





The Impact of Autonomy Reform on the Efficiency of Public Hospitals in China: A DEA-ITSA Combination Analysis

Ningbo An ^{1,2}, Quan Zou³, Ji-Bin Li ⁴, Kaiyuan Luo ⁵, Gang Sun ⁶, Xing Ni⁷, Oudong Xia^{1,8,9}

¹School of Public Health, Southern Medical University, Guangzhou, Guangdong, People's Republic of China; ²Dermatology Hospital of Southern Medical University, Guangzhou, Guangdong, People's Republic of China; ³Shenzhen Nanshan Center for Chronic Disease Control, Shenzhen, Guangdong, People's Republic of China; ⁴Department of clinical research, Sun Yat-sen University Cancer Center, Guangzhou, Guangdong, People's Republic of China; ⁵The Third Affiliated Hospital, Guangzhou Medical University, Guangzhou, Guangdong, People's Republic of China; ⁶Department of Health Management, School of Health Management, Southern Medical University, Guangzhou, Guangdong, People's Republic of China; ⁷School of Public Administration and Policy, Renmin University of China, Beijing, People's Republic of China; ⁸Zhujiang Hospital, Southern Medical University, Guangzhou, Guangdong, People's Republic of China; ⁹Shantou University Medical College, Shantou, Guangdong, People's Republic of China

Correspondence: Xing Ni; Oudong Xia, Email nixing@ruc.edu.cn; 791966640@qq.com

Purpose: Since 2014, China has been rolling out a new autonomy reform for public hospitals, aiming to enhance their efficiency and better utilize the health budgets. The purpose of this research is to assess the reform's success and explore its effects on hospital outcome efficiency, laying a foundation based on empirical evidence for future policy decisions.

Methods: The data envelopment analysis(DEA) and interrupted time-series analysis (ITSA) approaches were combined to analyze the reform impacts on the 16 samples of Shenzhen municipal public hospitals in China, using data extracted from the Shenzhen Health Statistics Yearbook from 2002 to 2023.

Results: The results revealed that from 2002 to 2023, 15 out of 16 sample hospitals achieved total factor productivity improvement in Shenzhen city of China, with the average growth rate of Malmquist total factor productivity index(MI) was 3.05% and the highest growth rate was 6.93%, yet only one hospital showing a growth rate of -0.02%. The results of ITSA show a significant intervention in 2014. After the policy intervention, the fixed reference Malmquist total factor productivity index(FRMI) for the general and the specialty hospital group increased at rates of 0.04680($P<0.000$) and 0.1746($p<0.000$) per year by the Newey-West model, similarly, the rates of 0.04689($P<0.000$) and 0.1762($p<0.000$) per year by the Prais-Winsten model.

Conclusion: The reform has positively impacted public hospitals' total factor productivity(TFP). The TFP of the general hospitals was increasing before the policy intervention of autonomy hospitals, but the time of its implementation was associated with a more significant rise. Meanwhile, the TFP of specialty hospitals decreased before the intervention; however, its trend shifted to growth after the intervention. This research further emphasizes the applicability of the DEA-ITSA combination method as an effective tool for health policies evaluation using public data within China's healthcare framework.

Keywords: public hospital reform, decentralization, autonomy, data envelopment analysis, interrupted time-series analysis, China

Introduction

China has dedicated itself to promoting the reform of public hospital autonomy to solve the problems of shortage of healthcare resources and inefficiency of medical services since 1978.¹ The reform adopted a gradualist reform model, introducing market mechanisms in public hospitals, such as property rights reform, outsourcing services, and establishing public-private partnerships.²⁻⁴ In the past three decades, the governance of public hospitals in China could be characterized as a distorted semi-autonomous model.⁵ Beginning in 2009, China initiated a series of new health reforms, often with enhanced autonomy of hospitals, to draw public focus towards financial productivity, healthcare quality, and fostering social unity.⁶ In this context, the pilot reform of public hospitals was officially launched in 2010, and the "Guidance on Comprehensive Reform Urban Public Hospitals with Pilot Program" was issued by the central

government.⁷ Between 2010 and 2016, 200 cities in China implemented reforms in public hospitals, exploring new policies, including contemporary hospital management systems, corporate governance, and public hospital financing models. These pilot cities were authorized by the central government to experiment with different policy combinations to achieve the goals of the reform.⁸ Shenzhen, a major city in the Guangdong province of China with a large population and a strong economy, was selected as one of the first pilot cities and has introduced a series of reform policies. The Shenzhen Municipal Government has gradually introduced a series of policies aimed at the autonomy of public hospitals, including the reform of the corporate governance structure of public hospitals, the “quota system” human resource management model, and the diagnosis-intervention packet (DIP) payment model, and so on.⁹

A significant number of nations remain dedicated to realizing a crucial aspect of their healthcare systems: efficiency.^{10,11} Based on this, some international scholars have also conducted extensive research on the impact of autonomy reform on the efficiency of public hospitals. The reform of public hospital autonomy has different implications for medical service efficiency among different countries or regions. Some developing countries have reported improvements in resource utilization efficiency, such as a reduction in average length of stay days and better inventory management control, following the implementation of autonomy reforms.¹² Two studies from Kenya and Colombia found improvements in technical efficiency¹³ and total factor productivity of hospitals undergoing autonomy reform.¹⁴ Regarding bed occupancy rates, a study in Kenya suggested an increase in the rates due to autonomy reform, while Turkey and Vietnam had no significant impact. In contrast,^{15–17} two studies in Indonesia concluded that reforming hospital autonomy did not notably impact efficiency,^{12,18} and a research paper from Poland indicates that fiscal decentralization may decrease hospital efficiency, although these results lacked statistical significance.¹⁹ It is apparent that it remains controversial whether the autonomy reform of public hospitals has a significant impact on the efficiency of public hospitals.

Data envelopment analysis(DEA) is particularly suitable for analyzing the efficiency of organizations with multiple inputs and outputs, especially for evaluating the efficiency of health organizations.²⁰ A systematic review summarized 317 studies on the evaluation of health system efficiency. Among these, DEA is used in 82% of frontier efficiency analyses.^{21–23} In another systematic review, this proportion was even higher, reaching 90%.²⁴ Based on the above research, we are confident that DEA is a universal method for studying the efficiency of health systems. DEA’s advantage is found in spotting inefficient and optimal units, but its weak ability to reveal reasons for the inefficiencies in processes hinders the further promotion and extension of this method.^{25,26}

This study will attempt to use a combined approach of interrupted time-series analysis (ITSA, offers a quasi-experimental research design) and DEA to compensate for the insufficiency of causal inference capabilities of DEA.^{27,28} Taking Shenzhen City, a pilot city for public hospital reform in China, as the research subject, this study has two objectives: firstly, to assess the impact of the autonomy reform of public hospitals on their efficiency; secondly, this research further emphasizes the applicability of the DEA-ITSA combination method as an effective tool for health policies evaluation using public data within China’s healthcare framework.

Samples and Methods

Research Design

This study was divided into three steps. First, we initially selected input and output variables based on the literature study and two-stage clustering method. In the second step, we used the appropriate DEA model to input the selected variables. We obtained the Malmquist Total Factor Productivity Index(MI) and Fixed Reference Malmquist Total Factor Productivity Index(FRMI), as well as the decomposition EC and TC of each sample hospital during different periods. Third, we utilized ITSA to analyze these indices to evaluate the efficiency changes by time series and the impact of policies on them.

Data

The data are primarily collected from Shenzhen Health Statistics Yearbook from 2002 to 2023, with the data in 2023 being in an electronic spreadsheet obtained by emailing the Shenzhen Municipal Health Commission. Overall, the study’s sample consists of public hospitals in Shenzhen, totaling 16 medical institutions, including nine general hospitals and

seven specialty hospitals. This study excluded the Shenzhen Occupational Disease Prevention and Treatment Hospital, a prevention institution that does not match the characteristics of other sample hospitals; it also excludes district-level public hospitals to meet the homogeneity requirement of the DEA. The data from the electronic documents was directly imported into WPS 12.0, while the yearbook data was manually entered using a double-checking method to ensure data entry quality.

Methods

Variable Selection

Based on literature research,^{29–36} we initially selected the input and output variables for hospitals. Then, according to the descriptive statistical results, we removed variables with high zero-value rates, as excessive zero values lead to unstable model outputs.³⁷ Next, we used clustering methods to preliminarily classify the sample hospitals, as the DEA model requires homogeneity among the samples. Simultaneously, we utilized the importance index of predictor variables in the two-stage clustering method to eliminate variables with low informational content. This study did not use correlation coefficients to select variables to avoid omitting variables purely on the grounds of correlation.³⁸ Descriptive statistics and cluster analysis were performed using SPSS 26.

DEA and Model Selection

DEA, a non-parametric linear programming technique, evaluates production units' relative efficiency by determining the ratio of a unit's output weighted sum to the total weighted of its input.³⁹ Efficiency indicates how well an organization has used its resources to produce the best outcome over a period. There are two main components of efficiency: allocative and technical efficiency.⁴⁰ Technical efficiency refers to achieving the maximum possible output with the least available sets of inputs;²⁴ allocative efficiency refers to the ability of an organization to utilize different input resources in optional proportion to produce a mix of different outputs.^{41–43}

Considering Shenzhen has a population of over 20 million, we hope medical institutions can provide more healthcare services to meet the growing demand for medical treatment. Therefore, this study adopts the output-oriented model.⁴⁴ The production technology of the healthcare system exhibits variable returns to scale, so this paper selects the Variable Returns to Scale(VRS) model.^{27,37} The standard radial model can only achieve a maximum efficiency value of 1. Andersen and Petersen proposed a method to further differentiate the efficiency levels of effective Decision Making Units(DMUs), which later became known as the super-efficiency model.⁴⁵ This study requires continuous annual efficiency values for regression analysis as observation variables; thus, this model is used to further distinguish the most efficient hospitals. Technological progress must be considered when analyzing the technical efficiency of cross-period DMUs, so the Malmquist total factor productivity index DEA model is chosen.

The policy impact emerged in 2014 as the fixed frontier in the fixed-reference-Malmquist model for every DMU.⁴⁶ The average value of FRMI from 16 sample hospitals between 2002 and 2023 will be used as the dependent variable in the ITSA.

Mix-sample analyzing leads to efficiency overestimation or underestimation. Thus, it is necessary to measure the efficiency separately for each type of hospital. We applied the Meta-Frontier-DEA model by Rao et al^{28,47} and used the Technology Gap Ratio (TGR) to measure efficiency differences across hospital types. If the TGR is more than 1, it indicates an apparent difference between different groups, making it necessary to divide all samples into various groups. The above DEA model analysis was completed using MaxDEA 8.22.

ITSA

When evaluating the effects of alterations in public policies, like introducing new legislations or taxes, scholars frequently encounter just one effective example. It's usual in such scenarios for only aggregate data, such as unemployment rates and efficiency.⁴⁸ ITSA differs from typical intervention study formats as it focuses solely on a single sample instead of contrasting it with a control group.⁴⁹ Imagine acquiring several data points on a specific outcome variable both before and after the intervention.⁴⁸ Under such circumstances, an ITSA adopts a quasi-experimental research style, holding promise for considerable internal reliability.⁴⁹

This study uses ITSA to assess changes in the total factor productivity index of sample hospitals. Typically used in natural experiments, this approach assesses observed changing trends in variables before and after a known intervention. It's effective in evaluating non-control group interventions and circumvents issues like bias in selecting unrecorded factors due to differences between groups.⁴⁹ However, continuous observations of at least 20 points are required.⁵⁰ The single-group ITSA regression model assumes the following form:^{51,52}

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \varepsilon_t$$

The model illustrates β_0 as the initial observed variable's intercept; β_1 as the gradient of variable pre-intervention; β_2 as the immediate alteration in the observed variable's value post-intervention; β_3 as the variance in observational slopes before and after intervention; Y_t as the cumulative outcome variable at every evenly spaced time point t ; T_t as the interval from the study's commencement; X_t as a placeholder (indicator) for the intervention (with 0 pre-intervention, or 1 otherwise); $X_t T_t$ the interaction term, and ε_t as the residual at time t .⁴⁸ The above ITSA was completed using STATA 16.

Results

Variable Selection

Selection of variables was guided by prior empirical research and literature. Input variables usually include labor, capital, and investment. Among the 256 samples, due to the adjustment of statistical indicators by the Shenzhen Municipal Health Commission, nine indicators are no longer included in the yearbook. We have removed these indicators: 1) recovery rate, 2) mortality rate, 3) bed workdays, 4) bed utilization rate, 5) bed turnover rate, 6) bank loans, 8) total actual bed days occupancy, and 9) discharged patients bed days.

Frequency statistics show that some labor variables, such as radiologists, clinical technologists, support staff, and as well as capital, such as the annual actual total investment, total construction investment, and total equipment purchase amount, exhibit over 20% zero values, then removed them. Finally, we used the two-step cluster method to select the indicators on the importance of predictor variables above 0.8⁵³ and excluded several indicators, such as the management staff and pharmacists. Ultimately, this study used the total number of employee staff, the total number of medical and technical, and the number of registered doctors and nurses to represent human resources, while the number of beds served as a capital input variable.

Output variables usually include the number of outpatient visits, inpatients, medical services, income, quality, etc. After removing non-continuous indicators and those with more than 20% zero values, we used a two-step cluster classification method to predict variable importance below 0.8, eliminating indicators such as average medical expenses per patient visit, etc. Ultimately, in this study, the number of patient visits, outpatient visits, and discharges were used to represent medical service factors, while outpatient and inpatient medical revenue were used to describe revenue factors as output variables. Descriptive statistics of the input-output variables are shown in Table 1.

Test and Analysis of the TGR

Considering the DEA requirements for the homogeneity of DMUs, we conducted TGR tests on different types of sample hospitals. First, we conducted a non-parametric test on two groups of hospital data, and the statistical results indicated that neither conformed to a normal distribution.

The Mann–Whitney *U*-test suitably revealed statistically significant differences between the two groups of TGR, as shown in Table 2. Next, comparing the mean TGR values of the two groups, the results indicated differences in the mean TGR values and the meta-technology frontier. Compared to the meta-frontier, the general group was higher, while the specialty group was lower, as shown in Table 2. Clearly, it is necessary to measure their MI separately, ensuring that their technical efficiency values are closer to reality. This result also corroborates the findings of the previous cluster analysis.

Table 1 Descriptive Statistics

Type	Name	Unit	Abbreviation	Min	Max	Mean	SD
Input indicators	Beds	Unit	BEDS	71	2896	877	648
	Overall staff	Person	OS	102	5319	1496	1100
	Medical staff	Person	MES	85	4604	1251	917
	Doctors	Person	DOC	36	1617	458	339
	Nurses	Person	NUR	36	2434	588	455
	Medical laboratory technician	Person	MLT	1	170	53	39
Output indicators	Total visit to health institution numbers	Person	TVN	7633	3,710,012	1,220,812	973,267
	Inpatients	Person	INP	7633	3,181,034	1,038,901	819,126
	Outpatients	Person	OUP	68	142,791	32,470	27,974
	Inpatient revenue	10 thousand yuan	INR	70.80	169,137.08	35,792.27	36,407.59
	Outpatient revenue	10 thousand yuan	OUR	52.22	253,146.60	44,517.43	49,355.67

Abbreviation: SD, Std. Deviation.

Table 2 Comparison of Technical Efficiency Gap Between General and Specialized Public Hospitals in Shenzhen From 2002 to 2023

Group	Mean TGR	Z			Asymp. Sig.
		Specialized	Entire	General	
General	1.083	−5.621	/	/	0.000
Specialized	0.976	/	−3.106	/	0.002
Entire	1.030	/	/	−3.389	0.001

Abbreviations: TGR, Technology Gap Ratio; Asymp. Sig., Asymptotic Significance Level (2-Tailed).

Results of DEA

This study applied the Super Efficiency and MetaFrontier-Fixed Reference Malmquist model with output-oriented parameters and the VRS model. The year (2014) is confirmed as the fixed frontier period to measure each DMU's Malmquist total factor productivity index (MI and FRMI). The cumulative MI was used to analyze whether each sample hospital improved the total factor productivity from 2002 to 2023. The accumulative MI from 2002 to 2023 is used to evaluate the samples and determine whether these hospitals achieved TFP progress. The FRMI is used as the outcome variable for the ITSA to analyze the impact of policy intervention.

From 2002 to 2023, 15 out of 16 sample hospitals achieved total factor productivity improvement, with only one hospital showing a growth rate of −0.02%. The highest growth rate was 6.93%, and the average growth rate was 3.05%, as shown in Table 3. Using the FRMI, we observed the time-series trend of efficiency change for two groups of hospitals during different periods (Figure 1). Both the general and the specialty groups showed an upward trend after 2014. Before 2014, the specialized group showed a downward trend, while the general group showed an upward trend. The trend change for the specialty group before and after the intervention is easily observable (Figure 1b); unfortunately, the general group cannot be accurately determined (Figure 1a), requiring further analysis.

Results of ITSA

This study uses ITS to assess the impact of the autonomy policy on improving Shenzhen public hospitals' total factor productivity progress, using a single-group design. More specifically, we evaluate whether the introduction of the autonomy policy in public hospitals has led to changes in the level and trend of FRMI in these hospitals.

Next, we specify a single-group ITSA, using the mean FRMI of two group sample hospitals in each period as the observed variable and 2014 as the start of the intervention. We request the post-intervention trend estimates and plot the results. The model is estimated using Newey (zero lag) and the Prais model.

Table 3 Malmquist Index of 16 hospitals in SHENZHEN Between 2002 and 2023

Hospital	MI	EC	TC
H1	1.0298	0.9976	1.0323
H2	1.0277	1.0083	1.0192
H3	1.0454	0.9895	1.0566
H4	1.0529	0.9970	1.0560
H5	0.9998	0.9980	1.0018
H6	1.0339	1.0019	1.0320
H7	1.0244	1.0256	0.9989
H8	1.0400	0.9464	1.0989
H9	1.0693	0.9628	1.1107
H10	1.0177	1.0207	0.9970
H11	1.0185	0.9962	1.0224
H12	1.0280	1.0099	1.0180
H13	1.0573	1.0148	1.0419
H14	1.0000	1.0000	1.0000
H15	1.0223	1.0109	1.0113
H16	1.0207	0.9370	1.0894
>1	14	7	13
<1	1	8	2

Notes: H1-10: 2002–2023, H11: 2012–2023, H12-13: 2016–2023, H14: 2018–2023, H15: 2019–2023, H16: 2018–2023.

The ITSA Results of the General Hospital Group

As shown in the Table 4 model (1), the initial level of FRMI was estimated at 0.919, and FRMI appeared to increase every year before 2014 by 0.00668 ($P=0.189$, $CI=[-0.003, 0.016]$), but this increase was not statistically significant. In the first year of policy intervention (2014), FRMI appeared to be a substantial increase of 0.182 ($P<0.000$, $CI=[0.110, 0.255]$), followed by a significant increase in annual trend (relative to the pre-intervention trend) of 0.0401 ($P<0.000$, $CI=[0.025, 0.054]$). We also see, from the lincom estimate produced by specifying post trend, that after the introduction of the autonomy policy, the FRMI increased annually at the rate of 0.0468 per year ($P<0.000$, 95% $CI=[0.037, 0.056]$), as shown in Table 4, Model ID (1). Figure 1a provides a visual display of these results.

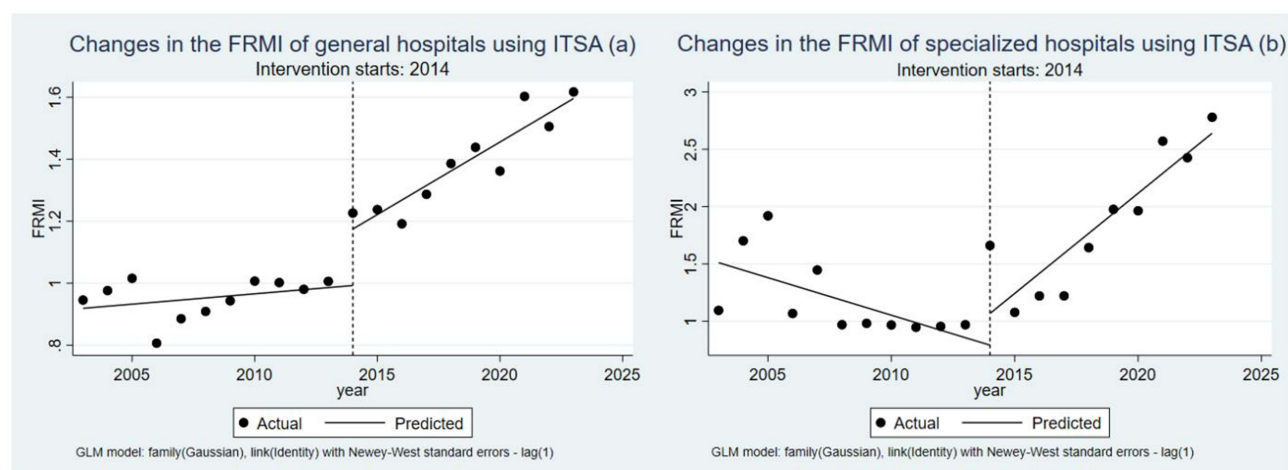


Figure 1 Single-group ITSA with Newey–West standard errors and one lag. (a) General-hospitals Group, (b) Specialized-hospitals Group.

Table 4 ITSA Results for General-Hospitals Group Only

Model ID	(1)	(2)	(3)	(4)	(5)	(6)
Variable	FRMI of General-Hospitals Group					
Model	Newey-West (1)			Prais-Winsten AR(1)		
Intervention Time	2014	2015	2016	2014	2015	2016
Pre-Intervention Trend(β_1)	0.00668	0.0157*	0.0210**	0.00697	0.0156**	0.0214***
Std. Err.	(0.00509)	(0.00893)	(0.00942)	(0.00552)	(0.00636)	(0.00687)
Immediate Effect After Intervention(β_2)	0.182***	0.121**	0.0880	0.179***	0.124*	0.0713
Std. Err.	(0.0370)	(0.0593)	(0.0831)	(0.0512)	(0.0665)	(0.0783)
Post-Intervention Trend(β_3)	0.0401***	0.0354***	0.0343***	0.0399***	0.0353***	0.0360**
Std. Err.	(0.00727)	(0.0109)	(0.0101)	(0.00835)	(0.0117)	(0.0158)
Constant(β_0)	0.919***	0.889***	0.870***	0.918***	0.889***	0.870***
Std. Err.	(0.0423)	(0.0568)	(0.0625)	(0.0325)	(0.0412)	(0.0489)
Post-intervention Linear Trend	0.0468***	0.0511***	0.0553***	0.0468***	0.0508***	0.0574**
Std. Err.	(0.00487)	(0.00419)	(0.00538)	(0.00640)	(0.00984)	(0.0140)
R ²				0.957	0.922	0.875
R ² _a				0.949	0.908	0.853
AIC	-2.503	-2.096	-1.950			
BIC	-51.69	-51.65	-51.64			
d_0				2.221	2.027	1.731
d_t				2.004	1.979	1.930

Notes: d_0: Durbin-Watson statistic (original), d_t: Durbin-Watson statistic (transformed), R²: R-Squared, R²_a: R-squared adjusted. Standard errors in parentheses, *: significance level, *** p<0.01, ** p<0.05, * p<0.1.

Then, actest was used to ensure that a fitting model could accurately explain the autocorrelation structure. As shown in the Output table, autocorrelation is not present from lag 1 to 9. Thus, the initial model specifying lag (0) should correctly account for this autocorrelation.

We use another Prais model to cross-validate the results with the Newey model. The former is designed to adapt to the AR (1) model and add robust standard errors, while the latter is based on an OLS model.

The two models cannot be directly compared with the output parameters since the estimates produced using Prais are transformed. However, these results confirm a significant increase in the annual trend of FIMI of 0.0399 (relative to the trend before policy intervention, $P < 0.000$, CI = [0.022, 0.058]). The Prais model provides the Durbin-Watson d statistic to indicate the model's correction for first-order autocorrelation. d can take on values between 0 and 4; under the null hypothesis, d equals 2. A value of d less than 2 indicates positive autocorrelation ($p > 0$), while a value of d greater than 2 indicates negative autocorrelation ($p < 0$). After transformation, the d value decreased from 2.221 to 2.004, as shown in Table 4, Model ID (4).

The ITSA Results of the Specialty Hospital Group

We repeated the above steps for the specialty hospitals group and obtained the estimated results, as shown in Table 5 Model ID (7), (10) and Figure 1b.

Results of the Robust Test

We conducted the ITSA robust test using two approaches: setting different intervention starting times and altering different model estimation methods. Using the Newey model to output results, we observed that the general group's results showed a significant increase in the annual trend of FRMI changes (relative to the pre-intervention trend of 0.0511 ($P < 0.000$) and 0.0553 ($P < 0.000$), and the specialty group's result showed the change of 0.224 ($P < 0.000$) and 0.235 ($P < 0.000$) per year at the intervention start years in 2015 and 2016. We also obtained significant results regarding the observed variables' changes in intervention effects using another Prais model. The results are shown in Tables 4 and 5.

Table 5 ITSA Results for Specialized-Hospitals Group Only

Model ID	(7)	(8)	(9)	(10)	(11)	(12)
Variable	FRMI of Specialized-Hospitals Group					
Model	Newey-West (1)			Prais-Winsten AR(1)		
Intervention Time	2014	2015	2016	2014	2015	2016
Pre-Intervention Trend(β_1)	-0.0654**	-0.0320	-0.0299	-0.0656**	-0.0327	-0.0303
Std. Err.	(0.0275)	(0.0349)	(0.0279)	(0.0260)	(0.0237)	(0.0206)
Immediate Effect After Intervention(β_2)	0.277	-0.0364	0.151	0.261	-0.0275	0.152
Std. Err.	(0.251)	(0.244)	(0.218)	(0.240)	(0.247)	(0.245)
Post-Intervention Trend(β_3)	0.240***	0.256***	0.264***	0.242***	0.256***	0.265***
Std. Err.	(0.0485)	(0.0396)	(0.0311)	(0.0394)	(0.0435)	(0.0477)
Constant(β_0)	1.511***	1.399***	1.392***	1.517***	1.403***	1.395***
Std. Err.	(0.202)	(0.215)	(0.199)	(0.153)	(0.154)	(0.146)
Post-intervention Linear Trend($\beta_2+\beta_3$)	0.1746***	0.2240***	0.2345***	0.1762***	0.2233***	0.2347***
Std. Err.	(0.0373)	(0.0127)	(0.0134)	(0.0300)	(0.0366)	(0.0431)
R ²				0.814	0.798	0.804
R ² _a				0.781	0.762	0.770
AIC	0.518	0.516	0.507			
BIC	-50.35	-50.35	-50.36			
d_0				1.997	1.966	2.007
d_t				1.873	1.934	1.936

Note: d_0: Durbin-Watson statistic (original), d_t: Durbin-Watson statistic (transformed), R²: R-Squared, R²_a: R-squared adjusted. Standard errors in parentheses, *: significance level, *** p<0.01, ** p<0.05, * p<0.1.

However, the AIC and BIC values of the Newey model outputs for the three different intervention points from 2014 to 2016 gradually increased, and the adjusted R² value of the Prais model outputs gradually decreased, indicating a decline in model fit. Fortunately, the Newey and Prais models yielded significant analytical results, giving us confidence that the intervention effectively influences the observed variables.

Discussions

Autonomy and the Efficiency of Public Hospitals

Challenges in public hospital systems common to public services include technical and distributional inefficiency; diminished productivity; lack of patient responsiveness; waste generation; among others. Lately, the concepts of autonomization and corporatization, akin to recent public sector organizational advancements, have been increasingly considered to enhance hospital performance.¹⁰ Autonomy reform of public hospitals leads to intensified market competition, which can improve healthcare efficiency and quality.^{54,55} The concept of hospital autonomy involves the transfer of administrative authority to the hospital management groups.⁵⁶ The core idea is to grant hospitals greater autonomy to enhance operational efficiency.⁵⁷

Hospitals play an important role in boosting healthcare expenses and form the primary segment of healthcare spending in numerous nations,⁵⁸ hence the focus of various reforms aiming to curb costs and enhance the value of healthcare expenditures.⁵⁹ Hospital autonomy reform initiatives began in developed nations including France, the Netherlands, Italy, New Zealand, the United Kingdom, and the United States, and from 1980 onwards, extended to developing countries like Ghana, India, Indonesia, Uganda, Zambia, and Kenya.²⁰ A holistic review summarized six major themes, based on 27 articles, about the effects of autonomy reform on hospitals:^{5,60} healthcare quality, hospital management indicators, type and number of services, social functions, financial management, and individuals, both of staffs and patients.⁵⁶ Adopting the Preker Harding model, one Chinese research indicates that hospital autonomy reform has impacted hospital costs and public welfare, medical service quality and efficiency, and accountability.⁵⁷ From the literature review, we can observe that the impact of hospital autonomy reforms on healthcare services varies across different countries.

Positive Impact on the TFP of Public Hospitals

Descriptive analysis shows that 15 of 16 sample hospitals from 2002 to 2023 achieved progress in total factor productivity. Based on MI growth, we can use FRMI as the outcome variable for the ITSA method; otherwise, the analysis results would be inaccurate.³⁷

The results of this study indicate that between 2002 and 2023, the efficiency levels of municipal public hospitals in Shenzhen varied depending on the type of hospital. Through the mean FRMI scatter plot, general hospitals displayed a gradual upward trend with a more significant increase after 2014; however, the slope change is difficult to distinguish. Meanwhile, specialty hospitals followed a V-shaped trend, as shown in Table 1 and Figure 1.

Consistent with the descriptive analysis results, the ITSA method showed a significant intervention in 2014. After the policy intervention, the FRMI for the general and the specialty hospital groups increased at rates of 0.04680 ($P < 0.000$) and 0.1746 ($P < 0.000$) per year. Our findings can support the conclusion that the autonomy reform of public hospitals is proceeding as planned and significantly affects the efficiency of Shenzhen municipal public hospitals, which may be optimistic.

We observed that the FRMI did not show statistically significant changes over time in the general hospital group's ITSA results before the policy intervention. Therefore, we attempt to adjust the intervention period to 2015 and 2016, and then obtain the statistically significant estimated parameters both in the Newey and the Prais models.

However, the AIC and BIC of the Newey model outputs for the three different intervention points from 2014 to 2016 gradually increased, and the R^2 of the Prais model outputs gradually decreased, indicating a decline in the model's fit (Table 4 Model 2,3,5,6,8,9,11,12).

According to the results of ITSA in the specialized hospital group, except for the first year of intervention in 2014, the level changes of the outcome variable were not statistically significant. The intervention did not immediately change the level of the variable but significantly increased its annual growth rate. These results indicated that policy interventions have a positive long-term impact on the observed variable (Table 5).

The robust test results are acceptable. Nevertheless, we also found that the AIC and BIC for the Newey model in the general hospital group gradually increased at the three different intervention points, indicating a decline in model fit. Additionally, the R^2 for the Prais model in 2014, 2015, and 2016 showed a downward trend in both groups, further suggesting a decline in model fit. The trend may be related to the reduced number of observations as the intervention period is backward, meaning fewer observations lead to worse model fitting.⁵⁰

This study demonstrates that the nationwide public hospital reform initiated in 2014 may have positively impacted the improvement of public hospitals' efficiency. The ITSA results show that the FRMI of general hospitals increased from 0.00668 ($P > 0.05$) to 0.0401 ($P < 0.000$) annually; the FRMI of specialty hospitals shifted from a yearly decrease of -0.065 ($P = 0.017$) to an increase of 0.240 ($P < 0.000$). Through decomposition analysis of EC and TC, the efficiency improvements mainly stemmed from technological advances (81.25% of sample hospitals had a cumulative TC greater than one from 2002 to 2023), while the contribution of technical efficiency was limited (43.75% of sample hospitals had a cumulative EC greater than one from 2002 to 2023). Additionally, we found that 31.25% of sample hospitals saw contributions from technical efficiency and technological advances to overall efficiency improvements, achieving optimal efficiency. See K.'s research, which indicates that the TFP of public hospitals in Shenzhen from 2005 to 2013 was declining,⁶¹ consistent with the conclusion for specialty hospitals in this study but not general hospitals. See's research may have led to an underestimation of the efficiency of general hospitals. This result also confirms the necessity of using the Meta-DEA model.

Our research indicates that the reform has a more significant impact on specialized hospitals. This result is consistent with the studies of Feng Ying,⁶ Liu Song,⁶² Chen Xinlan,⁶³ and Xia Qing⁶⁴ but inconsistent with the findings of Wu Jian⁶⁵ and Wu Guangyi.⁶⁶ By decomposing the MI, we observed that only one specialized hospital achieved simultaneous progress in EC and TC, while the majority of specialized hospitals experienced a decline in EC. There are several reasons why the TFP of specialized hospitals is slightly lower than the Meta-frontier, possibly due to their smaller scale and relatively insufficient investment in human resources compared to general hospitals; specialized hospitals, due to their limited service population, are restricted in expanding their medical service volume. However, in cities, smaller hospital areas imply better transportation convenience, and by focusing on a specific field of expertise, they are more likely to maximize the advantages of medical technology and attract more patients.⁶⁶ Producing greater output with fewer inputs may be an essential reason for the more significant efficiency changes they experience after policy impacts.

Promotion of Local Hospital Management by Autonomy Reform

This study asserts that the autonomy reform has a positive impact on the efficiency of public hospitals, which may be the result of the combined effect of four policy tools in the following aspects.

First, the reform of autonomy expanded the management authority of hospitals. This allowed hospitals to make timely decisions in internal management matters without needing government approval or using a filing process. The decision-making procedures were shortened, saving time.⁶⁷

Secondly, the new human resources management model adopts a system where a relatively fixed total number of staff is determined based on the number of hospital beds and the hospital's grade but allows hospitals to adjust the actual total staff number freely according to operational needs.⁶⁷ Hospitals are organizations that are intensive in technical personnel, and the provision of medical services relies on a large number of experienced medical staff. Determining a fixed total number of staff based on bed numbers often leads to a dilemma where there is both redundancy in personnel and ineffective motivation. The optimal strategy for hospitals is to dynamically adjust the ratio between labor costs and effective incentives while ensuring the service workload and quality, maintaining a balance in human resource management efficiency.

Third, the hospital funding reform mainly implemented the DIP payment system, which is similar to the internationally popular diagnosis-related groups (DRGs).⁶⁸ Due to its simplicity in operation and relatively low difficulty in implementation, this method can be adapted to regions across the country with different economic levels. A study from a city in China shows that the DIP payment model has achieved positive results in reducing patients' economic burden and improving care quality.⁶⁹

Fourth, a comprehensive performance evaluation and patient satisfaction survey were implemented. Since 2013, sample cities have conducted comprehensive hospital performance evaluations for all municipal public hospitals in the region, linking the results to the appointment of hospital directors.⁹ Since 2013, annual and quarterly random patient satisfaction surveys have been conducted for all public hospitals in the region, and the results have been made publicly available on a quarterly and annual basis.⁹ The comprehensive performance evaluation and patient satisfaction surveys are important policy tools for accountability, effectively promoting the progress of hospital management.

Further Policy Analysis

Firstly, reforming the corporate governance structure of public hospitals enhances hospital autonomy and improves the efficiency of hospital decision-making by defining the scope of hospital operation authority. Secondly, the quota system human resource management model has been adopted, which determines government subsidy standards based on the workload for medical services rather than a fixed staffing quota amount. A post-management model featuring de-administration and de-institutionalization is implemented in newly established hospitals. These measures have enhanced the autonomy of hospitals in human resource management and reduced human capital expenditure. Thirdly, a financing model for public hospitals is primarily based on government procurement of services. Medical insurance institutions purchase medical services from public hospitals through a payment method via a DIP. The medical pricing structure has been adjusted, eliminating the markup on public hospital drug sales while increasing the prices of technical medical services. The fourth is to enhance the informatization capabilities of hospitals, build a regional public hospital information data platform centered around electronic medical records, and promote the refinement, intelligence of hospital management, and the convenience of patient medical services. Lastly, performance assessment and patient satisfaction evaluation should be implemented in public hospitals, and the assessment results should be linked to government investment in these hospitals.⁷⁰

Additionally, Shenzhen City has adopted the "separation of ownership and operation" model since 2013 to collaborate with internationally and domestically renowned medical institutions such as The University of Hong Kong, Southern Medical University, Chinese Academy of Medical Sciences, and Sun Yat-sen University to co-construct public hospitals.⁶⁷ The introduction of these hospitals has, on one hand, promoted the enhancement of medical technology and improvement of hospital management, and on the other hand, stimulated medical market competition, encouraging public hospitals to strive to improve their service technology and service levels to attract more patients.^{70,71}

Compared to the Other Pilots

Compared with the medical reforms in other pilots of China, the autonomous reform of public hospitals in Shenzhen seems to be more successful. *Xia Qing*⁶⁴ and *Wu Jingjing*⁷² reported that the public hospital reform evaluation results in the pilot city of Jiangsu Province showed a decline in TFP. *Bai Jie*'s study showed that the TFP of public hospitals in Zhuhai City also declined.⁷³ *Zheng's*⁷⁴ research also found that two-thirds of the hospitals in Chongqing still have space for efficiency improvement. *Cao Xinxin*⁶³ studied the efficiency evaluation of public hospitals in Tianjin, and the results showed that TFP progress was mainly due to TE progress. At the same time, some studies have yielded positive results. The research samples from Shanghai and Weifang City showed that the reform is conducive to the progress of TFP in public hospitals. Different research findings illustrate that a poor policy mix or insufficient complementary policy measures in medical reform may lead to unsuccessful outcomes.

What issues arise from solely pursuing efficiency improvements? *Tsuei*⁷⁵ and *Zhang X*⁷⁶ suggest that although efficiency has improved, hospital costs have not been effectively controlled, and overall, the reform has not achieved its expected goals. The fundamental reason is the unaltered motivation system for providers in service delivery.⁷⁶

Conclusion

This study used the Meta-Frontier-Malmquist and super-efficiency model to assess Shenzhen municipal public hospitals' total factor productivity index between 2002 and 2023. Then, we evaluated the effect of autonomy reform on hospital efficiency by using descriptive analysis and the ITSA method with a single group. Studies have confirmed that the autonomy reform has positively impacted the total factor productivity (TFP) of public hospitals. Therefore, we have demonstrated that the policies introduced by the Shenzhen municipal government to promote the autonomy of public hospitals have effectively improved their efficiency. This study suggests that conducting policy pilots simultaneously across multiple cities can help the central government quickly identify effective policy measures and find the optimal policy combination, thereby improving policy quality. This model is also a policy-making method frequently used by China's politicians. This research further emphasizes the applicability of the DEA-ITSA combination method as an effective tool for health policy evaluation using public data within China's healthcare framework.

Data Sharing Statement

This study analyzed publicly available datasets. The data can be found here: Shenzhen Health Statistical Yearbooks published from 2002 to 2022, and the 2023 data is in an electronic spreadsheet obtained by emailing the Shenzhen Municipal Health Commission.

The initial work of the study is part of the main article; additional questions can be addressed to the corresponding author or first author.

Ethics Approval and Consent to Participate

The Medical Ethics Committee of Dermatology Hospital of Southern Medical University confirmed: Ningbo An's paper "The impact of autonomy reform on the efficiency of public hospitals in China: a DEA-ITSA combination analysis" does not involve the category of medical ethics, so there is no need for medical ethics review.

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Disclosure

The authors declare that their study was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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