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Do chinese industry spur innovation to embrace the challenges of the world's new scientific and technological revolution. Data envelopment approach

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Abstract

The manufacturing sector's capacity base is critical to any country's wealth creation and economic growth. An economy's industrial innovative performance is dependent on the rigorous application of new ideas, production methods, and modern techniques. This study uses the Malmquist productivity index of Data Envelopment Analysis (DEA), and the Generalized ordinal model to investigate the actual innovation growth of China's industrial enterprises. It further analyses the possibilities of the low innovative industries transforming into high innovative industries. The findings highlight that, although China's industrial enterprises above high designated are on average experiencing a negative growth rate in terms of technical progress, yet they have spurred innovation with an average growth of 0.7% in total factor productivity. It concludes that there is a general need for the authority concern to lay more emphasis on reducing technical inefficiency, thereby improving technological innovation level and subsequent increase in overall efficiency scale.

Keywords: Innovation, High designated Industries, High Innovation industries M

Introduction

Faced with the opportunities and challenges brought about by the world's new scientific and technological revolution, innovation has become a nuclear weapon central to promoting economic and social development. Presently, countries around the globe are leveraging several innovation activities including capital, human resources, and technology to improve the performance of their operational industries [1]. Recently, China unveiled its ambitious "Made in China 2025" (MIC25) industrial strategy with the aim to shift its manufacturing industrial enterprises from being the world's largest manufacturer to the world's best. This means innovation activities are needed to accomplish the desired industrial upgrade and restructuring, thereby improving the added value generated by a different unit. Although relevant industrial enterprises have started changing the landscape of China manufacturing at a remarkable level of automation across catalyzing mass production industries in both automotive and non-automotive industries, yet the way to high-level innovation leadership is still very long [2,3].

Technically, production is possible with variations in factor intensities and production technologies. However, there are substantial inter-industrial differences in the application of science and technology among China's industrial enterprises that are above high designated size [3]. Overall, to some degree, such disparities have impeded the harmonious growth of the Chinese economy [4]. One of the key issues facing policymakers in China is how to build and strengthen the innovation structures of the lagged industries, for the entire industries to develop their innovation capacity at relatively the same pace, and thus, enable them to achieve the MIC25 agenda. Consequently, it is of paramount importance to empirically examine China's industrial enterprise's innovation performance at the firm level and explore the following questions. Do China's industrial enterprises spur innovation to embrace the challenges of the new scientific and technological revolution in the world? To what extent do Chinese industrial enterprises convert innovation inputs into outputs with varying degrees of efficiency? Therefore, this study considers China's industrial enterprises that are above designated size by the industrial sector as the study case.

However, one of the most common measures of innovation performance of an industry is its efficiency in resource utilization [4]. This is because innovation is not a linear operation that simply converts input into output; rather, it relies on the industrial capacity to convert innovation input into innovation output. Thus, analysis of industrial performance is necessary to distinguish between innovation efficiency to obtain the desired information for necessary action. However, given that measure of innovation performance entails comparing peer performance in highly environmental settings and assessing trends over time, empirical study at the firm level sounds the best approach to investigate Chinese national innovation systems, thereby investigating and analyzing industrial enterprise innovation transition processes and innovation performance variations among industries.

Many studies in the literature have examined the importance of innovation efficiency in the Chinese context and other countries of the world, at different levels, using national and regional level datasets. For instance, the study of innovation measurement that finds the effect of technology and non-technological innovation on a firm's performance [6,7]. A crosscountry analysis of national innovation efficiency, and regional studies [8-10]. Nonetheless, the existing literature has clear limitations as many of the analysis focuses on what innovation measurement should be, how innovation should be measured, and on comparative innovation performance studies based on cross-sectional studies at regional and country level. Thus, less attention is paid to measuring the innovation output of a given economy and to finding the appropriate innovation inputs that match the industry at its specific level of success in innovation, which is the focus of this study. The efficiency of innovation performance of an industry can be estimated by comparing the composite scores of the inputs-outputs. The underlying argument regarding the theoretical models of the innovation process makes the formulation of clear inputoutput functional relationships quite difficult. Thus, this study employed the use of the nonparametric approach of Malmquist Productivity Index techniques of data enveloping analysis (DEA) inter-alia, at the onset of the analysis. The use of DEA is based on its number of applications in empirical research in various studies of performance evaluation [11,12]. Therefore, the findings of this study are set to guide policymakers in the management of the industries examined and the government of China on the best practices to achieve the government's ambitious innovation agenda. It will also proffer some suggestions on optimizing the current innovation challenges raised by the world's new science and technology revolution. Lastly, the conceptual and analytical contexts could be of application to other fields of innovation performance evaluation.

This study begins with the measurement of the technological progress (TFP), which reflects the degree of innovation spurs, or industrial progress at the frontier of technological innovation, and the variability in industrial innovation efficiency. Subsequently, the study uses generalized ordinal logistic regression to further examine the impact of measurement variables on the industries at their different level of innovation performance. This will help in understanding the industry's innovation dynamics based on three categories: low, moderate, and highly innovative industries. The second section reviews related literature and theoretical concepts, the third section presents the methodology, followed by empirical analysis in the fourth section and the final section offers conclusion, policy, and managerial implication.

Literature Review and Theoretical Concept

The World's New Science and Technology Revolution

The advent of the twenty-first century has witnessed the proliferation of science and technology revolution in the world. The advanced economies have gone far in the radical development of highly innovative industries using best practices. The variations in national conditions have led to the creation of different relevant innovative policies among nations across the globe. For example, the U.S. government launched manufacturing resilience, Germany came up with to keep the leading position of manufacturing in the world, Japan with I-Japan, and China with made in China 2025 (MIC25) among others.

However, despite variations in the innovation strategy among different economies, the central idea and challenges of the modern science and technology revolution remain the same. The crux of the new world's science and technology revolution is marked by the transformation of industrial operations to a new level of socio-technical interaction designed to increase productivity, boost economic growth and development and increase social well-being [13]. Some of the challenges of this new world science and technology revolution include considerable capital, complexity, information sharing, customization of products, and the integration of individual customers, among others.

Unlike other developed economies (market economy), China's innovation model is government-driven. In May 2015, the Chinese government launched "Made in China 2025" (MIC25) with the aim of pushing its manufacturing industry from the current position of largest and cheapest industrial base in the world to the world's best in 2025. However, one of the major challenges of this ambitious innovation policy is the development of smart industrial enterprise solution that relies on competitive cheap labor using digitalization, networking, and intelligence as a key to technological innovation. Thus, this study seeks to examine the innovation performance of industrial enterprises of China based on innovation inputs that can lead to success across the industries. Finally, policy recommendations will be provided for the government of China and the management of the industries as the government remains committed for the industries to achieve the China MIC25 innovation agenda.

Concept of Innovation and Prior Research on Innovation Performance Measurement

Innovation means value creation through a transformation of knowledge and ideas [14]. Innovation is possible through the combination of inputs to produce outputs. It is a process of transformation in which the innovation production unit uses science and technology resources from a variety of channels to generate new knowledge and increases economic wealth [11]. Once there is innovation, there is a need to know how much a firm grows in that process which brought about innovation efficiency. At an industry level, continuous application of innovation in the production process is expected to reflect on overall productivity and efficiency performance over time. Importantly, the industry should measure the extent of growth in innovation at its level which is ultimately driven by innovation efficiency. Innovation efficiency implied the firm's capacity to translate innovation inputs into innovation outputs [15].

Classically, the concept of innovation measurement was first forward in the literature of management and economics. However, there is a stark difference in their perspective on innovation measurement. The economic perspective of innovation is to explore the rationale and driving forces behind industrial innovation, along with the macro-economic impact of innovation and barriers to innovation on economic agents. In contrast, the management perspective is based on how innovation can alter an industry's market position and how innovative ideas can be generated. Some of the famous available literature on innovation are; the idea of "creative destruction" coined by Schumpeter (1934), which explained innovation as the disruption of existing economic activity by inventing new ways of producing goods or services. The diffusion theory explores the mechanisms through which innovations are transmitted and adopted by the participants in a social system over time [16]. The evolutionary theories found innovation as a path-dependent mechanism through which inventions are created by interactions between different actors and then evaluated on the market [17].

Table 1 presents a summary of some of the studies that addressed 'innovation efficiency' and their method of analysis, the sample size used, and the main idea. The main thrust of these studies (see Table 1), was based on the analysis of what should be the innovation measurement, how to measure innovation, and comparative innovation performance studies based on crosssection studies at regional and country level. Thus, little evidence is found on measuring the innovation output of a given economy on one hand, and on finding the appropriate innovation inputs that match the industry at its specific level of success in innovation. This is a black box that this study is intended to open.

Table 1: Conceptual and Empirical findings of Innovation Efficiency Literatures

Authors	Technique	Sample	Main idea
Athawale and Chakraborty, (2011)	Comparative studies	10 MCDM	Focusses on the comparison of the relative efficiency of the ten most famous multi-criteria decision-making MCDM method for the rankings of alternative robots observed for a given place-pick operation.
Evangelista and Vezzani, (2010)	Empirical studies	A Stratified sample data representing all Italian service and manufacturing firms with more than 9 employees.	Investigates the impact of technological and non- technological innovations on firms' performances, and found these types of technological innovations to be present and vital in all industries but have different influence on a firm's efficiency.
Hailing et al., (2013)	Comparative studies	29 provincial data for eight years.	Comparison of technology innovation efficiency based on time and region of Chinese large and medium-sized industrial enterprises. It found eastern china's region's technological efficiency to be high compared to the north and central region.
Mazur, (2017)	Conceptual framing	125 research papers	Classifies innovation performance measures implemented in the IT research sector. It found innovation performance to be considered in two ways; inventive performance (referring to workforce creativity and knowledge sharing) and Technology performance (referring to R&D outputs and inputs like patents and new products.
Wei, et al., (2017)	Action research	China Firm-level data 1995-2014	Evaluates China's innovation policy, and concludes that, to improve the efficiency of resource allocation, policy changes should perhaps lead to a balancing of the playing fields for businesses across all levels of ownership, with corresponding cuts indirect subsidies and taxes.
Yam et al. (2010)	Modeling	200 manufacturing firms	Develops a framework that enables the link between innovation capabilities and innovation performance. They argued that any innovation efficiency measurement shall cover the size of the innovation potential of three actions: financial, strategic, and achievement.
Yang et al. (2013)	Empirical studies	Investigates innovation status of two sub-stages during innovation process of high tech industries in China.	
Zhao and Cheng (2013)	Empirical studies	Built evaluation index of innovation capability of high tech industries, and further evaluates china's high tech innovation efficiency at the regional level. It concludes that there is a series innovation efficiency gap at a regional level and the gap is widening.	

Measurement of Innovation Efficiency

Despite several models for the measurement of innovation efficiency developed in the literature, data enveloping Analysis (DEA) is commonly applied in empirical research. Efficiency is an essential concept in both economics and management which is defined as the ratio of output to input. Innovation efficiency uses the term of technical efficiency which is often used in a narrow sense. By measuring innovation efficiency with the DEA approach, it implies quantitatively evaluating the relationship of output and input based on technical innovation. Innovation efficiency is categorized into scale efficiency, pure technical efficiency, technical efficiency, and technical progress. Table 2 depicts previous studies that evaluate innovation efficiency with the use of DEA methods. With DEA each decision-making unit (DMU) is assessed in comparison with other decision-making units (DMUs) in the group. The use of DEA to evaluate the relative efficiency of innovation activities gives a clear understanding of the relationship between resource utilization and output of the different companies (J. Asmara et al., 2019).

Authors	Performance measurement of innovation		DMUs	Output indicator	Technical intensity
	Inputs	Output			
Abbasi, and Haukka (2010)	number of scientists in R&D, expenditure on education, and R&D expenditures	Royalty incomes and license fees, Patents, High-tech export, and manufacturing export	Countries	Differences in innovative performance	No
Asmara et al., (2019)	Global journals, Local journals, Global books, Global proceedings, Local books, Local proceedings	Number of researchers, and Total human resources in R&D units	Research Units	Production change-publications	No
Chen and Guan, (2012)	Labour, capital stock, Science and technology expenditure, number of science and technology employee, foreign direct investment, expenditure on import of technology, expenditure on purchase of domestic technology, the value of contractual inflows in domestic technical markets	The invention, Gross domestic products, utility model, external design, the value of export, sales of new products, and Annual income in urban residents per capita	Industries	Innovation performance	No
Chiu et al.,(2016)	Employees, Inventory	Price of industrial output	High designated Industries	Technical efficiency, Technical progress, and Total factor efficiency	Yes
Ding, (2016)	Number of full-time R&D personnel, Expenditure on new product development, internal expenditure on R&D, and Investment in fixed assets	Number of patent applications, Output Value of new products, and sales revenue for new products	High-tech industries	Technical efficiency	Yes
Germán et al., (2016)	Machinery and equipment acquisition, Software acquisition, R&D internal activities, External acquisition of R&D, training, Commercialization and product launch activities, External acquisition of knowledge, Industrial project, and other technical preparations.	The impact caused by innovation	Industries	The impact caused by innovation	No

Guan et al (2016)	R&D employees, Gross expenditure on R&D, R&D knowledge stocks	The impact caused by innovation	Industries	The impact caused by innovation	No
Lee, Kim, and Choi, (2019)	R&D employees, Expenditure on R&D, Number of R&D success, Number of non-R&D employees	Patents, Journal Publications	Countries	Productivity Change- Publications	Yes
Lu, et al. (2010)	Total public expenditure on education, Imports of goods and commercial services, Total expenditure on R&D, Direct investment stocks abroad, and Total R&D personnel nationwide	General patents through R&D, Number of commercial success, Total sales amount through innovation	SMEs	National innovation system	No
Park and Shin, (2018)	R&D investment, R&D time, and R&D personnel	Patents, and papers	Biotechnology R&D projects	Technical efficiency	Yes

Innovation consists of the knowledge production process and commercial activities where the knowledge production process refers to research and development (R&D) activities, and commercial activities referring to sales and marketing activities [11]. In general, based on extant literature, there is no uniformity in innovation measurement due to its intangibility and uncertainty (Germán et al., 2016; Albaladejo and Romijn 2000). For instance, sales accrued from new project developments were found to be relatively used in the evaluation of innovation, unlike patents application as innovation research output indicators in measuring innovation performance. Therefore, this study employs non-parametric and parametric techniques as instruments for the analysis. In the non-parametric technique, DEA-based on Malmquist productivity index is applied to fundamentally examine and compare the innovation efficiency of China industrial enterprises above high designated during the period under study. This study considers both research and development activities and commercial activities as its innovation measurement for an in-depth analysis. Lastly, the parametric technique of generalized ordinal logistic regression is applied.

Methodology

This study employed an output-oriented DEA model to answer the fundamental research questions on how much growth in innovation is occurring in China industrial enterprises and the extent to which Chinese industries convert innovation inputs into outputs with varying degrees of efficiency. The output-oriented DEA model is deemed apt in this analysis because of its advantages in the analysis of industry-level data. Understanding the actual innovation of a firm lies in its technical progress. Thus, the non-parametric Malmquist Productivity Index (MPI) is often applied in the literature for evaluating technical progress and technological change or productivity growth over time. This technique has the advantage of judging the stability of each assessment unit in terms of efficiency and also playing a critical role in the assessment of trends in units' efficiency value. MPI can be used to measures changes in technological innovation growth of China industrial enterprises above designated from period (t) to (t+1). The MPI based on output orientation is given by and is written in form of algebraic equation as;

$$M_o(y^{t+1},x^{t+1},y^t,x^t) = \left[\frac{d_o^t(x^{t+1},y^{t+1})}{d_o^t(x^t,y^t)} \times \frac{d_o^{t+1}(x^{t+1},y^{t+1})}{d_o^{t+1}(x^t,y^t)}\right]^{1/2} \quad (1)$$

This study assumes x to stand for inputs, and y to stand for outputs. d_o is the output distance function, o subscript stands for output orientation, $d^t_o(x^t, y^t)$ indicates output distance function assessing period t data in relation to technology in t+1 period [18]. M Stand for the recent productivity (x^{t+1}, y^{t+1}) using period (t+1) technology concerning the earlier point of production (x^t, y^t) using period (t) technology.

$if\ M_o(y^{t+1}, x^{t+1}, y^t, x^t) > 1$ Means there is positive innovative growth between the periods $if\ M_o(y^{t+1}, x^{t+1}, y^t, x^t) < 1$ Signifies decline/negative innovation growth is occurring $M^o(y^{t+1}, x^{t+1}, y^t, x^t) = 1$ Means stagnation/No technological innovation growth MPI is the product of technical efficiency change (TE) meaning managerial efficiency, which is the first expression in the equation (ii), and technical progress (TC) referred to as technical change, which is the second expression in the equation (ii) [18]. Malmquist productivity index can be decomposed into two terms:

$$M_o(y^{t+1},x^{t+1},y^t,x^t) = \quad (2)$$

$$\frac{d_o^{t+1}(x^{t+1},y^{t+1})}{d_o^t(x^t,y^t)} \left[\frac{d_o^t(x^{t+1},y^{t+1})}{d_o^{t+1}(x^{t+1},y^{t+1})} \times \frac{d_o^t(x^t,y^t)}{d_o^{t+1}(x^t,y^t)}\right]^{1/2}$$

$$Technical\ Efficiency = \frac{d_o^{t+1}(x^{t+1},y^{t+1})}{d_o^t(x^t,y^t)} \quad (3)$$

$$\text{Technical Progress} = \frac{d_0^{t}(x^{t+1}, y^{t+1})}{d_0^{t+1}(x^{t+1}, y^{t+1})} \times \frac{d_0^{t}(x^{t}, y^{t})}{d_0^{t+1}(x^{t}, y^{t})} \quad (4)$$

The technological changes occur when there is an entire shift of the production frontier between the two periods (t and t+1). The efficiency change in the study is examined as the degree to which an individual enterprise improves or worsens its efficiency. In other words, whether there is an innovation growth, stagnation, or decline. Therefore; If (i) TE > 1 means improvement in managerial efficiency (ii) TE < 1 means decline in managerial efficiency However, as per Technical Change, TC > 1 means Technological progress and TC < 1 indicates Technological regresses. And TC = 1 means No change in technical innovation

Data Collection Techniques with Input and Output dimensions
The study data is obtained from the China statistical Book of Science and Technology from 2016 to 2019, published by the National Bureau of Statistics and Ministry of Science and Technology. A central database is commonly considered to be valid and publically available for statistical records. These industries are chosen based on their significant role in the advancement of science and technology in China. The size of the industries was decided on following, that they must be three times the number of inputs and outputs. The study period 2016-2018 was chosen based on the MIC25 policy enacted period and data availability [19].

The industrial levels analysis requires input and output variables for computing the change in the firm's technology. From the available data, this study chooses five variables as supported by the literature. The innovation performance measurement indicators of this study include both measure indicators for research and development (RD) activities and commercial activities indicators. The output indicator comprises, number of patent applications (PAT), and Sales amount through innovation (SAI) [20-23]. The study employs both sales and patents as its output innovation measure indicators because patents or sales alone cannot sufficiently explain the nature of China's industrial enterprise innovation efficiency. Input indicators include the number of R&D dedicated personnel (RDP), expenditure on R&D (EXPRD), the expenditure on new project development (EXPNPD), and the number of R&D projects (NRDP) [24-28].

Table 3 presents input and output variables data for China's high designated industries. (A) Under the output variables; patents (PAT), sales accrued through innovation (SAL), and the number of successful research projects (NRDP) from 2016 to 2018 have an average value of 9.0140, 16.5386, and 8.5190 respectively. The maximum output variables are 15.74, 10.87, and 19.87 respectively, and the lowest output variables are 5.31 for patents, 5.46 for successful research projects, and 10.05 for sale amount accrued through innovation. (B) The average value of input variables is 10.48, 14.03, and 14.02 for full-time R&D dedicated personnel, expenditure on R&D, and expenditure on new projects respectively for the year 2016-2018.

Table 3: Descriptive statistics

	Inputs			Outputs		
	FTRDP	**EXPRD**	**EXPNRDP**	**PAT**	**NRDP**	**SAL**
Max	19.06	16.94	17.25	15.74	10.87	19.87
Min	7.71	9.35	10.59	5.31	5.46	10.05
Mean	10.4827	14.033	14.0279	9.0140	8.5190	16.5386
Std. Div.	1.6646	1.5325	1.62761	1.68343	1.40304	1.85034
Valid Number	114	114	114	114	114	114

Table 4: Correlation coefficient among Inputs and Outputs

		Inputs		
		FTRDP	EXPRD	EXPNRDP
Outputs	PAT	0.790**	0.689**	0.752**
	SAL	0.720**	0.800**	0.845**
	NRDP	0.860**	0.802**	0.850**

Furthermore, it is vital to consider the effect of time lag when evaluating the transformation of innovation inputs into innovation output. This is because the innovation process takes time to reflect on overall productivity. Many studies have measured time lag using a different methodology. For example input and output variables correlation tests and regression [29]. However, lack of theoretical development and quality of innovation data have ruled out the accuracy in measuring time lag, thus there is no generally accepted approach for the measurement of time lag of innovation [24,20]. Hollandes and Esser have empirically found that the effect of time lag on estimating innovation performance was not substantial. In line with the extant literature, correlation analysis was conducted in this study using input and output variables at all periods [12]. The result presented in Table 4 shows that input and output indicators hold an isotonic relationship which justifies including the variables in the model.

Statistical Regression Model
The technological change index derived from the Malmquist DEA analysis is the dependent variable for the estimation of the parametric model. The independent variables comprise of EXPRDsal, EXPRDpat, FTRPaaemp, PATemp, and SALexpnpd. The entire model's indicators chosen for the analysis are presented in Table 5. The target here is to explore the measure that best suits the low, moderate, and high innovative industries by further investigating the impact of the study measurement indicator on the different levels of innovation performance of the study industries.

Table 5: OLM Model Estimation Variables

Variables names	Meaning
EXPRDsal	Expenditure on R&D related to sales amount accrued through innovation, signifying continuity in technology innovation
EXPRDpat	Expenditure on R&D related to patent application signifying continuity in technology innovation
FTRPaaemp	R&D personnel related to the average annual number of employment, signifying investment in human capital
PATten	Patent application divide ten thousand employees, signifying independence research in technological progress
SALexpnpd	The ratio of sales output related to expenditure on new project development, signifying fertility in continuous technological innovation developments

The dependent variables of the study are categorized into high Innovative, Moderate Innovative, and low Innovative industries. Since the dependent variable of the study has ordinal values, the ordinal logistic model (OLM) is thus used in the analysis. The OLM model is written as:

$$\delta_j = \frac{e^{\alpha_j+\beta_j x}}{\sum_h e^{\alpha_h+\beta_h x}} \tag{5}$$

In this study, we denoted the probability of high innovative industries as a baseline category by δ_o and the estimate by δ_{oo}.

The moderate innovative industry by δ_1 and the estimates δ_{11}. The low innovative is denoted by δ_3 and the estimate δ_{33}. by the response probability satisfying with our base category (high innovative), we can calculate these probabilities as follows.

$$Log\left(\frac{\delta_{11}}{\delta_{00}}\right), \left(\frac{\delta_{22}}{\delta_{00}}\right), Log\left(\frac{\delta_{33}}{\delta_{00}}\right) \tag{6}$$

Since we have three categories, (j=3) thus we have the following equations: lets

$$y_1 = Log\left(\frac{\delta_{11}}{\delta_{00}}\right), y_2 = Log\left(\frac{\delta_{22}}{\delta_{00}}\right), y_3 = Log\left(\frac{\delta_{33}}{\delta_{00}}\right) \tag{7}$$

To calculate the base of the system of the actual logarithm we have;

$$\delta_1 = \frac{\exp(y_1)}{1+\exp(y_1)+\exp(y_2)+\exp(y_3)} \tag{8}$$

$$\delta_2 = \frac{\exp(y_2)}{1+\exp(y_1)+\exp(y_2)+\exp(y_3)} \tag{9}$$

$$\delta_3 = \frac{\exp(y_3)}{1+\exp(y_1)+\exp(y_2)+\exp(y_3)} \tag{10}$$

Where the first term in each denominator and numerator reflects changes in exp($\alpha_0 + \beta_0$) for $\alpha_0 = \beta_0 = 0$

Result Analysis

Innovation Performance across China Industrial Enterprises Above High Designated Size by Industrial Sector

This section starts with the analysis of the output-oriented DEA model. Table 6 and Table 7 presents the optimal efficiency solution and technological change of the 38 selected industrial enterprises above high designated for the year 2016-2018. Table 6 shows the High Designated Industries (HDI) nature of scale economies: Constant Return to Scale (CRS), Variable Return to Scale (VRS), Scale (R-Scale), and Decision. The R-scale value was obtained by dividing the CRS by the VRS. The letters (icr, cns and dcr) in the decision column represent a return to scale translated as innovation efficiency of the industries as increasing, constant, and decreasing based on R-scale. The Malmquist output table comprises changes in technical efficiency (ECCH), changes in technical progress (TCCH), changes in pure technical efficiency (PECH), changes in scale technical efficiency (SECH), and technological innovation change or total factor productivity change (TFPCH). MPI tends to calculate productivity changes over time that may result from changes in technical efficiency (EC) and technical progress (TC). The evaluation of MPI is based on the value of one (fare et al 1992). Any value greater than one means that industry for a given (t+1) period has incurred positive growth compared to time (t). The value of less than one means a decline in productivity. Value equals one means productivity is stagnant.

Table 6: Malmquist Index of firm means

Industries	CRS	VRS	SCALE	R-Scale
HDI1	0.976	0.982	0.995	dcr
HDI2	0.986	0.987	1.000	cns
HDI3	0.983	0.984	1.000	cns
HDI4	0.999	0.999	1.000	cns
HDI5	0.995	0.996	0.999	dcr
HDI6	0.995	0.995	1.000	cns
HDI7	0.965	0.993	0.972	dcr
HDI8	0.963	0.999	0.964	dcr
HDI9	0.981	1.000	0.981	icr
HDI10	0.974	0.981	0.993	dcr
HDI11	0.975	0.985	0.990	dcr
HDI12	0.983	0.992	0.991	dcr
HDI13	0.993	0.993	1.000	cns
HDI14	0.967	0.983	0.983	dcr
HDI15	0.975	0.995	0.980	dcr
HDI16	1.000	1.000	1.000	cns
HDI17	0.996	0.999	0.997	dcr
HDI18	0.994	0.999	0.995	dcr
HDI19	0.988	0.993	0.995	dcr
HDI20	0.989	1.000	0.989	icr
HDI21	0.996	0.997	0.999	dcr
HDI22	0.985	0.988	0.997	dcr
HDI23	0.986	0.989	0.997	dcr
HDI24	0.984	0.986	0.998	dcr
HDI25	0.991	0.994	0.996	dcr
HDI26	0.986	0.987	0.999	dcr
HDI27	0.997	0.998	0.999	dcr
HDI28	0.992	0.994	0.998	dcr
HDI29	0.994	0.995	0.999	dcr
HDI30	0.989	0.995	0.993	dcr
HDI31	0.975	0.984	0.991	dcr
HDI32	0.979	0.987	0.992	dcr
HDI33	0.982	0.991	0.990	dcr
HDI34	0.968	0.984	0.984	dcr
HDI35	0.974	0.979	0.994	dcr
HDI36	0.976	0.987	0.989	dcr
HDI37	0.957	0.980	0.977	dcr
HDI38	0.986	0.987	0.998	dcr
Mean	0.984	0.991	0.992	

Table 7: Malmquist Index of firm means

Industries	TECH	TCCH	PECH	SECH	TFPCH
HDI1	1.029	0.991	1.029	1.000	1.019
HDI2	1.018	1.012	1.018	0.999	1.030
HDI3	1.025	1.006	1.024	1.000	1.031
HDI4	1.000	1.020	1.000	1.000	1.020
HDI5	1.000	0.997	1.000	1.000	0.997
HDI6	0.996	0.998	0.996	1.000	0.993
HDI7	1.051	1.071	1.008	1.042	1.125
HDI8	1.052	0.983	0.998	1.055	1.034
HDI9	1.029	0.977	1.000	1.029	1.005
HDI10	1.039	0.981	1.028	1.010	1.019
HDI11	1.000	0.997	1.017	1.011	1.025
HDI12	1.028	1.030	1.012	1.015	1.057
HDI13	0.999	0.965	0.990	1.000	0.955
HDI14	1.032	0.967	1.008	1.024	0.988
HDI15	1.009	0.984	0.992	1.016	0.992
HDI16	1.000	0.972	1.000	1.000	0.972
HDI17	1.002	1.019	1.002	1.000	1.020
HDI18	0.999	1.014	0.999	0.993	1.006
HDI19	1.004	1.015	1.011	0.993	1.018
HDI20	0.992	1.021	1.000	0.992	1.013
HDI21	0.994	1.014	0.996	0.998	1.008
HDI22	1.012	1.008	1.011	1.001	1.020
HDI23	1.006	0.985	1.006	1.000	0.991
HDI24	1.020	1.020	1.019	1.001	1.040
HDI25	0.991	0.955	0.994	0.977	0.946
HDI26	0.983	0.970	0.985	0.998	0.953
HDI27	0.995	0.984	0.996	0.999	0.980
HDI28	0.997	1.003	0.994	1.003	1.004
HDI29	1.001	1.003	1.001	1.000	1.004
HDI30	0.986	1.035	0.996	0.990	1.020
HDI31	0.992	1.026	0.998	0.994	1.017
HDI32	1.016	1.010	1.014	1.003	1.027
HDI33	1.013	0.983	1.011	1.001	0.996
HDI34	1.009	0.977	1.013	0.996	0.985
HDI35	1.011	0.981	1.013	0.998	0.992
HDI36	1.007	0.981	1.019	0.988	0.988
HDI37	1.000	0.985	1.031	0.970	0.985
HDI38	1.020	0.996	1.017	1.003	1.015
Mean	1.009	0.998	1.006	1.003	1.007

As shown in Table 6, only two industries out of thirty eights are exhibiting increasing returns to scale. However, a total of six industries have exhibited a mean efficiency of stagnation (constant return to scale). In contrast, the remaining industries are found to have a decrease in scale efficiency. The scale value of less than one. This signifies a wide gap among the industries under study, causes by differences in technical efficiency. Six industries were found to have a scale value of 1, which exhibited a mean efficiency of stagnation (constant return to scale) in their productivity.

From Table 7, the average growth rate of technological change (TFPCH) is 0.7%, with an average growth rate of technical efficiency (TECH) of 0.9%, and an average negative growth rate in technical progress (TCCH) of -2%. The result indicates that innovation is essential to TFP growth. However, the positive average TFP growth rate of 0.7% was not brought by technical progress but rather a technical efficiency. This demonstrates that management efficiency exceeds technological efficiency during the study period. And that China industrial enterprises above high designated are on average experiencing a negative growth rate in terms of technical progress for the period under study.

Similarly, the contribution of technical progress was lower than anecdotal, based on the overall industrial efficiency. Overall, the industries have exhibited technical inefficiency within the range of 1.9% to 18.8% for the technical progress during the study period. Based on the current world's science and technology revolution, it means that Chinese industries have a low level of technological innovation, but working for the improvement of technology is quite promising. However, despite a decline in TCCH, there is a positive increase in TECH and TFPCH of zero-point-nine and zero-point-seven percent respectively, which signifies that China's industrial enterprises above high designated are spurring innovation during the study time frame. However, more initiatives are needed to sustain the pace of innovation for the industries to be better equipped to withstand the innovation challenges of the world of science and technology revolution.

By decomposing the mean of technical progress inefficiency (0.998) into pure technical efficiency mean and scale of technical efficiency, it can be observed that the overall technical inefficiency of Chinese industrial enterprises is primarily due to pure technical efficiency. It suggests that management of China's industrial enterprises should concentrate on reducing technical inefficiency thereby improving technological innovation in their industries first, and then move on to increase their efficiencies on the scale. Regarding pure technical inefficiency, it is found that on average industries can improve their technical innovation by the same level of measured inputs with 0.7% less output keeping the current ratio of input constant. Meaning, inefficient companies have great potential to improve their innovation output so that they can run at the same degree of efficiency just like the most efficient company in the study sample.

The average innovation performance trend of the study industry's efficiency scores is shown in Fig. 1. It comprises TECH, TCCH, and TFP. It has been seen that there exist high changes in technical efficiency in low innovative performance industries like HDI13, HDI15, HDI33, HDI35, HDI37, and invariably a high changes in technical progress among high innovative output industries such as HDI17, HDI11, and HDI25. These disparities indicate a low technical innovation for the low innovative industries. Similarly, the trend of TECH was shown to be more close to TFPCH, indicating an excellent level of managerial skills in the resource allocation and utilization of each factor of production. Overall, the China industrial enterprise should focus on improving their technological innovation to meet the current challenges posed by the world's new science and technological revolution.

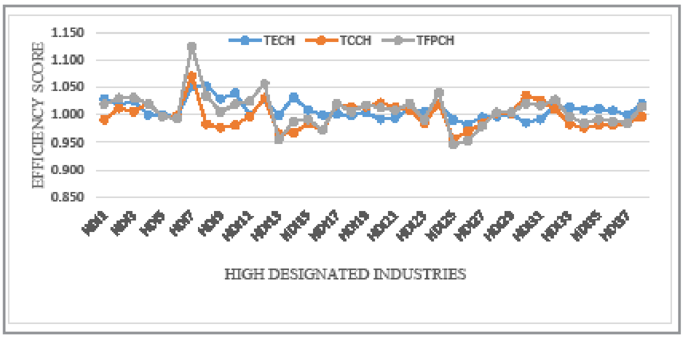

Figure 1: Innovation performance across China industries above designated size by Industrial sector

Discussion of Empirical Result Analysis

In this section, the present study introduced ordinal regression analysis to further explain the variation of innovation performance of the industries under study. Reference to the outputoriented DEA result obtained from Table 7, the study ranks the innovation performance of the study industries into three categories. High innovative, moderate innovative, and low innovative industries, based on the average efficiency score of total factor productivity change of industry. A score level of fewer than 1 means low innovation, a score level falling between (1-1.20) as moderate innovative, and a score level falling between (1.21-1.60) as highly innovative. However, the study dependent variable for the estimation of a parametric model is formed based on these categories and was derived from the technological change index derived from the Malmquist DEA analysis. The independent variables cover EXPRDsal, EXPRDpat, FTRPaaemp, PATemp, and SALexpnpd (see Table 5).

Table 8 shows the case processing summary of the ordinal regression result, the proportion of cases falling at each level of independent variables are 26, 12, and 38 for the Low Innovative, Moderate innovative, and High Innovative industry respectively. The result of the likelihood Chi-square ratio reveals that there is a significant improvement in the fit of the final model over the null model [x^2 (3) = 21.628, p < 0.001].

Table 8: Case process summary and Model fitting

Category	Level	Falling No	Marginal percentage
Low Innovative	< 1.00	26	34.2
Moderately innovative	1-1.20	12	15.8
High Innovative	1.21 – 1.60	38	50.0
Valid		76	100%

The estimation technique of ordinal logistic regression (OLR) assumes that the relationship between the independent variables is the same across all possible comparisons (Osborne, 2017, p. 147) involve in the dependent variable - an assumption referred to as proportional Odds. The study result of the test of parallel lines reveals that the assumption is satisfied (p= 0.743) and the Pseudo R-square value is 0.28.6. The Pearson Chi-square test stood at [x^2 (3) $= 156.90, p = 0.236, p > 0.001$] and deviance test [$x^2$ (3) = 131.13, $p = 0.789$, $p > 0.001$] were both non-significant that the study model is of good fit. A non-significant text result of the goodness of fit model indicates the model fits the data well (Field, 2018), thus, the variables used in this study serves as good measurement indicators for innovation performance of the industries under study.

Table 9 depicts regression coefficients and significance tests for each independent variable in the model. The Exp(B) column contains odds ratios signifying the multiplicative change in the odds of being in a highly innovative category, for every unit increase on the innovative indicator used in this study holding the remaining indicators constant. The odds ratio greater than 1 means a high probability of being at a high level, less than 1 means less probability of being at a high level. The odds ratio equals unity means no predicted change. As observed, for the most part, the p-value from both tables is very consistent.

Table 9: Model Estimates

Parameters		β	Std. Error	Exp(β)	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Threshold	[Low Innovative= 1]	23.411	7.467	1.470E+10	.002	8.777	38.045
	[Moderate Innovative = 2]	24.247	7.505	1.390E+10	.001	9.538	38.955
Location	EXPRDsal	6.182	6.163	484.096	.316	-5.897	18.262
	EXPRDpat	.083	.042	255228.62	.047	.001	.166
	FTRPaaep	-.019	.010	0.982	.050	-.037	1.455E-5
	PATten	12.450	4.126	4.367	.003	4.363	20.537
	SALexpnpd	1.474	.471	1.087	.002	.550	2.398
Link function: Logit.							

From the model estimate in Table 9, the result shows that for every single unit increase of (EXPRDsal and EXPRDpat) there is a projected increase of 6.182 and 0.083 in the odds that the industry will be in a highly innovative (as opposed to a lower) category of innovation. This shows that Chinese industrial enterprises falling into the category of high-innovative are likely to resolve the ongoing revolution in new science and technology in the world within the period of the government MIC25 plan. The (EXPRDsal and EXPRDpat) odds ratio reveals that, the odds of being in a higher category of innovation increases by a factor of 484.10 and 255228.62 for every one-unit increase on R&D expenditure per sale and R&D expenditure per patents respectively.

The coefficient of research and development expenditure per sale is not statistically significant indicating the existing gap in technical progress across the study sample. Expenditure per sale (EXPRDsal) and expenditure per patent (EXPRDpat) are referred to as the continuous development of technology innovation in this research [30].

R&D personnel (FTRDPemp) is a non-significant predictor in the model. This indicates the need for less use of human capital to overcome the current technological innovation. The result shows that every one unit increase in (FTRDemp) would lead to a projected decrease of (-019) in the chances of a moderate and low innovative category falling into the category of high-innovative industry and achieving the desired MIC25 plan. The odds ratio of (FTRDemp) shows that the chances of a moderate innovative and low-innovative category falling into the higher innovative category increases by a factor of (0.982) for each unit increase in R&D workers per average annual number of employees. This result is in line with the Chinese government MIC25 plan, and the current world's new science and technology revolution. That is a production of goods and services to be fully automotive with less or without any human effort. There is thus a need for the change in innovation strategic formula for the industries under study. From their old strategic formula of winning through cheap labor to winning through technological innovation.

Patent per thousand employees (PATten) is defined as the role of independent research in technological progress for the industries under study. It is found to have a positive significant indicator of innovation in this model. It shows that a one-unit increase in patents would lead to a predicted increase of 12.45 in the odds of being in the category of the high-innovative industry by the moderate and low-innovative category. The odd ratio of PATten is found to be 4.367. This reveals high odds of falling into a highly innovative industry with a one-off rise in independent research in technological progress in relation to moderate and low innovation industries. This result reveals no evidence of the importance of collaborative research in technological progress, which is contrary to the existing nature of the world's new science and technology revolution. The nature of current science and technology revolution advocate the needs for industries to design and develop innovative experience environment based on collaborative ICT-infrastructures that can enable network organization and customer communities to interact [31].

(SALexpnpd) represent the ratio of sales accrued from innovation related to the expenditure of new project research development. It means fertility in continuous technological innovation developments. It is also found to be a significant positive predictor of innovation. The result shows that for every one-unit increase on SALexpnpd, there is a predicted increase of 1.474 in the odds of an industry being in a higher (as opposed to lower) category innovation industry.

Meaning, an industry with high performance in innovation is more likely to quickly overcome the new challenges brought by the world's new science and technology revolution, and thus achieve China's government MIC25 plan within the stipulated period. The ratio of sales accrued through innovation related to the expenditure of new project research development helps the industry to foster innovation and innovate more. Therefore, the result shows the advantage taken by high innovative industries to wider their innovation gap with moderate and low innovative industries. The SALexpnpd odds ratio reveals that the odds for low and moderate innovative industries falling into the high innovative category increases by a factor of 1.087 for every one unit increase in sales accrue from innovation.

Findings and Conclusion

This study categorized the study industries into three: high innovative, moderate innovative, and low-innovative industries. The categorization is based on the average efficiency score of the total productivity change from the DEA result. The reason is to further understand the degree of variation in innovation efficiency and the impact of innovation measurement indicators on the study industries at their varying degrees of innovation efficiency. Generalized Ordinal regression based on maximum likelihood is applied to obtain the parameter estimates for the analysis. The results obtained found (EXPRDpat, PATemp, and SALexpndp) to be significant positive predictors of innovation. (FTRDPemp) is found negative but significant predictor of innovation. EXPRDsal is found positive but non-significant predictor of innovation. Moreover, based on the model's odds ratio, there was a high likelihood for the low and moderate innovative industries to leapfrog high-innovative industries in the new world of science of technology revolution.

Policy Implication

This study fills the existing literature gap by measuring the innovation output of a given economy and finding the appropriate innovation inputs that match the industry at its specific level of success in innovation. Therefore, the findings provide policymakers in major emerging economies with some new insights. First, policymakers need to recognize the positive effect of science and technology activities on the performance of innovation in the industry. Industrial policy should be made to boost firms' indigenous technical potential through policy initiatives such as through intramural spending on science and technology activities and encouraging firms to be more responsive and collaborative for innovation, further enabling firms to integrate expertise from diverse sources with regional technologies into commercial goods.

Secondly, the results of the DEA study show that there is a significant difference in the efficiency of innovation during the study period. Therefore, this study suggests the need for customizing R&D planning in line with the technological characteristics of the organization and innovation performance of the industries. In this regard, more efficient innovation progress can be obtained through this process, and the existing innovation efficiency gap between the industrial enterprises' understudy can be minimized if not eliminated. The study provides sufficient evidence which confirmed the crucial role of technical efficiency in the industry's innovation level.

Managerial Implication

The new science and technology of the world today is an innovation-driven development strategy through the use of technology. It requires the achievement of industrial output growth through technical progress as opposed to the obtained DEA result of this study. The China industrial enterprises above high designated have on average failed in the use of technological innovation to meet or shift their production frontier to achieve technological change. Therefore, the management of China's industrial enterprises above high designated size should stay focus on improving their technical innovation, for improving their innovation output to meet the contemporary challenges prompted by the new science and technology revolution of today's world.

However, the study found that on average, the industry can improve its technical innovation using the same level of measured inputs with 6% less output keeping the current input ratio constant. Therefore, this result would help the industries in acting fast by applying the right mix of strategies to squarely face the challenges of the world's new science and technology revolution, and in achieving the desired target of the Chinese government's MIC25 innovation agenda. However, the management concern of China industrial enterprises above high designated should concentrate on improving their productivity level through an increase in technical innovation not an increase in technical efficiency.

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