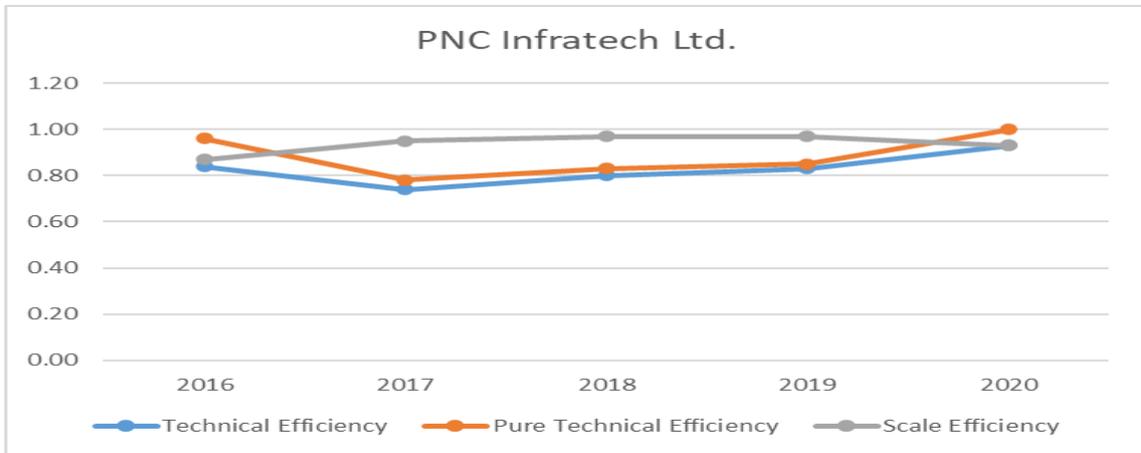


Figure 4. 32: Efficiency levels of PNC Infratech Ltd. from 2016-2020

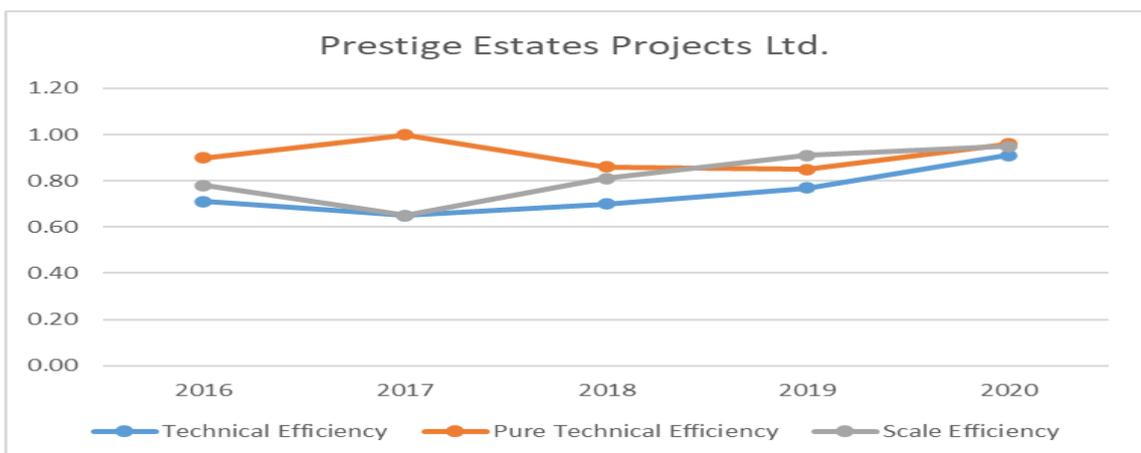


Figure 4. 33: Efficiency levels of Prestige Estates Projects Ltd. from 2016-2020

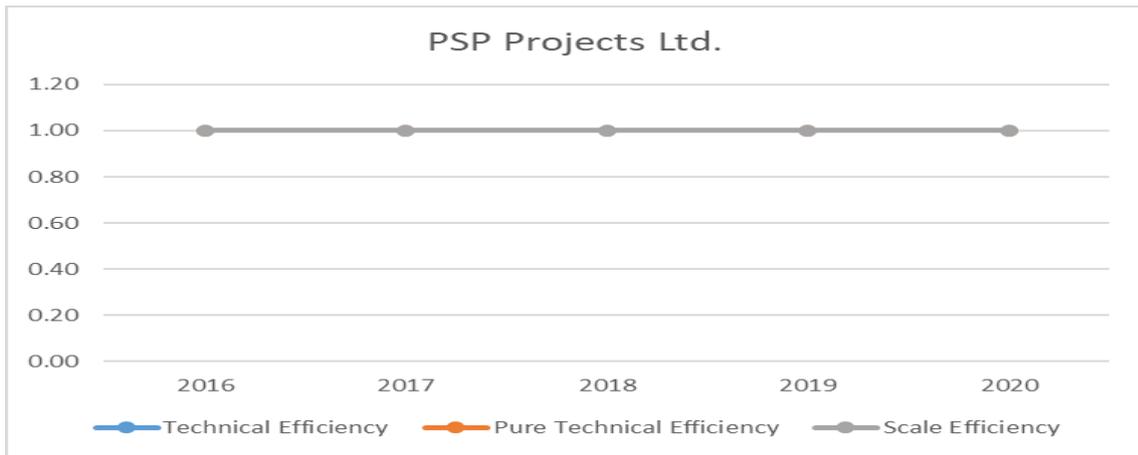


Figure 4. 34: Efficiency levels of PSP Projects Ltd. from 2016-2020

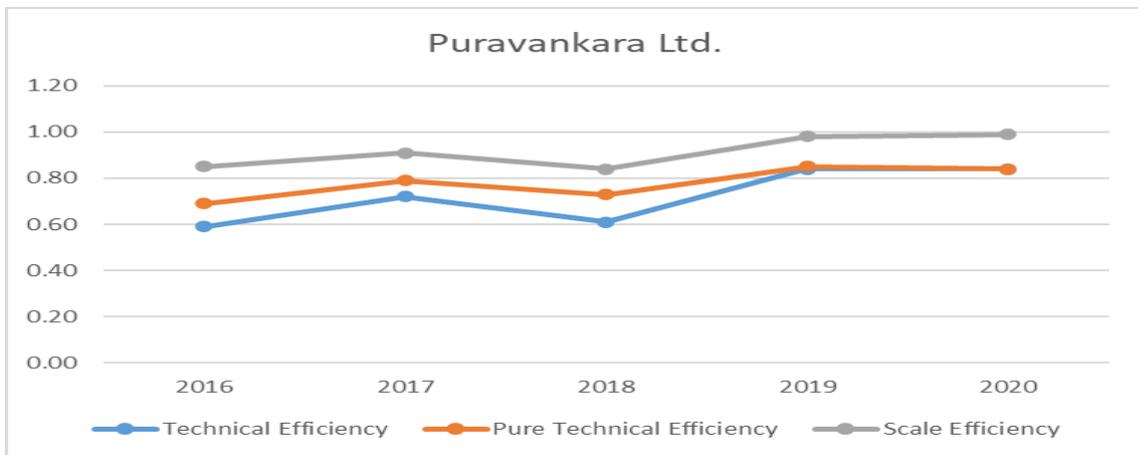


Figure 4. 35: Efficiency levels of Puravankara Ltd. from 2016-2020

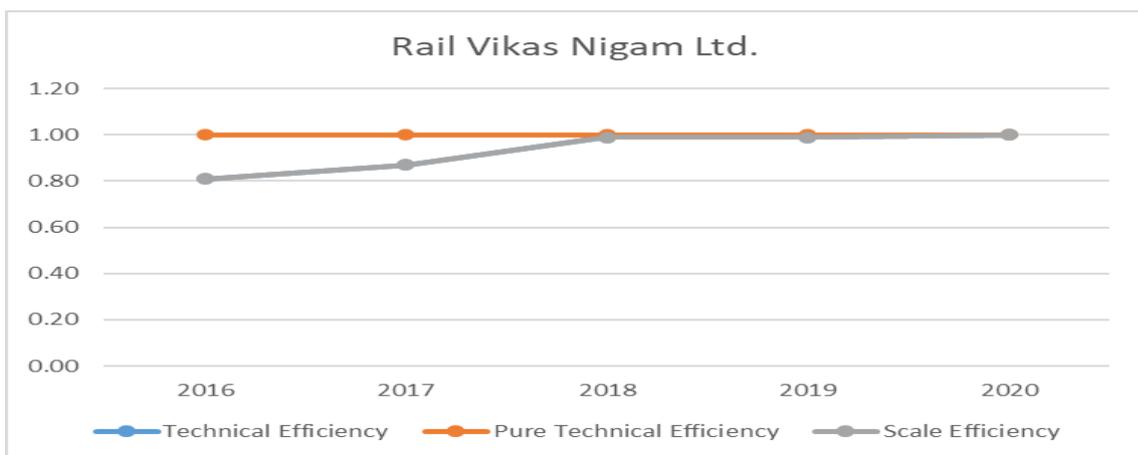


Figure 4. 36: Efficiency levels of Rail Vikas Nigam Ltd. from 2016-2020

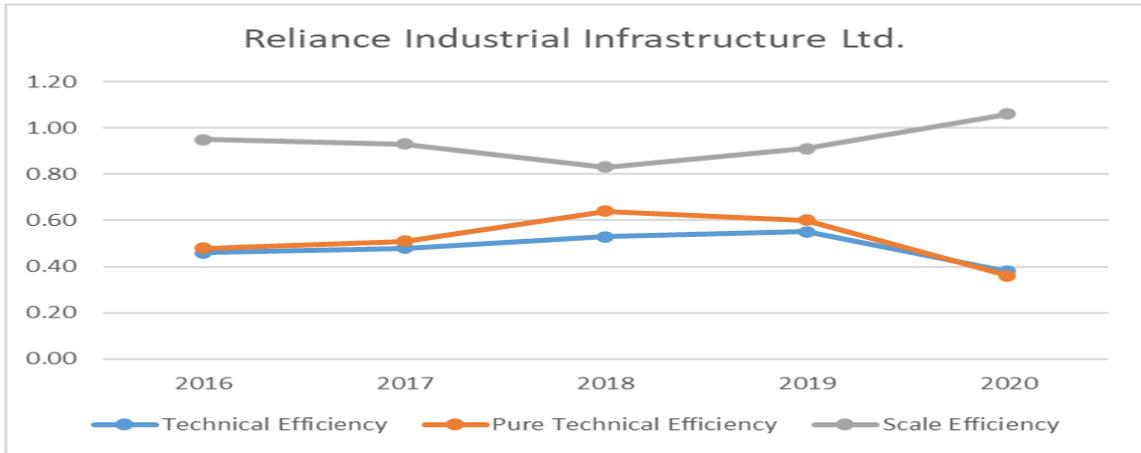


Figure 4. 37: Efficiency levels of Reliance Industrial Infrastructure Ltd. from 2016-2020

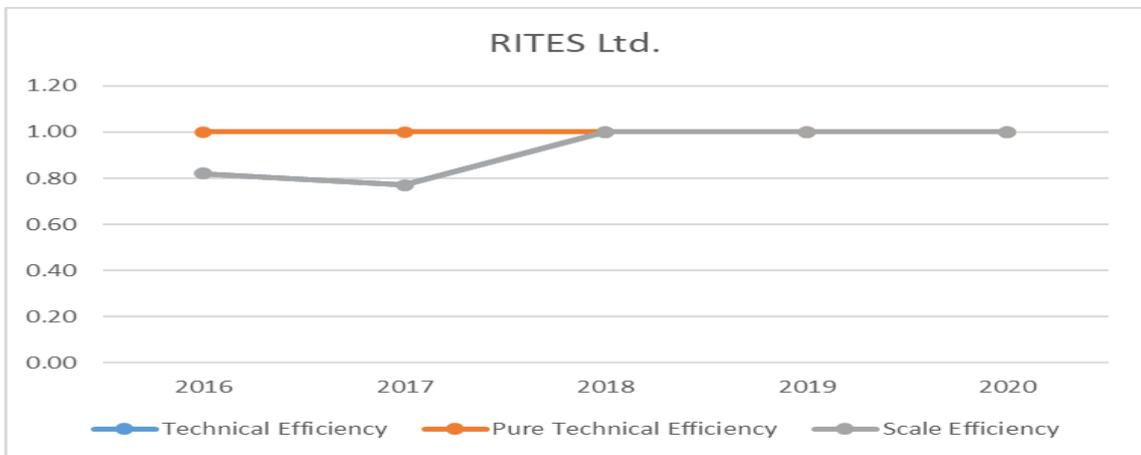


Figure 4. 38: Efficiency levels of RITES Ltd. from 2016-2020

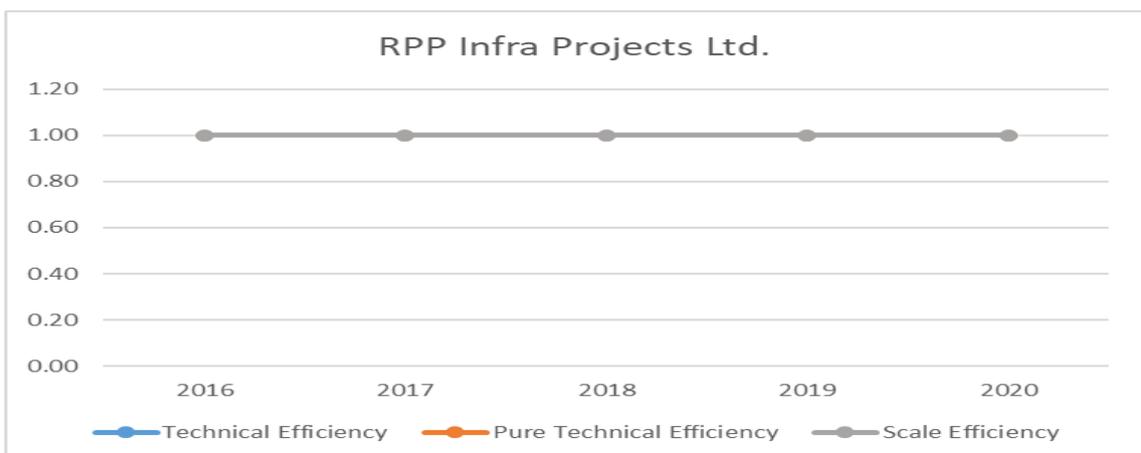


Figure 4. 39: Efficiency levels of RPP Infra Projects Ltd. from 2016-2020

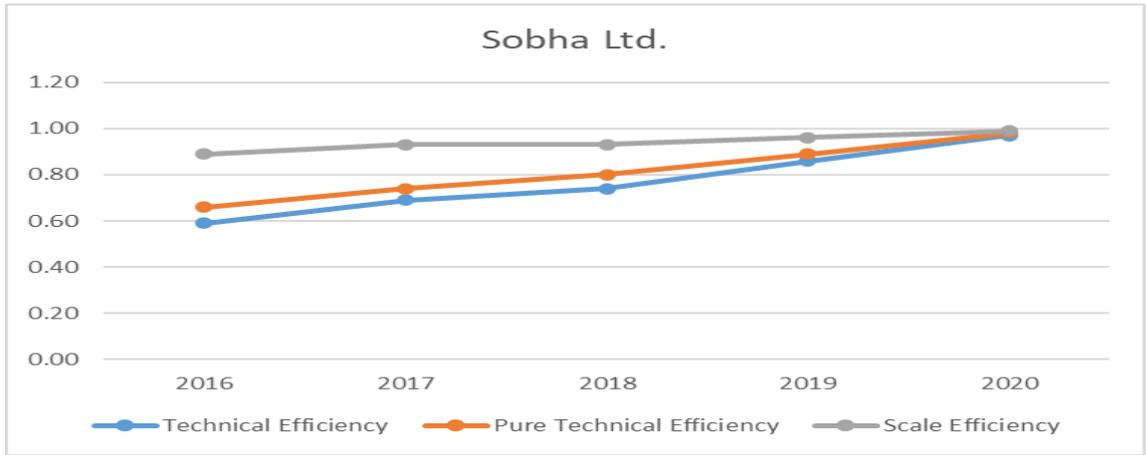


Figure 4. 40: Efficiency levels of Sobha Ltd. from 2016-2020

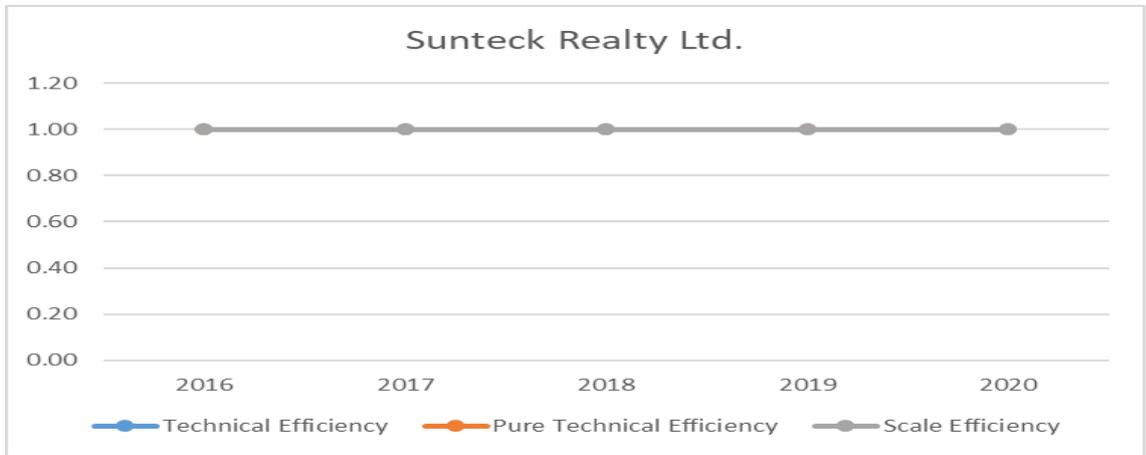


Figure 4. 41: Efficiency levels of Suntech Realty Ltd. from 2016-2020

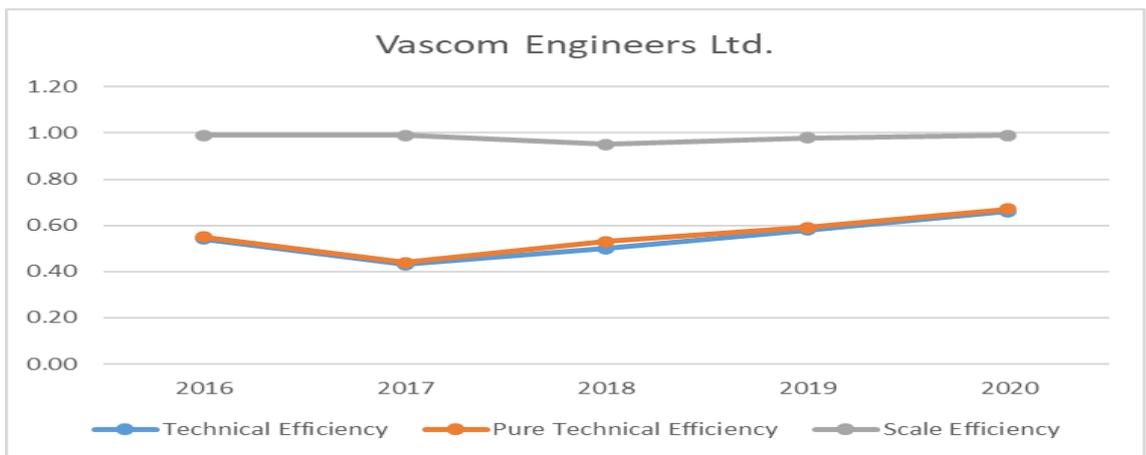


Figure 4. 42: Efficiency levels of Vascom Engineers Ltd. from 2016-2020

4.4. Future Projections

The results obtained through DEA models provide definite values of the slack variables. These slack variables exemplify the residual portions of inefficiencies after proportionate diminutions in inputs and outputs. Thus, the companies can reach an efficient frontier by managing the slacks appropriately. The input slacks denote the portion of inputs that are not utilized efficiently, and the output slacks symbolize the under-produced outputs. In the short run, companies may operate in IRS or DRS. However, the companies will try to function in CRS by expanding or contracting their sizes in the long run, as CRS signifies the maximum average output and minimum average input consumption.

In order to measure efficiency, three input variables, namely, Materials consumed, Employee Benefit Expenses, and Capital Investment, and two output variables – Operating Revenues and Profit After Tax (PAT) have been considered. On the basis of performance for the financial year ending 2020, benchmark targets based on DEA–CCR (Charnes, Cooper and Rhodes) model have been provided to the inefficient companies that they should focus upon to attain the efficiency level. The Table 4.14. and Table 4.15. below give the present and target inputs and outputs derived from the CCR model for all nineteen inefficient companies.

The outcomes from the model provide valuable insights to the companies regarding the operating, financing, and investing policies. From the TE scores, we can recognize that companies with a score less than 1 have the potential and scope to perform better. The TE of the oil and gas companies was found in the range of score of 0.38 to 1. The efficiency score of x implies the company is producing $(1-x)$ percent less than the efficient production level.

Most of the construction sector companies appear to have effectively utilized the capital invested. Except 2 companies, none of the companies are suggested to reduce the capital investment. As far as employee benefit expenses are concerned, the companies' actual level and target level have been shown in Tables 4.14. and 4.15., respectively, along with other input and output variables. Revenue enhancement is one of the main objectives of the companies as it positively affects the company's overall performance. Therefore, all the technically inefficient companies are required to increase the operating revenues. Reliance Industrial Infrastructure Ltd., Vascom Engineers Ltd., GeeCee Ventures Ltd., Capacite Infra Ltd., and Arvind SmartSpaces Ltd. have to increase the revenues by 174.24, 48.99, 35.80, 28.42, and 23.18 percent, respectively, which is an achievable target. Along with increasing revenues, Reliance Industrial Infrastructure Ltd., Vascom Engineers Ltd., GeeCee Ventures Ltd., Capacite Infra Ltd., and Arvind SmartSpaces Ltd. have to focus on increasing PAT by 174.24 percent, 69.21 percent, 35.80 percent, 82.44 percent, and 23.18 percent, respectively. Ahluwalia Contracts India Ltd., Ajmera Realty and Infra India Ltd., Anant Raj Ltd., J Kumar Infraprojects Ltd., NCC Ltd., and Puravankara Ltd. also need to focus on ways to increase PAT by 178.50 percent, 152.54 percent, 275.23 percent, 63.60 percent, 45.09 percent, and 355.15 percent, respectively.

Table 4. 14: Input and Output levels of inefficient companies for the year 2020 (in Crores)

DMU	Materials Consumed	Employee Benefit Expenses	Capital Investment	Operating Revenues	PAT
Ahluwalia Contracts India Ltd.	1577.59	154.32	924.07	1868.67	64.44
Ajmera Realty and Infra India Ltd.	196.41	25.13	1401.71	322.62	28.22
Anant Raj Ltd.	340.20	10.67	3609.10	408.36	27.33
Arvind SmartSpaces Ltd.	104.01	12.84	344.82	151.34	19.38
Brigade Enterprises Ltd.	1237.14	121.39	4161.83	1845.12	260.80
Capacite Infra Ltd.	1135.00	137.03	1398.58	1528.74	90.92
Engineers India Ltd.	1915.65	844.36	2359.88	3203.05	430.24
GeeCee Ventures Ltd.	18.76	4.35	415.87	42.67	15.19
Godrej Properties Ltd.	1335.84	152.43	5048.55	1747.05	312.82
IRCON International Ltd.	4464.54	261.37	6740.84	5202.45	489.78

J Kumar Infraprojects Ltd.	2242.92	298.70	1976.19	2970.54	183.58
KNR Constructions Ltd.	1631.95	125.22	1821.98	2244.24	225.22
Kolte-Patil Developers Ltd.	519.91	46.19	1094.88	712.26	64.20
NCC Ltd.	6753.42	435.23	5363.33	8218.80	382.04
Prestige Estates Projects Ltd.	2147.10	209.40	6881.30	3355.80	262.40
Puravankara Ltd.	921.21	88.07	1733.35	1271.36	30.51
Reliance Industrial Infrastructure Ltd	50.27	22.18	350.59	79.80	9.26
Sobha Ltd.	2402.41	246.42	2491.75	3800.51	289.48
Vascom Engineers Ltd.	278.75	42.18	843.12	366.00	38.14

Table 4. 15: Target Input and Output levels of inefficient companies (in Crores)

DMU	Materials consumed	Employee Benefit Expenses	Capital Investment	Operating Revenues	PAT
Ahluwalia Contracts India Ltd.	1577.59	154.32	924.07	2227.26	179.47
Ajmera Realty and Infra India Ltd.	196.41	25.13	1401.71	396.57	71.27
Anant Raj Ltd.	340.20	10.67	1919.46	463.82	102.55
Arvind Smart Spaces Ltd.	104.01	12.84	344.82	186.42	23.87
Brigade Enterprises Ltd.	1237.14	121.39	4161.83	2008.17	283.85
Capacite Infra Ltd.	1135.00	137.03	1398.58	1963.24	165.88
Engineers India Ltd.	1915.65	414.64	2359.88	3252.81	436.92
GeeCee Ventures Ltd.	18.76	4.35	415.87	57.94	20.63
Godrej Properties Ltd.	1335.84	152.43	5048.55	2035.92	364.54
IRCON International Ltd.	4464.54	261.37	6740.84	5580.79	525.40
J Kumar Infraprojects Ltd.	2242.92	298.70	1976.19	3647.83	300.33
KNR Constructions Ltd.	1631.95	125.22	1821.98	2268.74	227.68
Kolte-Patil Developers Ltd.	519.91	46.19	1094.88	836.10	79.43
NCC Ltd.	6753.42	435.23	5363.33	8750.69	554.30
Prestige Estates Projects Ltd.	2147.10	209.40	2856.65	3477.22	285.07
Puravankara Ltd.	921.21	88.07	1733.35	1504.55	138.86
Reliance Industrial Infrastructure Ltd.	50.27	22.18	350.59	218.84	25.39
Sobha Ltd.	2402.41	246.42	2491.75	3874.63	302.53
Vascom Engineers Ltd.	278.75	42.18	843.12	545.31	64.54

4.5. Malmquist Productivity Index

As discussed earlier, the DEA method delivers an outline of the operation of the Indian construction sector across the companies in the data set. However, the efficiency measures calculated using DEA reflect the static performance and show the performance at a particular time point. To evaluate the Indian construction sector's performance over

time, the DEA-based Malmquist Productivity Index approach has been adopted. This section unveils the change in productivity and classification of such productivity change for the years 2016-2020. Table 4.16. displays the annual MPIs and their components for the Indian Construction Sector for the year 2016-2020. The Malmquist index averages are based on geometric means. The values greater than 1 indicate improvement and progress in productivity during the period and vice versa. Value 1 depicts no alteration in total factor productivity. Table 4.16. results show that the TFP of Indian construction sector companies declined for the year 2016-17 and then increased for three consecutive years, i.e., 2017-18. 2018-19 and 2019-20. The mean value of TFP came out to be 1.001, which implies a slight increase in the productivity performance during the period considered in the study. The product of technological change and technical efficiency change yields the total factor productivity change.

Further, the product of pure technical efficiency changes and scale efficiency changes yields the technical efficiency change. From Table 4.16., we can find that the score of technical efficiency change for the period 2016-17 is 0.982, which is the product of the score of pure technical efficiency change of 0.977 and scale efficiency change score of 1.005. However, the decline in technological change with a score of 0.987 makes the total factor productivity change score 0.969. Similarly, various scores have been depicted.

Table 4. 16: Annual MPIs and their components for the Indian Construction Sector (Year 2016-2020)

Year	Change in Technical Efficiency	Technological Change	Pure Technical Change	Scale Efficiency Change	Total Factor Productivity Change
2016-17	0.982	0.987	0.977	1.005	0.969
2017-18	1.032	0.973	1.018	1.013	1.005
2018-19	1.005	1.010	1.010	0.994	1.015
2019-20	0.998	1.019	0.992	1.006	1.017
Mean	1.004	0.997	0.999	1.005	1.001

Table 4.17. contains the Malmquist Productivity Index (MPI) summary of all companies undertaken in the study, which incorporates the mean productivity scores of individual companies for the study period. The mean scores of various efficiency change scores have been included at the end of the table. From the scores, it can be concluded that Sunteck Realty Ltd. has the highest TFP change attributed to the change in technical efficiency. Marathon Nextgen Realty Ltd. has the lowest TFP change score because of its low technical efficiency score. The mean technological change score is 0.972. Overall, the construction companies need to invest more in technology and development alongside proficient operations scale to achieve productivity improvement and efficiency.

Table 4. 17: MPI Summary of Indian Construction Sector

Sl.	DMU	Change in Technical Efficiency	Technological Change	Pure Technical Change	Scale Efficiency Change	Total Factor Productivity Change
1	AGI Infra Ltd.	1.002	0.975	1.000	1.002	0.976
2	Ahluwalia Contracts India Ltd.	0.994	0.984	0.995	0.999	0.978
3	Ajmera Realty and Infra India Ltd.	0.991	1.002	0.986	1.005	0.993
4	AMJ Land Ltd.	1.158	0.995	1.000	1.158	1.153
5	Anant Raj Ltd.	1.028	1.007	1.026	1.002	1.035
6	Arvind Smart Spaces Ltd.	1.018	1.003	1.000	1.018	1.022
7	Ashoka Buildcon Ltd.	0.984	1.013	0.985	1.000	0.997
8	Brigade Enterprises Ltd.	0.997	1.008	0.999	0.998	1.006
9	Capacite Infra Ltd.	0.977	1.010	0.975	1.001	0.986
10	Cera Sanitaryware Ltd.	0.969	1.022	0.968	1.001	0.991
11	Dilip Buildcon Ltd.	0.994	1.013	0.996	0.998	1.007
12	Engineers India Ltd.	1.000	0.989	1.000	1.000	0.989
13	GeeCee Ventures Ltd.	1.031	1.000	1.032	0.999	1.030
14	Godrej Properties Ltd.	0.966	1.005	0.969	0.997	0.972
15	GPT Infra Projects Ltd.	0.968	1.024	1.000	0.968	0.990

16	IRB Infrastructure Developers Ltd.	0.982	1.004	0.982	1.000	0.986
17	IRCON International Ltd.	0.991	1.011	0.99	1.001	1.003
18	J Kumar Infraprojects Ltd.	1.005	1.014	1.005	1.000	1.019
19	Kajaria Ceramics Ltd.	0.987	1.001	0.971	1.016	0.987
20	Karda Construction Ltd.	0.981	1.009	1.001	0.979	0.989
21	Kec International Ltd.	1.000	0.936	1.000	1.000	0.936
22	KNR Constructions Ltd.	0.976	1.013	0.977	0.999	0.989
23	Kolte-Patil Developers Ltd.	0.992	1.007	0.987	1.005	0.999
24	Larsen & Toubro Ltd.	0.996	1.012	1.000	0.996	1.009
25	Man Industries Ltd.	1.000	1.021	0.999	1.001	1.021
26	Marathon Nextgen Realty Ltd.	0.779	0.896	0.79	0.987	0.698
27	NBCC India Ltd.	1.000	1.012	1.000	1.000	1.012
28	NCC Ltd.	0.969	0.996	0.976	0.993	0.965
29	Nila Infrastructures Ltd.	1.006	1.006	0.992	1.014	1.012
30	Oberoi Realty Ltd.	0.970	0.998	0.971	0.998	0.967
31	Phoenix Mills Ltd.	1.068	0.994	1.061	1.007	1.062
32	PNC Infratech Ltd.	0.981	1.012	0.982	0.999	0.993
33	Prestige Estates Projects Ltd.	0.963	1.005	0.964	0.999	0.968
34	PSP Projects Ltd.	0.988	0.925	1.000	0.988	0.913
35	Puravankara Ltd.	1.061	0.988	1.061	1.000	1.048
36	Rail Vikas Nigam Ltd.	0.996	1.010	1.000	0.996	1.006
37	Reliance Industrial Infrastructure Ltd.	1.055	0.996	1.036	1.018	1.051
38	RITES Ltd.	1.020	0.962	1.021	0.999	0.981
39	RPP Infra Projects Ltd.	1.003	1.029	1.003	1.001	1.032
40	Sobha Ltd.	0.972	1.015	0.971	1.001	0.987
41	Sunteck Realty Ltd.	1.530	0.993	1.429	1.071	1.519
42	Vascom Engineers Ltd.	0.976	0.978	0.978	0.998	0.954
	Mean	1.004	0.997	0.999	1.005	1.001

4.6. Comparison using Super-Efficiency DEA Models

Table 4.18. presents the efficiency scores obtained by employing different Super-Efficiency DEA Models for the year 2019-20. The Super-Efficiency DEA models have been classified as Radial-Based and Slack-Based models. The scores obtained for various classified models have been shown in the table in which the scores of the efficient units are 1 or more than 1 while the scores of inefficient units lie below 1. The units having higher super-efficiency scores are ranked higher among the efficient units and vice-versa. In Radial-Based model, CCR-Input Oriented and CCR-Output gives the same efficiency scores, so there is a single column in the table for the scores of both these models. Based on the rule of thumb, the units having super-efficiency scores higher than 3 are considered outliers.

Among the various models of Super-Efficiency, SSBM-V-NO model i.e., Slack-based super-efficiency model under the assumptions of Variable returns and Non-Orientation has been considered as most suitable in our study considering that the companies generally face variable returns to scale situation. Also, no particular orientation towards only output escalation or input reduction gives a room to the companies to operate in both the direction. Larsen and Toubro Ltd. has the highest score of 6.78. It has been considered as an outlier. The next highest score is 2.59 which is of AMJ Land Ltd. which depicts its most efficient performance in the year 2019-20.

Similarly, Table 4.20. shows the Super-Efficiency Scores based on SSBM-V-NO model for the year 2015-2016 to 2019-2020.

Table 4.19. presents the descriptive statistics of the efficiency scores for all the Super-Efficiency models for the last year 2019-20. It includes the maximum score, minimum

score, mean score, median score, standard deviation and co-efficient of variation in the scores.

Table 4. 18: Super Efficiency Scores for the year 2019-20 obtained by employing different Super- Efficiency DEA Models

Sl. No.	Decision Making Units	SSBM-C-I	SSBM-C-O	SSBM-V-I	SSBM-V-O	SSBM-C-NO	SSBM-V-NO	S-CCR-I	S-BCC-I	S-BCC-O
1	AGI Infra Ltd.	0.81	0.94	1.07	1.33	0.81	1.07	0.95	1.17	1.56
2	Ahluwalia Contracts India Ltd.	0.69	0.42	0.72	0.45	0.39	0.43	0.82	0.83	0.83
3	Ajmera Realty and Infra India Ltd.	0.66	0.43	0.67	0.47	0.45	0.45	0.81	0.81	0.81
4	AMJ Land Ltd.	1.19	1.16	3.22	1.00	1.16	2.59	1.39	3.92	1.00
5	Anant Raj Ltd.	0.59	0.36	0.61	0.38	0.30	0.31	0.87	0.88	0.88
6	Arvind SmartSpaces Ltd.	0.72	0.69	0.74	0.73	0.74	0.71	0.79	0.82	0.81
7	Ashoka Buildcon Ltd.	0.85	0.90	1.04	1.03	0.85	1.02	0.95	1.06	1.05
8	Brigade Enterprises Ltd.	0.85	0.83	0.89	0.91	0.85	0.89	0.89	0.91	0.91
9	Capacite Infra Ltd.	0.67	0.55	0.67	0.57	0.53	0.53	0.77	0.78	0.77
10	Cera Sanitaryware Ltd.	1.12	1.15	1.13	1.15	1.11	1.12	1.33	1.33	1.33
11	Dilip Buildcon Ltd.	1.02	1.03	1.03	1.03	1.02	1.03	1.05	1.08	1.08
12	Engineers India Ltd.	0.77	0.93	0.81	0.98	0.77	0.81	0.94	0.98	0.98
13	GeeCee Ventures Ltd.	0.74	0.78	0.91	0.82	0.74	0.78	0.76	0.97	0.73
14	Godrej Properties Ltd.	0.74	0.74	0.82	0.85	0.76	0.82	0.78	0.83	0.85
15	GPT Infra Projects Ltd.	0.86	0.43	1.02	0.50	0.42	1.02	0.93	1.07	1.13
16	IRB Infrastructure Developers Ltd.	1.01	1.01	1.01	1.02	1.01	1.01	1.03	1.04	1.03
17	IRCON International Ltd.	0.69	0.72	0.84	0.91	0.70	0.83	0.84	0.92	0.93
18	J Kumar Infraprojects Ltd.	0.69	0.58	0.72	0.65	0.56	0.64	0.78	0.80	0.81
19	Kajaria Ceramics Ltd.	1.06	1.06	1.14	1.11	1.06	1.09	1.07	1.36	1.24
20	Karda Construction Ltd.	0.94	0.71	1.04	0.72	0.89	1.04	0.98	1.08	1.09
21	Kec International Ltd.	1.02	1.02	1.32	1.49	1.01	1.30	1.05	1.88	1.72
22	KNR Constructions Ltd.	0.90	0.93	0.97	0.98	0.90	0.97	0.97	0.98	0.98
23	Kolte-Patil Developers Ltd.	0.70	0.67	0.72	0.73	0.70	0.69	0.85	0.85	0.85
24	Larsen & Toubro Ltd.	0.65	0.72	1.00	6.78	0.63	6.78	0.79	1.00	8.45

25	Man Industries Ltd.	1.00	0.72	1.00	0.72	1.00	1.00	1.00	1.00	1.00
26	Marathon Nextgen Realty Ltd.	1.14	1.32	1.25	2.09	1.14	1.25	1.35	1.70	2.17
27	NBCC India Ltd.	0.87	0.27	1.05	1.04	0.26	1.04	0.91	1.09	1.08
28	NCC Ltd.	0.75	0.56	0.77	0.74	0.52	0.73	0.87	0.93	0.93
29	Nila Infrastructures Ltd.	0.90	0.91	1.01	0.90	0.91	1.01	0.95	1.01	1.02
30	Oberoi Realty Ltd.	1.03	1.03	2.43	1.34	1.03	1.33	1.06	3.57	1.81
31	Phoenix Mills Ltd.	1.10	1.06	1.16	1.11	1.06	1.11	1.14	1.27	1.26
32	PNC Infratech Ltd.	0.82	0.88	1.01	1.02	0.82	1.01	0.93	1.02	1.02
33	Prestige Estates Projects Ltd.	0.75	0.64	0.75	0.85	0.64	0.73	0.91	0.96	0.96
34	PSP Projects Ltd.	1.51	1.62	1.47	1.64	1.47	1.47	1.85	1.85	1.90
35	Puravankara Ltd.	0.67	0.25	0.69	0.28	0.27	0.28	0.84	0.84	0.84
36	Rail Vikas Nigam Ltd.	1.22	1.24	1.79	1.76	1.19	1.67	1.36	3.32	1.85
37	Reliance Industrial Infrastructure Ltd.	0.40	0.42	0.52	0.43	0.40	0.38	0.38	0.64	0.36
38	RITES Ltd.	1.37	1.21	2.06	1.30	1.21	1.26	1.54	2.75	1.89
39	RPP Infra Projects Ltd.	1.01	0.67	1.13	1.13	1.00	1.12	1.01	1.22	1.30
40	Sobha Ltd.	0.96	0.91	0.96	0.95	0.90	0.95	0.97	0.98	0.98
41	Sunteck Realty Ltd.	1.30	1.38	1.37	1.42	1.30	1.31	1.91	1.92	1.91
42	Vascom Engineers Ltd.	0.56	0.54	0.57	0.58	0.57	0.56	0.66	0.67	0.67

Table 4. 19: Descriptive Statistics for the Super Efficiency Scores for the year 2019-20

Descriptive Statistics	SSB M-C-I	SSB M-C-O	SSB M-V-I	SSB M-V-O	SSB M-C-NO	SSB M-V-NO	S-CC R-I	S-BC C-I	S-BC C-O
Mean	0.89	0.82	1.07	1.09	0.81	1.10	1.00	1.29	1.30
Max.	1.51	1.62	3.22	6.78	1.47	6.78	1.91	3.92	8.45
Min.	0.40	0.25	0.52	0.28	0.26	0.28	0.38	0.64	0.36
SD	0.23	0.31	0.50	0.96	0.29	0.97	0.29	0.75	1.18
CV	0.26	0.38	0.47	0.88	0.36	0.89	0.28	0.59	0.91
Median	0.86	0.81	1.01	0.97	0.84	1.01	0.95	1.01	1.01
No. of efficient units	15	15	23	23	15	23	15	23	23

Table 4. 20: Super Efficiency Scores based on SSBM-V-NO for the year 2016 to 2020

Sl.	Decision Making Units	2016	2017	2018	2019	2020
1	AGI Infra Ltd.	1.12	1.13	1.05	1.00	1.07
2	Ahluwalia Contracts India Ltd.	0.58	0.63	0.86	0.69	0.43
3	Ajmara Realty and Infra India Ltd.	0.22	0.41	0.73	0.49	0.45
4	AMJ Land Ltd.	3.66	2.15	2.33	2.91	2.59
5	Anant Raj Ltd.	0.25	0.29	0.27	0.18	0.31
6	Arvind SmartSpaces Ltd.	0.60	0.52	0.64	1.02	0.71
7	Ashoka Buildcon Ltd.	0.63	0.62	0.70	0.69	1.02
8	Brigade Enterprises Ltd.	0.44	0.56	0.58	0.67	0.89
9	Capacite Infra Ltd.	0.58	0.65	0.49	0.56	0.53
10	Cera Sanitaryware Ltd.	1.00	1.05	1.13	1.14	1.12
11	Dilip Buildcon Ltd.	1.20	1.25	1.29	1.25	1.03
12	Engineers India Ltd.	0.48	1.17	1.17	0.80	0.81
13	GeeCee Ventures Ltd.	1.03	1.27	1.16	0.82	0.78
14	Godrej Properties Ltd.	0.11	0.66	0.68	0.54	0.82
15	GPT Infra Projects Ltd.	0.34	0.34	1.00	1.04	1.02
16	IRB Infrastructure Developers Ltd.	1.36	1.05	1.04	1.04	1.01
17	IRCON International Ltd.	0.60	0.68	0.55	0.56	0.83
18	J Kumar Infraprojects Ltd.	0.55	0.49	0.50	0.61	0.64
19	Kajaria Ceramics Ltd.	1.44	1.42	1.16	1.09	1.09
20	Karda Construction Ltd.	1.34	1.23	1.22	1.11	1.04
21	Kec International Ltd.	1.12	1.06	1.16	1.05	1.30
22	KNR Constructions Ltd.	0.86	0.88	1.15	1.04	0.97
23	Kolte-Patil Developers Ltd.	0.16	0.55	0.84	0.63	0.69
24	Larsen & Toubro Ltd.	10.84	11.99	9.12	9.00	6.78
25	Man Industries Ltd.	0.82	0.41	0.88	1.04	1.00
26	Marathon Nextgen Realty Ltd.	1.18	1.20	1.11	1.07	1.25
27	NBCC India Ltd.	1.30	1.23	1.03	1.23	1.04
28	NCC Ltd.	1.09	1.01	0.51	1.05	0.73
29	Nila Infrastructures Ltd.	0.53	1.06	1.04	0.95	1.01

30	Oberoi Realty Ltd.	1.48	1.22	1.47	1.50	1.33
31	Phoenix Mills Ltd.	1.06	1.07	1.06	1.00	1.11
32	PNC Infratech Ltd.	0.94	0.68	0.71	0.74	1.01
33	Prestige Estates Projects Ltd.	0.69	1.16	0.51	0.62	0.73
34	PSP Projects Ltd.	1.62	1.43	1.11	1.18	1.47
35	Puravankara Ltd.	0.26	0.44	0.41	0.47	0.28
36	Rail Vikas Nigam Ltd.	1.04	1.05	1.01	1.08	1.67
37	Reliance Industrial Infrastructure Ltd.	0.30	0.34	0.51	0.35	0.38
38	RITES Ltd.	1.09	1.04	1.01	1.16	1.26
39	RPP Infra Projects Ltd.	1.12	1.10	1.27	1.18	1.12
40	Sobha Ltd.	0.37	0.45	0.53	0.81	0.95
41	Sunteck Realty Ltd.	2.22	1.81	1.40	1.70	1.31
42	Vascom Engineers Ltd.	0.07	0.04	0.17	0.19	0.56

CHAPTER 5

CONCLUSION

Chapter 5

Conclusion

India has emerged as the fastest-growing major economy in the world and is expected to be one of the top three economic powers in the world over the next 10-15 years, backed by its robust democracy and strong partnerships (IBEF, <https://www.ibef.org/economy/indian-economy-overview>). The preceding discussion highlights that the Indian construction sector has been a major driving force of India's economy. The industry is responsible for boosting the overall growth and development of India. The government has increased its focus on improving the construction sector's growth potential. It has received priority treatment from the government in the Union Budget for the fiscal year 2020-21. The Finance Minister of India laid down the foundation for increasing consumption while ensuring that the government's investment is deployed to build infrastructure leading to a USD 5 trillion economy by Fiscal 2024-25. In addition, the Indian government announced a number of initiatives aimed at assisting all sections of society in cushioning the impact and threats posed by the COVID-19 pandemic. Construction, being the second largest employer after agriculture, has seen a number of structural changes in the recent decade. The government has responded positively to the industry's concerns and requests.

Data Envelopment Analysis has wide applications in the solution of real-world decision-making problems. Performance measurement methods can assist the organizations in evaluating their resource allocation and managing such resources for value-adding activities. DEA method helps in identifying the areas where resources need more careful allocation. We substantiated our argument for DEA over ratios or regression analysis

since DEA performs better than ratios or regression in handling multiple output-input scenarios. This study used three input variables (Materials consumed, Employee Benefit Expenses, and Capital Investment) and two output variables (Operating Revenues and Profit After Tax (PAT)) for efficiency measurement. The goal of this dissertation was to map the Technical, Pure Technical, and Scale Efficiencies of 42 Indian construction sector companies, to measure the deviations in the various efficiency levels of the companies over the five years, to analyze the reasons for the changes in efficiency levels: total factor productivity change, technological change and technical efficiency change; and to assign reference set to relatively less efficient companies to improve the efficiency level for the FY period 2015-16 to 2019-20. Our empirical findings show that a larger number of Indian construction sector companies were Pure Technically Efficient than Scale Efficient over the period of study, i.e., 2015-16 to 2019-20. Five firms, namely Dilip Buildcon Ltd., IRB Infrastructure Developers Ltd., PSP Projects Ltd., RPP Infra Projects Ltd., and Sunteck Realty Ltd., were technically efficient throughout the study period.

Seventeen firms were pure technically efficient, and 6 firms were scale efficient. The relative efficiency score of the companies is based on how optimally input variables are used to generate output variables. The low-efficiency score implies either more use of input variables than the target level or low generation of output variables than the target level or both. All the technically inefficient companies are required to increase the operating revenues. The results obtained through a combination of the Malmquist Productivity Index (MPI) and Super-Efficiency DEA Models are found to be robust. Total Factor Productivity of Indian construction sector companies declined for the year 2016-17 and then increased for three consecutive years, i.e., 2017-18, 2018-19 and 2019-20.

Overall, the construction companies need to invest more in technology and development alongside proficient operations scale to achieve productivity improvement and efficiency.

Contributions

The following points can acknowledge the contribution of this study:

- This study provided a more holistic view of Indian Construction sector companies than the traditional ratio-based measures.
- This study applied non-parametric techniques to estimate the Technical, Pure Technical, and scale efficiency of Indian construction sector companies.
- The study covered a period of five years to analyse the deviations in the efficiency scores.
- The study analyzed the reasons for the change in the efficiency scores by using Malmquist Productivity Index.
- Super efficiency DEA models have been used in the study to check the relative performance of the efficient companies.
- Relatively less efficient companies have been provided targets for the improvement in performance and efficiency scores.

Limitations

The study conducted has certain limitations which can be listed as –

- This study was limited to Indian context only, and it can be extended to evaluate the comparative construction sector performance analysis of different countries.
- To validate the relevance and reliability of the efficiencies criteria found in this study, a series of in-depth case studies on diverse public and private projects should be conducted in the future in other nations.

- The duration of the present study was not sufficient to analyze the dynamic relation of PTE, TE, and SE with environmental factors that influence the efficiency.
- Also, the number of Indian construction sector companies and the number of variables were important factors in the DEA approach.

CHAPTER 6

RESEARCH IMPLICATIONS AND FUTURE SCOPE

Research Implications and Future Scope

The present study has practical as well as managerial implications. Considering the crucial role of the construction sector in Indian economy, it is important to keep a check on the performance of the companies present as well as the sector as a whole. The study has covered the analysis of 42 profit companies of this sector for a period of five years to check the levels of efficiency and to analyze the deviations in the efficiency levels over the study period.

The findings of the study provide an insight to the managers of the companies to check the performance of the company in comparison to other companies which have been included in the study. The analysis of the efficiency over the period of five years provides the deviations in the performance levels which can be used by the managers to identify the factors contributing to the optimal or non-optimal performance of the company in a year. In addition to the efficiency levels, targets have been assigned to the relatively less efficient companies on the basis of the performance in the year ending 31st March, 2020. The targets which include an increase in output levels and decrease in input levels should aimed to be achieved by the companies and managers should plan a strategy to improve the level of efficiency. In addition, the managers of the companies need to make the plans which can be adjusted according to the change in external factors. For instance, during the recent pandemic, various restrictions were imposed resulting into decline in production and economic slowdown. The managers need to periodically analyze the performance level and keep on working for the continuous improvement to fulfil the objectives of the company and meet the expectations of the stakeholders.

The industry's strategy for the future is to adapt its activities to the changing environment. Efficient use of technology, optimum use of available digital tools and platforms, and innovation and designing of custom-made tools should cater to the changing needs and challenges. As India embarks on a range of initiatives to boost its construction sector, it is important to recognize that a particular focus on the construction sector alone would not be sufficient. A holistic framework needs to be adopted that recognizes the interdependence between construction and other sectors of the economy. In this regard, less stringent regulatory reforms and FDI liberalization can help in providing the desired momentum. Also, a growing, competitive, and vibrant construction sector would create new employment opportunities and would strengthen India's overall growth.

Apart from its comprehensiveness, this study has various future scopes. Some of the future scopes of the present study are –

- The study has employed only a part of the frontier approach, i.e., Non-parametric in efficiency estimation. Other parametric and non-parametric techniques could also be used to check the empirical results.
- This study could be extended by using different sets (either increase or decrease) of construction companies and variables in the present DEA modeling.
- The analysis can be extended by classifying the companies on the basis of ownership, size, capitalization or other factors.
- The study can be further extended to evaluate the construction sector performance analysis of the companies of different countries.
- The efficiency analysis can be done for pre-period and post-period of a major event or crisis to measure the impact of the event on the efficiency. For instance, COVID-19 outbreak happened in India in Feb 2020 which led to nationwide lockdown and countrywide restrictions. In the FY 2020-21, most of the sectors

of the economy experienced steep slowdown. Many of the restrictions continue in the FY 2021-22 also. The efficiency evaluation of the companies can be done for the period segregated into period till FY 2019-20, during pandemic period and post pandemic period to assess the multi-dimensional impact of the pandemic.

References

Notes:

Available at <http://smartcities.gov.in/content/> (accessed on 24 October, 2020)

Available at <https://pmaymis.gov.in/> (accessed on 24 October, 2020)

Available at https://www.makeinindia.com/sector/construction_ (accessed on 25 October, 2020)

Available at <http://amrut.gov.in/content/> (accessed on 26 October, 2020)

¹ <https://www.investindia.gov.in/sector/construction> (accessed on 7 April 2021)

² <https://www.maiervidorno.com/industry-expertise/construction/#:~:text=India%20stands%20as%20the%20second,reach%20%24%20738.5%20billion%20by%202022> (accessed on 3 April 2021)

³ Factsheet on FDI - April 2000 to December 2020, Department for Promotion of Industry and Internal Trade, <https://dipp.gov.in/sites/default/files/FDI%20Factsheet%20December%2020.pdf>

⁴ “Department for Promotion of Industry and Internal Trade”, Consolidated FDI Policy, https://dipp.gov.in/sites/default/files/CFPC_2017_FINAL_RELEASED_28.8.17_1.pdf

⁵ Based on <https://www.ibef.org/industry/infrastructure-presentation> (accessed on 8 November 2020)

⁶ <https://pib.gov.in/PressReleasePage.aspx?PRID=1693908> (accessed on 10 May 2021)

⁷ <https://pib.gov.in/PressReleasePage.aspx?PRID=1693907> (accessed on 10 May 2021)

⁸ Expenditure Budget Profile - Centrally Sponsored Schemes, Union Budget website, <https://www.indiabudget.gov.in/doc/eb/stat4a.pdf>

⁹ Based on <https://prsindia.org/billtrack/the-national-bank-for-financing-infrastructure-and-development-bill-2021> (accessed on 9 April 2021)

¹⁰ Mahadevan, R. (2002). A DEA approach to understanding the productivity growth of Malaysia's manufacturing industries. *Asia Pacific Journal of Management*, 19(4), 587-600.

-
- ¹¹ Barros, C. P., & Alves, C. (2004). An empirical analysis of productivity growth in a Portuguese retail chain using Malmquist productivity index. *Journal of Retailing and Consumer Services*, 11(5), 269-278.
- ¹² Bassioni, H. A., Price, A. D., & Hassan, T. M. (2004). Performance measurement in construction. *Journal of management in engineering*, 20(2), 42-50.
- ¹³ Ram í rez, R. R., Alarcon, L. F. C., & Knights, P. (2004). Benchmarking system for evaluating management practices in the construction industry. *Journal of Management in Engineering*, 20(3), 110-117.
- ¹⁴ McCabe, B., Tran, V., & Ramani, J. (2005). Construction prequalification using data envelopment analysis. *Canadian Journal of Civil Engineering*, 32(1), 183-193.
- ¹⁵ Chau, K. W., Poon, S. W., Wang, Y. S., & Lu, L. L. (2005). Technological progress and the productive efficiency of construction firms in Hong Kong, 1981–2001. *Journal of Construction Research*, 6(02), 195-207.
- ¹⁶ Lee, S. H., Thomas, S. R., & Tucker, R. L. (2005). Web-based benchmarking system for the construction industry. *Journal of Construction Engineering and Management*, 131(7), 790-798.
- ¹⁷ Vitner, G., Rozenes, S., & Spraggett, S. (2006). Using data envelope analysis to compare project efficiency in a multi-project environment. *International Journal of Project Management*, 24(4), 323-329.
- ¹⁸ Iyer, K. C., & Jha, K. N. (2006). Critical factors affecting schedule performance: Evidence from Indian construction projects. *Journal of construction engineering and management*, 132(8), 871-881.
- ¹⁹ Andersen, E. S., Birchall, D., Jessen, S. A., & Money, A. H. (2006). Exploring project success. *Baltic journal of management*.
- ²⁰ Miller, S. M., Clauretíe, T. M., & Springer, T. M. (2006). Economies Of Scale And Cost Efficiencies: A Panel-Data Stochastic-Frontier Analysis Of Real Estate Investment Trusts. *The Manchester School*, 74(4), 483-499.
- ²¹ Crawford, P., & Vogl, B. (2006). Measuring productivity in the construction industry. *Building Research & Information*, 34(3), 208-219.
- ²² O'Mahony, M., & Van Ark, B. (2003). EU productivity and competitiveness: an industry perspective: can Europe resume the catching-up process?.
- ²³ Düzakın, E., & Düzakın, H. (2007). Measuring the performance of manufacturing firms with super slacks based model of data envelopment analysis: An application of

500 major industrial enterprises in Turkey. *European journal of operational research*, 182(3), 1412-1432.

²⁴ You, T., & Zi, H. (2007). The economic crisis and efficiency change: evidence from the Korean construction industry. *Applied Economics*, 39(14), 1833-1842.

²⁵ Aksorn, T., & Hadikusumo, B. H. (2008). Critical success factors influencing safety program performance in Thai construction projects. *Safety science*, 46(4), 709-727.

²⁶ Odeck, J. (2001). Comparison of data envelopment analysis and deterministic parametric frontier approaches: an application in the Norwegian road construction sector. *Transportation Planning and Technology*, 24(2), 111-134.

²⁷ Watanabe, M., & Tanaka, K. (2007). Efficiency analysis of Chinese industry: a directional distance function approach. *Energy policy*, 35(12), 6323-6331.

²⁸ Xue, X., Shen, Q., Wang, Y., & Lu, J. (2008). Measuring the productivity of the construction industry in China by using DEA-based Malmquist productivity indices. *Journal of Construction engineering and Management*, 134(1), 64-71.

²⁹ Aksorn, T., & Hadikusumo, B. H. (2008). Critical success factors influencing safety program performance in Thai construction projects. *Safety science*, 46(4), 709-727.

³⁰ Eilat, H., Golany, B., & Shtub, A. (2008). R&D project evaluation: An integrated DEA and balanced scorecard approach. *Omega*, 36(5), 895-912.

³¹ Martič, M. M., Novakovič, M. S., & Baggia, A. (2009). Data envelopment analysis-basic models and their utilization. *Organizacija*, 42(2).

³² Chan, T. K. (2009). Measuring performance of the Malaysian construction industry. *Construction Management and Economics*, 27(12), 1231-1244.

³³ Chen, Y. Q., Lu, H., Lu, W., & Zhang, N. (2010). Analysis of project delivery systems in Chinese construction industry with data envelopment analysis (DEA). *Engineering, Construction and Architectural Management*.

³⁴ Sueyoshi, T., & Goto, M. (2009). DEA-DA for bankruptcy-based performance assessment: Misclassification analysis of Japanese construction industry. *European Journal of Operational Research*, 199(2), 576-594.

³⁵ Li, Y., & Liu, C. (2010). Malmquist indices of total factor productivity changes in the Australian construction industry. *Construction management and economics*, 28(9), 933-945.

-
- ³⁶ El-Mashaleh, M. S., Rababeh, S. M., & Hyari, K. H. (2010). Utilizing data envelopment analysis to benchmark safety performance of construction contractors. *International Journal of Project Management*, 28(1), 61-67.
- ³⁷ Shi, G. M., Bi, J., & Wang, J. N. (2010). Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. *Energy policy*, 38(10), 6172-6179.
- ³⁸ Horta, I. M., Camanho, A. S., & Da Costa, J. M. (2010). Performance assessment of construction companies integrating key performance indicators and data envelopment analysis. *Journal of Construction engineering and Management*, 136(5), 581-594.
- ³⁹ El-Mashaleh, M. S. (2010). Decision to bid or not to bid: a data envelopment analysis approach. *Canadian Journal of Civil Engineering*, 37(1), 37-44.
- ⁴⁰ Tsolas, I. E. (2011). Modelling profitability and effectiveness of Greek-listed construction firms: an integrated DEA and ratio analysis. *Construction Management and Economics*, 29(8), 795-807.
- ⁴¹ Chen, K. H., & Yang, H. Y. (2011). A cross-country comparison of productivity growth using the generalised metafrontier Malmquist productivity index: with application to banking industries in Taiwan and China. *Journal of Productivity Analysis*, 35(3), 197-212.
- ⁴² Sun, C. C. (2011). Evaluating and benchmarking productive performances of six industries in Taiwan Hsin Chu Industrial Science Park. *Expert Systems with Applications*, 38(3), 2195-2205.
- ⁴³ Zheng, X., Chau, K. W., & Hui, E. C. (2011). Efficiency assessment of listed real estate companies: an empirical study of China. *International Journal of Strategic Property Management*, 15(2), 91-104.
- ⁴⁴ Al-Tmeemy, S. M. H. M., Abdul-Rahman, H., & Harun, Z. (2011). Future criteria for success of building projects in Malaysia. *International Journal of Project Management*, 29(3), 337-348.
- ⁴⁵ Balatbat, M. C., Lin, C. Y., & Carmichael, D. G. (2010). Comparative performance of publicly listed construction companies: Australian evidence. *Construction Management and Economics*, 28(9), 919-932.
- ⁴⁶ Tabish, S. Z. S., & Jha, K. N. (2011). Identification and evaluation of success factors for public construction projects. *Construction Management and Economics*, 29(8), 809-823.

-
- ⁴⁷ Abdel-Wahab, M., & Vogl, B. (2011). Trends of productivity growth in the construction industry across Europe, US and Japan. *Construction Management and Economics*, 29(6), 635-644.
- ⁴⁸ Wei, F., Li, Y., Gao, R., & Sun, J. (2011, August). Study on the evaluation model of the investment efficiency of real estate industry based on super efficiency DEA. In *International Conference on Applied Informatics and Communication* (pp. 111-118). Springer, Berlin, Heidelberg.
- ⁴⁹ de Araújo Junior, A. F., Nogueira, D. G., & Shikida, C. D. (2012). Analysis of the efficiency of national civil construction firms. *Brazilian Business Review*, 9(3), 45-70.
- ⁵⁰ Peng Wong, W., Gholipour, H. F., & Bazrafshan, E. (2012). How efficient are real estate and construction companies in Iran's close economy?. *International journal of strategic property management*, 16(4), 392-413.
- ⁵¹ Horta, I. M., Camanho, A. S., Johnes, J., & Johnes, G. (2013). Performance trends in the construction industry worldwide: an overview of the turn of the century. *Journal of Productivity Analysis*, 39(1), 89-99.
- ⁵² Chang, P. T., & Lee, J. H. (2012). A fuzzy DEA and knapsack formulation integrated model for project selection. *Computers & Operations Research*, 39(1), 112-125.
- ⁵³ Nihas, S., Barlish, K. C., & Kashiwagi, D. (2013). Construction industry structure in India. *New Delhi, India: RICS COBRA*.
- ⁵⁴ Rajaprasad, S. V. S., Rao, Y. V. S. S. V. P., & Chalapathi, P. V. (2013). Evaluation of safety performance in Indian construction segments using data envelopment analysis. *Asia Pac. J. Bus. Manage*, 4(1), 1-13.
- ⁵⁵ Amirteimoori, A., Daneshian, B., Kordrostami, S., & Shahroodi, K. (2013). Production planning in data envelopment analysis without explicit inputs. *RAIRO-Operations Research-Recherche Opérationnelle*, 47(3), 273-284.
- ⁵⁶ Tsolas, I. E. (2013). Modeling profitability and stock market performance of listed construction firms on the Athens Exchange: Two-Stage DEA Approach. *Journal of Construction Engineering and Management*, 139(1), 111-119.
- ⁵⁷ Chiang, Y. H., Li, J., Choi, T. N., & Man, K. F. (2013). Evaluating construction contractors' efficiency in Hong Kong using data envelopment analysis assurance region model. *Journal of facilities Management*.
- ⁵⁸ Zahedi-Seresht, M., Akbarijokar, M., Khosravi, S., & Afshari, H. (2014). Construction project success ranking through the data envelopment analysis. *Journal of Data Envelopment Analysis and Decision Science*, 2014, 1-13.

-
- ⁵⁹ Gandhi, A., & Shankar, R. (2014). Efficiency measurement of Indian retailers using data envelopment analysis. *International Journal of Retail & Distribution Management*.
- ⁶⁰ Amirteimoori, A., & Yang, F. (2014). A DEA model for two-stage parallel-series production processes. *RAIRO-Operations Research-Recherche Opérationnelle*, 48(1), 123-134.
- ⁶¹ Kapelko, M., Lansink, A. O., & Stefanou, S. E. (2014). Assessing dynamic inefficiency of the Spanish construction sector pre-and post-financial crisis. *European Journal of Operational Research*, 237(1), 349-357.
- ⁶² Liu, B., Wang, X., Chen, C., & Ma, Z. (2014). Research into the dynamic development trend of the competitiveness of China's regional construction industry. *KSCE Journal of Civil Engineering*, 18(1), 1-10.
- ⁶³ Taylan, O., Bafail, A. O., Abdulaal, R. M., & Kabli, M. R. (2014). Construction projects selection and risk assessment by fuzzy AHP and fuzzy TOPSIS methodologies. *Applied Soft Computing*, 17, 105-116.
- ⁶⁴ Widodo, W., Salim, R., & Bloch, H. (2014). Agglomeration economies and productivity growth in manufacturing industry: Empirical evidence from Indonesia. *Economic Record*, 90, 41-58.
- ⁶⁵ Xue, X., Wu, H., Zhang, X., Dai, J., & Su, C. (2015). Measuring energy consumption efficiency of the construction industry: the case of China. *Journal of Cleaner Production*, 107, 509-515.
- ⁶⁶ Park, J. L., Yoo, S. K., Lee, J. S., Kim, J. H., & Kim, J. J. (2015). Comparing the efficiency and productivity of construction firms in China, Japan, and Korea using DEA and DEA-based Malmquist. *Journal of Asian architecture and building engineering*, 14(1), 57-64.
- ⁶⁷ He, Q., Luo, L., Hu, Y., & Chan, A. P. (2015). Measuring the complexity of mega construction projects in China—A fuzzy analytic network process analysis. *International journal of project management*, 33(3), 549-563.
- ⁶⁸ Bian, Y., Liang, N., & Xu, H. (2015). Efficiency evaluation of Chinese regional industrial systems with undesirable factors using a two-stage slacks-based measure approach. *Journal of Cleaner Production*, 87, 348-356.
- ⁶⁹ Nazarko, J., & Chodakowska, E. (2015). Measuring productivity of construction industry in Europe with Data Envelopment Analysis. *Procedia Engineering*, 122, 204-212.

⁷⁰ Fernández López, X. L., & Coto Millán, P. (2015). From the boom to the collapse: a technical efficiency analysis of the Spanish construction industry during the financial crisis.

⁷¹ Chen, Y., Liu, B., Shen, Y., & Wang, X. (2016). The energy efficiency of China's regional construction industry based on the three-stage DEA model and the DEA-DA model. *KSCE Journal of Civil Engineering*, 20(1), 34-47.

⁷² Park, J. L., Yoo, S. K., Lee, J. S., Kim, J. H., & Kim, J. J. (2015). Comparing the efficiency and productivity of construction firms in China, Japan, and Korea using DEA and DEA-based Malmquist. *Journal of Asian architecture and building engineering*, 14(1), 57-64.

⁷³ Soetanto, T. V., & Fun, L. P. (2015). Super Slack-Based Model Efficiency and Stock Performance of Manufacturing Industry Listed in Indonesian Stock Exchange. *Procedia-Social and Behavioral Sciences*, 211, 1231-1239.

⁷⁴ Iyer, K. C., & Banerjee, P. S. (2016). Measuring and benchmarking managerial efficiency of project execution schedule performance. *International Journal of Project Management*, 34(2), 219-236.

⁷⁵ Hu, X., & Liu, C. (2016). Profitability performance assessment in the Australian construction industry: a global relational two-stage DEA method. *Construction management and economics*, 34(3), 147-159.

⁷⁶ Wang, J., Zhao, T., & Zhang, X. (2016). Environmental assessment and investment strategies of provincial industrial sector in China—Analysis based on DEA model. *Environmental Impact Assessment Review*, 60, 156-168.

⁷⁷ Chancellor, W., & Lu, W. (2016). A regional and provincial productivity analysis of the Chinese construction industry: 1995 to 2012. *Journal of construction engineering and management*, 142(11), 05016013.

⁷⁸ Hu, X., & Liu, C. (2016). Energy productivity and total-factor productivity in the Australian construction industry. *Architectural science review*, 59(5), 432-444.

⁷⁹ Bou-Hamad, I., Anouze, A. L., & Larocque, D. (2017). An integrated approach of data envelopment analysis and boosted generalized linear mixed models for efficiency assessment. *Annals of Operations Research*, 253(1), 77-95.

⁸⁰ Hu, X., & Liu, C. (2017). Slacks-based data envelopment analysis for eco-efficiency assessment in the Australian construction industry. *Construction Management and Economics*, 35(11-12), 693-706.

⁸¹ Nazarko, J., & Chodakowska, E. (2017). Labour efficiency in construction industry in Europe based on frontier methods: data envelopment analysis and stochastic frontier analysis. *Journal of Civil Engineering and Management*, 23(6), 787-795.

⁸² Zhong, S., Liu, Y., & Han, X. (2017). Efficiency Evaluation of Construction Industry under Environmental Regulation Based on Undesirable DEA. In *ICCREM 2017* (pp. 260-269).

⁸³ Kapelko, M. (2018). Measuring inefficiency for specific inputs using data envelopment analysis: evidence from construction industry in Spain and Portugal. *Central European journal of operations research*, 26(1), 43-66.

⁸⁴ Luo, M., Fan, H. Q., & Liu, G. (2018). Measuring regional differences of construction productive efficiency in China: A distance friction minimization approach. *Engineering, Construction and Architectural Management*, 27(4), 952-974.

⁸⁵ Hu, X., & Liu, C. (2018). Measuring efficiency, effectiveness and overall performance in the Chinese construction industry. *Engineering, Construction and Architectural Management*.

⁸⁶ Maghsoodi, A. I., & Khalilzadeh, M. (2018). Identification and evaluation of construction projects' critical success factors employing fuzzy-topsis approach. *KSCE Journal of Civil Engineering*, 22(5), 1593-1605.

⁸⁷ Zhang, J., Li, H., Xia, B., & Skitmore, M. (2018). Impact of environment regulation on the efficiency of regional construction industry: A 3-stage data envelopment analysis (DEA). *Journal of Cleaner Production*, 200, 770-780.

⁸⁸ Nahangi, M., Chen, Y., & McCabe, B. (2019). Safety-based efficiency evaluation of construction sites using data envelopment analysis (DEA). *Safety science*, 113, 382-388.

⁸⁹ Yang, G. L., Fukuyama, H., & Chen, K. (2019). Investigating the regional sustainable performance of the Chinese real estate industry: A slack-based DEA approach. *Omega*, 84, 141-159.

⁹⁰ Nguyen, N. T. (2020). Performance evaluation in strategic alliances: A case of Vietnamese construction industry. *Global Journal of Flexible Systems Management*, 21(1), 85-99.

⁹¹ Xian, Y., Yang, K., Wang, K., Wei, Y. M., & Huang, Z. (2019). Cost-environment efficiency analysis of construction industry in China: A materials balance approach. *Journal of Cleaner Production*, 221, 457-468.

⁹² Li, K., Ma, Z., & Zhang, G. (2019). Evaluation of the supply-side efficiency of China's real estate market: A data envelopment analysis. *Sustainability*, 11(1), 288.

⁹³ Huo, T., Tang, M., Cai, W., Ren, H., Liu, B., & Hu, X. (2020). Provincial total-factor energy efficiency considering floor space under construction: an empirical analysis of China's construction industry. *Journal of Cleaner Production*, 244, 118749.

⁹⁴ Sin, J. H. (2019). A study on the financial efficiency analysis method by redesigning the DEA model. *OPSEARCH*, 1-17.

⁹⁵ Prasad, S. R. (2019). Measuring the efficiency of Indian real estate firms during the pre-and post-demonetization period by adopting data envelopment analysis. *Baltic Journal of Real Estate Economics and Construction Management*, 7(1), 98-109.

⁹⁶ Murillo, K. P., Rocha, E., & Rodrigues, M. F. (2019). Construction sectors efficiency analysis on seven European countries. *Engineering, Construction and Architectural Management*.

⁹⁷ Yuan, F., Tang, M., & Hong, J. (2020). Efficiency estimation and reduction potential of the Chinese construction industry via SE-DEA and artificial neural network. *Engineering, Construction and Architectural Management*.

⁹⁸ Wen, Q., Hong, J., Liu, G., Xu, P., Tang, M., & Li, Z. (2020). Regional efficiency disparities in China's construction sector: A combination of multiregional input-output and data envelopment analyses. *Applied Energy*, 257, 113964.

⁹⁹ Zhang, J., Cai, W., Li, H., Olanipekun, A. O., & Skitmore, M. (2020). Measuring the capacity utilization of China's regional construction industries considering undesirable output. *Journal of Cleaner Production*, 252, 119549.

¹⁰⁰ Wen, Q., Hong, J., Liu, G., Xu, P., Tang, M., & Li, Z. (2020). Regional efficiency disparities in China's construction sector: A combination of multiregional input-output and data envelopment analyses. *Applied Energy*, 257, 113964.

¹⁰¹ Chen, K., Song, Y. Y., Pan, J. F., & Yang, G. L. (2020). Measuring destocking performance of the Chinese real estate industry: A DEA-Malmquist approach. *Socio-Economic Planning Sciences*, 69, 100691.

¹⁰² Tsolas, I. E. (2011). Modelling profitability and effectiveness of Greek-listed construction firms: an integrated DEA and ratio analysis. *Construction Management and Economics*, 29(8), 795-807.

-
- ¹⁰³ Hoe, L. W., Jinn, L. S., Siew, L. W., & Hai, T. K. (2018). Evaluation on the efficiency of the construction sector companies in Malaysia with data envelopment analysis model. In *Journal of Physics: Conference Series* (Vol. 995, No. 1, p. 012022).
- ¹⁰⁴ Mintzberg, H. and Waters, J.A. (1989) Of strategies, deliberate and emergent, in Asch, D. and Bowman, C. (eds) *Readings in Strategic Management*, Macmillan, London, pp. 5–19.
- ¹⁰⁵ Langford, D., Iyagba, R., & Komba, D. M. (1993). Prediction of solvency in construction companies. *Construction Management and Economics*, 11(5), 317-325.
- ¹⁰⁶ Downes, J., & Goodman, J. E. (1995). *Barron's finance & investment handbook*. Barron's Educational Series.
- ¹⁰⁷ Beyer, S. (2010), *International Corporate Finance – Impact of Financial Ratios on Long Term Credit Ratings: Using the Automotive Examples of BMW Group, Daimler Group and Ford Motor Company*, GRIN Verlag, Munich.
- ¹⁰⁸ Ketz, J.E., Doogar, R.K. and Jensen, D.E. (1990), *A Cross-industry Analysis of Financial Ratios: Comparabilities and Corporate Performance*, Quorum Books, New York, NY.
- ¹⁰⁹ Needles, B.E., Powers, M. and Crosson, S.V. (2010), *Financial and Managerial Accounting*, Cengage Learning, Madison, OH.
- ¹¹⁰ Argenti, J. (1983) Predicting corporate failure. *Accountant Digest*, No. 138, pp. 157–8.
- ¹¹¹ Balatbat, M. C., Lin, C. Y., & Carmichael, D. G. (2010). Comparative performance of publicly listed construction companies: Australian evidence. *Construction Management and Economics*, 28(9), 919-932.
- ¹¹² Kesimli, I. G., & Günay, S. G. (2011). The impact of the global economic crisis on working capital of real sector in Turkey.
- ¹¹³ Feroz, E. H., Kim, S., & Raab, R. L. (2003). Financial statement analysis: A data envelopment analysis approach. *Journal of the Operational Research Society*, 54(1), 48-58.
- ¹¹⁴ Düzakın, E., & Düzakın, H. (2007). Measuring the performance of manufacturing firms with super slacks based model of data envelopment analysis: An application of 500 major industrial enterprises in Turkey. *European journal of operational research*, 182(3), 1412-1432.

-
- ¹¹⁵ Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, 120(3), 253-281.
- ¹¹⁶ Koopmans, T. C. (1951). An analysis of production as an efficient combination of activities. *Activity analysis of production and allocation*.
- ¹¹⁷ Debreu, G. (1951). The coefficient of resource utilization. *Econometrica: Journal of the Econometric Society*, 273-292.
- ¹¹⁸ Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of econometrics*, 6(1), 21-37.
- ¹¹⁹ Murillo-Zamorano, L. R. (2004). Economic efficiency and frontier techniques. *Journal of Economic surveys*, 18(1), 33-77.
- ¹²⁰ Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of econometrics*, 6(1), 21-37.
- ¹²¹ Akhigbe, A., & McNulty, J. E. (2003). The profit efficiency of small US commercial banks. *Journal of banking & finance*, 27(2), 307-325.
- ¹²² De Borger, B., & Kerstens, K. (1996). Cost efficiency of Belgian local governments: A comparative analysis of FDH, DEA, and econometric approaches. *Regional science and urban economics*, 26(2), 145-170.
- ¹²³ Førsund, F. R., Lovell, C. K., & Schmidt, P. (1980). A survey of frontier production functions and of their relationship to efficiency measurement. *Journal of econometrics*, 13(1), 5-25.
- ¹²⁴ Berger, A. N., & Humphrey, D. B. (1992). Measurement and efficiency issues in commercial banking. In *Output measurement in the service sectors* (pp. 245-300). University of Chicago Press.
- ¹²⁵ Resti, A. (1997). Evaluating the cost-efficiency of the Italian banking system: What can be learned from the joint application of parametric and non-parametric techniques. *Journal of banking & finance*, 21(2), 221-250.
- ¹²⁶ Bowlin, W. F., Charnes, A., Cooper, W. W., & Sherman, H. D. (1984). Data envelopment analysis and regression approaches to efficiency estimation and evaluation. *Annals of Operations Research*, 2(1), 113-138.
- ¹²⁷ Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, 2(6), 429-444.

-
- ¹²⁸ Ali, A. I., & Seiford, L. M. (1993). The mathematical programming approach to efficiency analysis. *The measurement of productive efficiency: Techniques and applications*, 120, 159.
- ¹²⁹ Zhu, J. (2014). *Quantitative models for performance evaluation and benchmarking: data envelopment analysis with spreadsheets* (Vol. 213). Springer.
- ¹³⁰ Inman, O. L., Anderson, T. R., & Harmon, R. R. (2006). Predicting US jet fighter aircraft introductions from 1944 to 1982: A dogfight between regression and TFDEA. *Technological Forecasting and Social Change*, 73(9), 1178-1187.
- ¹³¹ Theodoridis, A. M., Psychoudakis, A., & Christofi, A. (2006). Data envelopment analysis as a complement to marginal analysis. *Agricultural economics review*, 7(389-2016-23358), 55-65.
- ¹³² Ruggiero, J. (2007). A comparison of DEA and the stochastic frontier model using panel data. *International Transactions in Operational Research*, 14(3), 259-266.
- ¹³³ Mahadevan, R. (2002). A DEA approach to understanding the productivity growth of Malaysia's manufacturing industries. *Asia Pacific Journal of Management*, 19(4), 587-600.
- ¹³⁴ Mahadevan, R. (2002). A DEA approach to understanding the productivity growth of Malaysia's manufacturing industries. *Asia Pacific Journal of Management*, 19(4), 587-600.
- ¹³⁵ Ruggiero, J. (2004). Performance evaluation when non-discretionary factors correlate with technical efficiency. *European Journal of Operational Research*, 159(1), 250-257.
- ¹³⁶ Mahadevan, R. (2002). A DEA approach to understanding the productivity growth of Malaysia's manufacturing industries. *Asia Pacific Journal of Management*, 19(4), 587-600.
- ¹³⁷ Atkinson, S. E., & Cornwell, C. (1994). Parametric estimation of technical and allocative inefficiency with panel data. *International Economic Review*, 231-243.
- ¹³⁸ Yannick, G. Z. S., Hongzhong, Z., & Thierry, B. (2016). Technical efficiency assessment using data envelopment analysis: an application to the banking sector of Cote d'Ivoire. *Procedia-Social and Behavioral Sciences*, 235, 198-207.
- ¹³⁹ Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de estadística*, 4(2), 209-242.

¹⁴⁰ Färe, R., Grosskopf, S., Lindgren, B., & Roos, P. (1992). Productivity changes in Swedish pharmacies 1980–1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis*, 3(1), 85-101.

¹⁴¹ Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, 120(3), 253-281.

¹⁴² Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica: Journal of the Econometric Society*, 1393-1414.

¹⁴³ Das, P. (2017). An evaluation of the determinants of total factor productivity growth in Indian information technology industry: an application of DEA-based Malmquist Index. *The Central European Review of Economics and Management (CEREM)*, 1(4), 175-224.

RESEARCH PROGRAMME EVALUATION COMMITTEE
(RPEC)

1. Dr. Jaya Srivastava
Head of Department
Department of Management Studies

2. Dr. Rohit Bansal (Supervisor)
Assistant Professor
Department of Management Studies

3. Dr. Sanjay Kumar Kar
Associate Professor
Department of Management Studies

4. Dr. Alpesh Kumar
Associate Professor
Department of Mathematics

PUBLICATION

Research Articles

1. Vikas, V., & Bansal, R. (2019). Efficiency evaluation of Indian oil and gas sector: data envelopment analysis. *International journal of emerging markets*.
2. Sv, P., Tandon, J., & Hinduja, H. (2021). Indian citizen's perspective about side effects of COVID-19 vaccine–A machine learning study. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*.

Book Chapter

1. Vikas, V., & Bansal, R., Today's Renewable Energy Market: Innovations, their commercialisation and impact on market in “*Latent Heat-based Thermal Energy Storage Systems: Materials, Applications, and the Energy Market*.” edited by Shukla, A., Sharma, A., & Biwolé, P. H. (Apple Academic Press)

Conferences

1. Presented paper titled “Efficiency Evaluation of Indian Construction Sector” in ISFIF Symposium, IIT, Kharagpur.
2. Presented paper titled “Efficiency Assessment of Indian Manufacturing Sector” in ECOES, RGIPT.
3. Presented paper titled “Customer Satisfaction in e-learning mode in India” in NASMEI Conference, IIM Indore.
4. First prize in paper presentation in Parishti 18', National Research Scholars' Symposium, RGIPT.

Workshops

1. Attended 7 days National Workshop on Research Methodology and Data Analysis in Banaras Hindu University from 6-12th Feb, 2017.
2. Attended 7 days' Workshop on Advanced Research Methods and Data Analysis in National Institute of Technology, Durgapur from 04-10th June, 2017.
3. Attended 5 days Doctoral Summer School on Quantitative Track in IIM Ahmedabad from 1-5th April, 2018.
4. Attended workshop on Conducting Meaningful Research in IIM Indore on 26th July, 2019.

CURRICULAM VITAE

Email: pm1611@rgipt.ac.in
Mob: +91-8178193240

Vikas

OBJECTIVE

To develop as a competent professional with strong academic background and practical experience in modern and innovative teaching techniques who is able to provide quality knowledge to students.

ACADEMICS

COURSE/EXAMINATION	YEAR	INSTITUTION/UNIVERSITY	PERCENTAGE
Ph.D.	2021	Rajiv Gandhi Institute of Petroleum Technology	Thesis Submitted
CMA (Inter)	2020	ICMAI	65.62%
NET-JRF	2016	UGC	66.28%
M.Com (Finance)	2016	Delhi School of Economics	68.45%
B.Com Hons.	2014	Hans Raj College, DU	72.88%
AISSCE (Class XII)	2011	G.R.S.S Vidya Mandir, Bhagalpur	90.25%
AISCE (Class X)	2009	D.A.V. Public School, Bhagalpur	87.2%

CAREER HIGHLIGHTS

- Secured Rank in BSNL, Jr. Accounts Officer Exam, Bihar Circle, 2018.
- Got distinction in “The Language and tools of Financial Analysis” and “Corporate Financial Decision Making for Value Creation” courses offered by **University of Melbourne** through www.coursera.org.
- Qualified NET-JRF in Commerce in December 2015 and June 2016.
- Secured 74/75 in Financial Management in B.Com Honors, 5th Semester, B.Com (Hons.).
- Awarded **CSSS-2011 Scholarship** from CBSE for 12th result.

HIGHLIGHTS OF Ph.D. THESIS

- Topic – Multi-Period Efficiency Evaluation of Indian Construction Sector
- The work analyzed the performance of 42 profit making companies of Indian Construction Sector over a period of five years from 2015-16 to 2019-20. The study determined the efficiencies of the companies in terms of technical, pure technical and scale efficiencies for the said period and measured the deviations in

the efficiency levels. The reasons for the changes in efficiency levels were identified and targets to the relatively less efficient companies were provided.

PUBLICATIONS

- Paper titled “Efficiency Evaluation of Indian Oil and Gas Sector: Data Envelopment Analysis” – In Journal “International Journal of Emerging Markets”, Emerald listed in ABDC-B list, SCOPUS and SCI Extended.
- Paper titled “Paper titled “Indian citizen’s perspective about side effects of COVID-19 vaccine – A Machine learning study” submitted to Diabetes & Metabolic Syndrome: Clinical Research & Reviews listed in SCOPUS.
- Book Chapter titled “Today’s Renewable Energy Market: Innovations, their commercialisation and impact on market” in Book “Latent Heat based Thermal Energy Storage Systems: Materials, Applications and their Market” published by Apple Academic Press, USA.

CONFERENCES

- Presented paper titled “Efficiency Evaluation of Indian Construction Sector” in ISFIF Symposium, IIT, Kharagpur.
- Presented paper titled “Efficiency Assessment of Indian Manufacturing Sector” in ECOES, RGIPT.
- Presented paper titled “Customer Satisfaction in e-learning mode in India” in NASMEI Conference, IIM Indore.
- First prize in paper presentation in Parishti 18’, National Research Scholars’ Symposium, RGIPT.

WORKSHOPS

- Attended 7 days National Workshop on Research Methodology and Data Analysis in Banaras Hindu University from 6-12th Feb, 2017.
- Attended 7 days Workshop on Advanced Research Methods and Data Analysis in National Institute of Technology, Durgapur from 04-10th June, 2017.
- Attended 5 days Doctoral Summer School on Quantitative Track in IIM Ahmedabad from 1-5th April, 2018.
- Attended workshop on Conducting Meaningful Research in IIM Indore on 26th July, 2019.

POSITIONS OF RESPONSIBILITY

- Working as Junior Accounts Officer in BSNL (Indian Government Public Sector Undertaking) (2018-21)
- Served As **Senior Member** of DU M.Com Alumni Association. (2015-16)
- **Senior Member** of Career Management Cell, DSE. (2015-16)
- Served as an Active member of Creative team, N.S.S, Hans Raj College. (2012-13)
- Served as an Active member of Haritima Environmental Society, Hans Raj College. (2012-13)

- Volunteer in Confluence, Hans Raj College Annual Cultural Fest in 2012 as well as 2013.

EXTRA-CURRICULAR ACTIVITIES AND ACHIEVEMENTS

- Won 1st prize in **Mock Stock** competition in Biz Street 2014 organized by **Commerce Society, SRCC**.
- Won 1st prize in **Bull Street** event in Zeitgeist, 2013 organised by **Commerce Society, Hindu College**.
- Won 1st prize in **Stockmind, Hans Raj College** organized by **ICICI Direct** in 2014.
- Won 1st prize in **Being Banker** competition in **Arbitrage 2016** organized by **Commerce Society, Ramjas College**.
- Won 1st prize in **Dalal Street** event in Appulse, 2014 organised by **Commerce Society, Kirorimal College**.
- Won 1st prize in **Breakout** event in Elumiere, 2015 organised by **Economics Society, SSCBS College**.
- Won 1st prize in **Bullzai** event in Vanijya Utsav, 2014 organised by **Commerce Society, Hans Raj College**.
- Won 1st prize in **The Ultimatum** event in Bullzire, 2015 organised by **D-Street, SRCC**.
- Won 1st prize in **Talking Business** event in Economics Society Fest, **Daulat Ram College**.
- Won 1st prize in **Bullion** event in Comquest, 2014 organised by **Commerce Society, Lady Shri Ram College**.
- Won 1st prize in **Mock You** event in Cognizance, 2012 organised by **DBS, Keshav Mahavidyalaya**.
- Won 1st prize in **Bull's Eye** event in Ecozest, 2015 organized by **Economics Society, Deshbandhu College**.
- Won 1st prize in **10 Rounds** event in Das Capital, 2014 organized by **The Finance and Investment Cell, St. Stephens College**.
- Won 1st prize in **Chess tournament** in 2014 organized by **Hans Raj College Hostel**.
- Won 2nd prize in **NSIT Stock Exchange** event at Consilium, 2015 event organised by **NSIT Business Conclave**.
- Won 2nd prize in **Wall Street, 2015** event organised by **Delhi School of Management, DTU**.
- Won 2nd prize in **Chess Competition** in Avalanche, 2011 organized by **University College of Medical Sciences**.
- Won 2nd prize in **Dalal Street** event in Technowiz, 2013 organized by **Maharaja Surajmal Institute**.
- Won 2nd prize in **The Big Board** event in Zenith, 2014 organized by **Economics Society, Miranda House**.
- Won 2nd prize in **Chess Competition** in Dr. Bharat Ram Sports Meet, 2012 organized by **Lady Shri Ram College**.
- Won 2nd prize in **Breaking the Bank** event in Enigma, 2013 organized by **The Finance and Investment Cell, Hindu College**.

- Won 2nd prize in **Foerex** event in Algorhythm, 2012 organized by **CSI Student Chapter, Jamia Millia Islamia.**
- Won 2nd prize in **Stock Sentinel** event, 2015 organized by **Finance and Investment Cell, Shri Ram College of Commerce.**
- Won 3rd prize in **Share Bazari** event in Pareto, 2013 organized by **Economics Society, Shivaji College.**
- Won 3rd prize in **Mock Stock** event in Eco Square, 2016 organized by **Economics Society, Shyam Lal College.**

PERSONAL DETAILS

- Date of Birth: 29-11-1994
- Father's Name: Shri Ashok Kumar Verma
- Mother's Name: Smt. Chanchal Verma
- Nationality: Indian
- Permanent Address: LIG 106, Housing Board Colony, Barari, Bhagalpur, Bihar - 812003, India.

References/Contact details

1. Dr. Rohit Bansal (Ph.D Thesis Supervisor)
Assistant Professor, Department of Management Studies
Rajiv Gandhi Institute of Petroleum Technology, Jais
Ph. No. - +91-9927285001
Email Id – rbansal@rgipt.ac.in

2. Dr. Vinay K. Nangia
Professor and Head of Department (Retd.), Department of Management Studies
Indian Institute of Technology, Roorkee
Adjunct faculty, BML Munjal University, Gurugram
Ph. No. - +91-9639184798
Email Id – vinaynangia@gmail.com

3. Dr. Ashu Khanna
Associate Professor, Department of Management Studies
Indian Institute of Technology, Roorkee
Ph. No. - +91-9756972391
Email Id – drashu.khanna@gmail.com