Can Integrated Care Improve the Efficiency of Hospitals? - Research based on 200 Hospitals in China

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Abstract

Backgrounds:

The shift towards integrated care (IC) represents a global trend towards more comprehensive and coordinated systems of care, particularly for vulnerable populations, such as the elderly. When health systems face fiscal constraints, integrated care has been advanced as a potential solution by simultaneously improving health service effectiveness and efficiency. This paper addresses the latter. There are three study objectives: first, to compare efficiency differences between IC and non-IC hospitals in China; second, to examine variations in efficiency among different types of IC hospitals; and finally, to explore whether the implementation of IC impacts hospital efficiency.

Methods

This study uses Data Envelopment Analysis (DEA) to calculate efficiency scores among a sample of 200 hospitals in H Province, China. Tobit regression analysis was performed to explore the influence of IC implementation on hospital efficiency scores after adjustment for potential confounding. Moreover, the association between various input and output variables and the implementation of IC was investigated using regression techniques.

Results

The study has four principal findings: first, IC hospitals, on average, are shown to be more efficient than non-IC hospitals after adjustment for covariates. Holding output constant, IC hospitals are shown to reduce their current input mix by 12% and 4% to achieve optimal efficiency under constant and variable returns-to-scale, respectively, while non-IC hospitals have to reduce their input mix by 26% and 20% to achieve the same level of efficiency; second, with respect to the efficiency of each type of IC, we show that higher efficiency scores are achieved by administrative and virtual IC models over a contractual IC model; third, we demonstrate that IC influences hospitals efficiency by impacting various input and output variables, such as length of stay, inpatient admissions, and staffing; fourth, while bed density per nurse was positively associated with hospital efficiency, the opposite was shown for bed density per physician.

Conclusions

Integrated Care has the potential to promote hospital efficiency by influencing an array of input and output variables. Policies designed to facilitate the implementation of IC in hospitals need to be cognizant of the complex way IC impacts hospital efficiency.

1 Background
China, like many other countries, is facing both a greying of the population and an increased prevalence of chronic, non-communicable diseases. Those over 65 years of age represented 11.9% of the population in 2018 but are expected to account for 20% by 2040.[1–2] Likewise, the prevalence of chronic, non-communicable disease (NCD) among those over 65 years of age was 65% in 2008 and increased to 75% by 2018.[3–4] Older people with chronic diseases usually suffer from problems in the physical, psychological and social domains,[5] and have diverse and complex needs in the areas of prevention, treatment, etc.[6] As people age, the risk of chronic conditions increases, and this is estimated to increase the national burden of NCDs in China to 40% by 2030.[7] Under the twin pressures of ageing and a high prevalence of chronic diseases, integrated care has been proposed as a potential solution for China. IC encompasses various methods of funding, organization and delivery of care to enhance system efficiency.[6, 8–10] Health systems realize their goals at all levels through enhanced hospital performance.[11] This is especially the case in China where hospitals may benefit most from IC through the provision of comprehensive and coordinated care. As shown in Fig. 1, Chinese hospitals cooperate with other institutions to achieve vertical and horizontal integration.[12]

Efficiency studies contribute to informed decision-making as the findings from such studies may identify opportunities to improve care performance in hospitals and at the same time contain resource consumption.[13] However, studies have seldom looked at the impact of IC on hospital efficiency. Most studies have focused on measuring health outcomes among the elderly that may be attributed to the implementation of IC.[14–24] Furthermore, it remains unclear from that literature the direction of effect, if any, of IC on hospital efficiency. Some studies demonstrated that integrated partnerships and a coordinated continuum of services dedicated to the treatment of specialized diseases or a defined population may improve hospital efficiency.[25–29] However, weak and, on occasions, negative impacts of IC on hospital efficiency were also found.[30–31] As such, there is an opportunity to add to the literature by directly assessing the impact of IC on hospital efficiency.

The purpose of this paper is three-fold: first, to investigate potential differences in efficiency between IC hospitals and non-IC hospitals; second, to examine variations in efficiency among different types of IC hospitals; and third, to explore whether the implementation of IC impacts hospitals efficiency. The paper is structured in the following manner: In Sect. 2, we explain data sources, variables and the methods of analysis. The results are outlined in Sect. 3 and discussed in Sect. 4. We end with a brief conclusion that highlights several policy implications.

2 Methods

2.1 Data sources

Our study chose C city as the sample for three reasons: first, C city is among the first batch of cities to implement IC in China. According to the "Notice Regarding the Determination of the First Batch of National-level Pilot Cities of Integrated Care",[32] C city is among the first of two cities to implement IC in
H province. Pilot cities provide financial and administrative support and hospitals participated on a voluntary basis. Second, C city is in central China and is representative of all China in having average economic and social development. Finally, the city was selected for reasons of data accessibility. Specifically, the data were obtained directly from the Provincial Bureau of Statistics that links a wide range of administrative databases to hospital-level data. We used a dataset which was formally collected by the Provincial Bureau of Statistics in 2016 and all the hospitals in C city reported their data according to the requirements of the government. To ensure maximum representativeness, all hospitals in C city were included in our research. The dataset used contains information on personnel, equipment, cost and revenue data for each of 200 hospitals in C city, H province in 2016.

2.2 Study variables

Average productivity is calculated as a ratio of outputs to inputs. Applications of efficiency measurement have extended this concept by using these ratios to construct “best practice” frontiers. In most cases, inputs to the production function of health services include capital (e.g., medical equipment, hospital beds, etc.), labor (e.g., human resources), land and raw materials. Outputs include health services provided (e.g., number of surgeries performed).[33] Guided by our literature review on efficiency analysis, [13, 34-39] we included as many input and output variables as possible. Specifically, length of stay, inpatient admissions, outpatient visits, emergency visits, annual family visits, revenues, number of surgeries and number of discharges from hospital. Input variables comprised operating cost, number of physicians, number of ancillary staff, number of nurses, number of other staff (including administrative, technical and logistic staff) as well as number of hospital beds.

In 2016, C city started to implement IC policy and hospitals could voluntarily decide whether to participate. Our research included the implementation of IC as a dummy independent variable and tests to see if it was positively association with hospital efficiency.[29] Additional control variables were also considered in our analysis. The increasing complexity of healthcare and resulting clinical specialization may result in the fragmentation of healthcare, thereby compromising patient safety and hospital efficiency.[40] In our research, we used the number of key clinical departments as a proxy for clinical specialization and we expected that it would be negatively correlated with hospital efficiency. Moreover, facility type was also found to be an useful predictor of hospital efficiency whereby facilities operating at
a large scale may realize greater technical efficiency due to increasing returns to scale.[30] Third, a higher mortality rate (low quality health services) was found to raise the costs of the hospitals[34] and thereby to erode hospital efficiency. Fourth, shorter average lengths of stay was expected to improve the use of medical beds and enhance efficiency.[41] Fifth, we also included bed density per physician and bed density per nurse as control variables, because we expected these variables to be positively associated with hospital efficiency.[13]

2.3 Statistical analysis

2.3.1 Data envelope analysis method

Non-parametric Data Envelopment Analysis and parametric Stochastic Frontier Analysis are the two main approaches to the measurement of efficiency. We employed DEA because of its ease of implementation, its nonparametric basis and substantial freedom on the specification of inputs and outputs.[42] As shown in equation (1), the efficiency score $\theta$ for a hospital $i$ is measured relative to the efficiency of the other hospitals ($i = 1,...,n$), subject to the restriction that all hospitals are on or below the efficient production frontier.[43] The value of each hospital’s measure of efficiency ranges from 0 to 1. Efficient hospitals are those on the efficient frontier and their efficiency score is 1, while inefficient hospitals lie below the efficiency frontier and their efficiency score is less than 1. The further these inefficient hospitals are away from the efficiency frontier, the lower is their efficiency score. In this paper, we adopted an input-oriented DEA model that focuses on minimizing the use of inputs in order to produce a given output.[13] Furthermore, both constant returns to scale (CRS) and variable returns to scale (VRS) were considered in order to provide comparisons. To investigate the efficiency differences among different types of IC, IC was classified into contractual, administrative, insurance-driven and virtual integration by our previously published study.[44] Ten contractual, administrative and virtual integration types were found in our research. The definition, core strategy, strengths and weakness of each IC type were summarized in Table 2.

$$\hat{\theta}_{DEA} = (x,v) \in R^{n \times n}; x \geq \sum_{i=1}^{n} \theta_i; v \geq \sum_{i=1}^{n} \theta_i x_i; \text{for } (\theta_1, \ldots, \theta_n) \text{ s.t. } \sum_{i=1}^{n} \theta_i = 1; \theta_i \geq 0, i = 1, \ldots, n$$
The efficiency score is the outcome of interest. This dependent variable is limited in its range with values that lie within the unit interval, i.e. between 0 and 1. To ease interpretation, the efficiency scores were transformed to represent inefficiency scores using the transformation in equation (2). After transformation, the inefficiency score for efficient hospitals is 0, while inefficient hospitals have inefficiency scores that exceed 0. Given the value of the dependent variable is censored at zero, Tobit regression was used in our study. In our research, inefficiency is measured by a set of input and output variables. To further explore the how IC influences the inefficiency score through these input/output variables, we regressed each input and output variable on the dummy IC variable.

\[
\text{Inefficiency score} = \left( \frac{1}{\text{Efficiency score}} - 1 \right)
\]

3.3 Propensity score matching

The causal effects of IC on hospitals efficiency cannot be estimated using ordinary regression due to potential selection bias associated with confounding variables. Propensity score matching (PSM) was used to reduce such potential bias associated with confounding variables in the decision to implement IC, and PSM is useful to identify potential causal effects of IC on hospital efficiency. Following the analytical process of Staffa,[45] Garrido,[46] Caliendo [47] and Austin,[48] we performed PSM in three steps: first, we calculated the probability of implementing IC given the observed covariates using logistic regression analysis. The covariates included were those that were expected to be related to both the implementation of IC and were expected to be important determinants of hospital inefficiency.[46] These variables included hospital type, inpatient mortality rate, hospital capacity, average length of stay for discharged patients, bed density per physician and bed density per nurse. Second, we employed the K-nearest neighbor matching method with a matching ration 1:1 and a caliper value of 20% of the standard deviation of the logit of the estimated propensity score.[49] Finally, balance diagnostics of the matching results were undertaken through use of a chi-square test (for categorical variables) and two sample t-test (for continuous variables). We set 0.20 as the threshold of the required standard deviation, given the size of the sample used in our study. [46, 50-52]

3.4 Sensitivity analysis
To check the robustness of our research results, we conducted the following sensitivity analysis: first, we conducted direct ordinary least squares regression analysis to investigate the difference associated with different estimation methods; second, we performed Tobit regression using all the sample hospitals. This allowed us to compare the results with PSM and without PSM.

3 Results

3.1 Descriptive results

Table 1 describes the characteristics of the sample of hospitals in this study. There were 24 IC hospitals (12%) in 2016. About 23.5% of hospitals (N=47) were regional medical centers. The number of key clinical departments recognized by the government varied from 0 to 31 with a mean and SD of 2.05 and 3.97, respectively. The number of key clinical departments in IC hospitals (mean=6.00; SD=8.06) was substantially larger than those in non-IC hospitals (mean=1.52; SD=2.64). The average length of stay for discharged patients in IC hospitals was 23.83 days (SD=43.44), which was substantially larger than that in non-IC hospitals (mean=10.40; SD=12.20) and in all the 200 hospitals (mean=12.02; SD=19.19). Overall, the mean inpatient mortality rate was small at 0.23% with SD of 0.01 and was smaller among IC hospitals than that in non-IC hospitals (P<0.001). Bed density per physician and bed density per nurse averaged at 5.09 (SD=5.31) and 3.68 (SD=3.90), respectively, with no significant difference found between IC and non-IC hospitals.

3.2 Efficiency of hospitals

Most hospitals obtained efficient scores, i.e. they were on the efficient production frontier. The mean efficiency score for hospitals was 0.81 when variable returns to scale (VRS) was used. A large percentage of these hospitals (N=83, 41.5%) operated at their optimal level. Furthermore, 17% of hospitals (N=37) had efficiency scores ranging from 0.7 to 0.9, here classified as being moderately efficient. Only 4 hospitals were identified as having an efficiency score of less than 0.4, here classified as being extremely inefficient. When the efficiency scores were estimated using constant returns to scale (CRS), the mean efficiency score fell to 0.76. In this CRS model, over 60 hospitals (31%) were identified as being efficient. Compared to the VRS model, fewer hospitals under the CRS model were efficient and the number of hospitals identified as moderately efficient (N=50, 25%) and extremely inefficient (N=9, 4.5%) also increased.

IC hospitals were expected to operate more efficiently than their non-IC counterparts. The mean CRS and VRS efficiency scores for IC hospitals was 0.88 and 0.96, respectively, which on average was larger than the scores for non-IC hospitals (0.74 and 0.80 respectively). These differences were statistically significant (P=0.004 in CRS model; P<0.001 in VRS model). The scale efficiency score, which is the mean of the CRS and VRS efficiency scores,[13] was 0.92 for IC hospitals and substantially larger (P=0.001) than that for non-IC hospitals (0.77). Meanwhile, the efficiency scores of the three different IC types were
reported in Table 3. It was found that virtual and administrative integration, on average, obtained higher efficiency scores than contractual integration.

3.2 The influence of IC on efficiency

Our research found out that the potential bias caused by confounding covariates was eliminated after matching. Adequate overlap between the IC hospitals and the non-IC hospitals was shown in Figure 2, and this implies that we could perform PSM using our dataset. Moreover, the results of the chi-square test and the Welch Two Sample t-test were shown in Table 4. After matching, no statistically significant difference in covariates were found between IC hospitals and non-IC hospitals. Figure 3 indicates that the mean of the difference in covariates between IC hospitals and non-IC hospitals was balanced after matching. Table 5 and Figure 4 show that no covariate had an absolute standard difference of more than 20% after matching and the mean standardized difference dropped from 42.62% to 13.71%.

Table 6 reports the Tobit regression results. Non-IC hospitals were expected to achieve higher inefficiency scores than IC hospitals. In model 1, the estimated coefficient of IC was -0.59 with a 95% CI between -0.01 and 0.17. When adjusting for all the covariates (model 2), the coefficient of IC was slightly smaller at -0.54 with a 95% CI between -0.85 and -0.23. This implies that compared with IC hospitals, non-IC hospitals were expected to achieve 0.54 higher inefficiency score. This model also identified that bed density per nurse was a positive predictor of higher inefficiency. In contrast, the inefficiency score of hospitals that were regional medical centers was found to be 0.34 lower than other hospitals. Similarly, the number of key clinical departments and the bed density per physician were found to be negatively associated with inefficiency scores. Meanwhile, the results of CRS model only presented slight differences compared with VRS model. In model 3 (without covariates) and model 4 (adjusting for covariates), the estimated coefficient of IC was slightly smaller at -0.43 (95% CI: -0.78 and -0.09) and -0.42 (95% CI: -0.72 and -0.13), respectively. Nevertheless, the positive influence of IC implementation on hospitals efficiency was found. McFadden's pseudo $R^2$ for models 1, 2, 3 and 4 were 0.09, 0.48, 0.07 and 0.22, respectively. Among all the models, model 3 had the highest model fit and explained 48% of the variation in inefficiency scores.

The influence of IC on each input and output variable was reported in Table 7. IC was expected to be associated with a set of input and output variables. The number of physicians, nurses, other employees and beds in IC hospitals were significantly larger than those in the non-IC hospitals. The same positive influence of IC on discharges, length of stay, inpatient visits and outpatient visits was found. The goodness of fit ($R^2$) was generally low at 10% for input variables and 8% for output variables. The P-value for the F-test for all the models was smaller than 0.05, implying that all the models passed the joint hypothesis test.

3.3 Sensitivity analysis

We first conducted ordinary least square regression analysis. It was demonstrated that in the VRS model, the coefficient on IC for hospital inefficiency was -0.35, which was smaller than the results derived from
the Tobit regression. When adjusting for all the covariates, the coefficient on IC was -0.33, which was also smaller than that in the model where Tobit regression was performed. Likewise, in the two CRS models using ordinary least squares, the coefficient on IC was also smaller at -0.32. Second, we compared the results with PSM and without PSM. Compared with models using PSM, the same negative, but larger, influence of IC on hospital inefficiency (coefficient was -0.65 and -0.61, respectively) was found in both the VRS and CRS model without PSM. When adjusting for all the covariates, the negative influence of IC on hospital inefficiency was still found in the VRS model. These results imply that our research results were robust to these considerations.

4 Discussion

We combined PSM and Tobit regression techniques to investigate the impact of IC adoption on hospital efficiency calculated through DEA methods after controlling for potential confounding. We demonstrated that the adoption of IC had a positive effect on hospital efficiency after controlling for a range of covariates. Our results suggest that the type of IC had a differential effect on hospital efficiency with vertical and administrative integration models yielding higher efficiency scores compared to the contractual integration model. Given the degree of governmental control over institutions in China, it was anticipated that the administrative model of IC would fare better in terms of hospital efficiency than the contractual model. At the same time, the success of the vertical integration model may be attributed to the rapid development of both information technology and artificial intelligence, which offers the potential to enhance outcomes and conserve resource inputs.

The main study finding that IC hospitals were more efficient than non-IC hospitals is congruent with previous research in the literature. However, our study is at variance with literature that reported negative effects of integration on efficiency. This discrepancy could be explained by differences in the unit of analysis and the way integration was measured in previous studies. Integration in those studies was measured by the number of integrated HIV and sexual and reproductive health services in the same clinical room. This may reveal that although integration might improve hospital efficiency in general, there might be negative effects of integration per clinical room.

Our study explored the pathways through which IC might promote hospital efficiency. Our research demonstrates that IC was statistically associated with a range of input and output variables, which may reveal the pathways through which IC impacts hospital efficiency. This is consistent with a previous research that has shown that IC could improve health services utilization significantly and therefore lead to higher efficiency. What’s more, our study demonstrated specific relationships between IC and each input/output variable. It was found that IC could influence a set of hospital output variables, such as length of stay, inpatient visits, outpatient visits and the number of patients discharged. Meanwhile, IC was also found to be associated to a range of input variables, including number of physicians, nurses, other employees and hospital beds. These findings provide preliminary evidence about how IC changes hospital efficiency by reallocating medical resources and impacting hospital production processes.
Our research has important policy implications which may be helpful for future healthcare reforms. This research showed how the adoption of IC resulted in improvements to hospital efficiency. Opportunities to foster the development of those types of IC that have the greatest potential to enhance hospital efficiency may be pursued. Policies such as “Guiding Opinions on Promoting the Integration of Healthcare and Elderly Care Services”[56] would help the diffusion of such IC models across China. Moreover, there is the potential to expand the scope of IC beyond hospitals to other health care settings.

Our research has some strengths: First, to the best of our knowledge, this is the first paper to investigate the influence of IC on hospital efficiency in China. This research adds empirical evidence to the pool of global IC evaluative research and offers practical suggestions for IC reform. Moreover, PSM was used in our study to remove potential confounding associated with the uptake of IC and Tobit regression analysis was adopted to deal with the censoring of the dependent variable (in our case hospital inefficiency). These techniques help to ensure reliable and robust estimates. Third, our research included all hospitals in one Chinese city and therefore was representative of hospitals in that city.

Several limitations warrant recognition: First, we were unable to assess the role of environmental factors, such as population size and poverty, on hospital efficiency due to a lack of available data. Future studies with datasets across different administrative regions will allow for more precise conclusions. However, our research results are still robust in terms of controlling the covariates included by our research. Second, there was an absence of cross-sectional data to explain the long-term causal effects of IC on hospital efficiency. Nevertheless, our research results were still useful in the evaluation of associations and the short-term effects of IC on hospital efficiency. Third, we only have data on all hospitals in one city which limits the generalizability of our results. While this limitation is common in studies, we were fortunate to have the universe of hospitals in our study city included, and moreover, this study city is located in central China and is representative of all China in having average economic and social development. Consequently, our findings are still applicable to the role of IC on hospital efficiency in China. Fourth, while our study addressed a range of statistical concerns, we were still unable to resolve the potential for endogeneity of the relationship between IC and efficiency. A higher degree of integration can improve hospital efficiency, but an efficient hospital is also good at integrating health services.[15] Such endogeneity problems could be addressed by applying appropriate instrumental variables in future studies.

5 Conclusions

This study has demonstrated the potential gains to hospital efficiency in China associated with the adoption of IC. The work has also highlighted the greater potential for gains in efficiency associated with the virtual and administrative models of IC relative to other types of IC. These findings may assist policy decision makers that are confronted with increased pressure on the health system due to an aging population and one with an increasing prevalence of chronic conditions. Integrated care has been shown to enhance health system performance and opportunities to facilitate uptake and remove barriers to its adoption have potential to improve population health and conserve scare health care resources.
Abbreviations
Integrated care (IC); Data Envelopment Analysis (DEA); Non-communicable disease (NCD); Constant returns to scale (CRS); Variable returns to scale (VRS); Propensity score matching (PSM)

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Availability of data and materials
The datasets generated and/or analysed during the current study are not publicly available due the dataset involves private information about each hospital but are available from the corresponding author on reasonable request.

Competing interests
The authors declare that they have no competing interests.

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Authors' contributions
ZP proposed the research idea and drafted the manuscript. LZ and GW contributed to collect data and relevant research materials. PCC supervised and revised the manuscript.

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Tables

Table 1 Descriptive Statistics for the Sample Hospitals
| Code | Explanation of the variable                                                                 | N   | Mean   | SD    | Median | Min | Max |
|------|------------------------------------------------------------------------------------------------|-----|--------|-------|--------|-----|-----|
| **Input variable**                                                                                       |     |        |       |        |     |     |
| NP   | Number of physicians                                                                        | 200 | 86.593 | 175.949 | 20 | 1 | 1265 |
| NAMS | Number of ancillary medical Staff                                                            | 200 | 3.722  | 3.953 | 3 | 0 | 30   |
| NN   | Number of nurses                                                                             | 200 | 144.742 | 338.667 | 33 | 0 | 2684 |
| NOE  | Number of other employees, including administrative, technical staff and logistic staff      | 200 | 111.792 | 176.389 | 54 | 2 | 1563 |
| NB   | Number of hospital beds                                                                      | 200 | 303.970 | 556.952 | 93 | 0 | 4042 |
| OO   | Operating cost                                                                               | 200 | 192476.615 | 599029.829 | 22317 | 8545283269 |
| **Output variable**                                                                                       |     |        |       |        |     |     |
| ND   | Number of discharges from hospital                                                            | 200 | 9835.319 | 20289.562 | 2688 | 0 | 136788 |
| UD   | Length of stay                                                                               | 200 | 9842.152 | 20305.706 | 2665 | 0 | 136926 |
| NIA  | Number of inpatient admissions                                                               | 200 | 119606.523 | 350487.324 | 14999 | 0 | 2870064 |
| NOV  | Number of outpatient visits                                                                  | 200 | 1019.411 | 3916.575 | 1019 | 0 | 53515 |
| NEV  | Number of emergency visits                                                                   | 200 | 179652.965 | 596434.739 | 15757 | 1085179985 |
| AVFP | Number of annual visits for family planning                                                  | 200 | 1019.411 | 3916.575 | 1019 | 0 | 53515 |
| ARH  | Annual revenues of hospitals                                                                  | 200 | 179652.965 | 596434.739 | 15757 | 1085179985 |
| NS   | Number of surgeries                                                                          | 200 | 3597.900  | 8437.977 | 2527 | 0 | 71788 |
| **Independent variable**                                                                                  |     |        |       |        |     |     |
| IC1  | Whether implementing IC or not                                                                | 200 | Yes: n=24 (12%); No: n=176 (88%) |
| ROPA | Average length of stay for discharged                                                         | 200 | 12.016  | 19.188 | 9 | 1 | 193  |
| NAPP | Beds density per physician                                                                    | 200 | 5.092   | 5.314 | 4 | 0 | 40   |
| NAPN | Bed density per nurse                                                                         | 200 | 3.683   | 3.896 | 3 | 0 | 31   |
| RMA  | Inpatient mortality rate                                                                       | 200 | 0.002   | 0.008 | 0 | 0 | 0    |
| WHC  | Facility type measure by whether the hospital is a regional medical center or not             | 200 | Yes: n=47 (23.5%); No: n=152 (76%) |
| TNS  | Clinical specialization measured by the number of key clinical department                      | 200 | 2.058   | 3.971 | 2 | 0 | 31   |
| **Dependent variable**                                                                                    |     |        |       |        |     |     |
| INEFF(VRS) | Inefficiency score of hospital                                                                 | 200 | 0.346  | 0.478 | 0 | 0 | 3    |
| INEFF(CSR) | Inefficiency score of hospital                                                                 | 200 | 0.512  | 0.836 | 0 | 0 | 8    |

Table 2 Different Types of IC in China
| Type | Definition | Strategy | Strengths | Weaknesses |
|------|------------|----------|-----------|------------|
| CI   | MC seeks to build cooperative relationships among different institutions through formal contracts. | Contract | Flexible: Healthcare institutions are flexible to cooperate in specific parts about IC according to their needs; Trustful: Formal legal cooperative relationships could be formed among member institutions. | Insufficient: Contracts can only cover certain parts of the whole process of implementing IC and is not sufficient to ensure the thorough and effective implementation of IC. |
| AI   | MA is featured with administrative characteristics that newly-built councils conduct united but limited management over financial, personnel and property resources within IC network. | Management | Equal: Governments implement united but limited management over resources and therefore the distribution of resources could be more equal; Powerful: MA is usually led by the officials of the government and therefore is powerful in implementing IC under the context of the Chinese political system. | Incentive-lacking: Resource-rich public hospitals are unwilling to support primary healthcare institutions who need help; Private healthcare institutions lack incentives to participate due to their interest-seeking behavioral pattern. |
| MI   | MI is mainly adopted by institutions covered by the same type of medical insurance. | Insurance | Consistent: Member institutions are less likely to encounter barriers caused by different funding polices; People could be referred to different institutions with the same reimbursement policy. | Geographically limited: Institutions covered by different funding and reimbursement policies, which are also usually institutions located across administrative regions, are difficult to cooperate. |
| VI   | MV is an emerging form making full use of modern information technology. | Technology | Accessible: It is beneficial for institutions located in remote rural areas to work together with healthcare institutions in developed areas; Resource-saving: Since services are | Inconsistent: Healthcare institutions can only receive virtual support, which is limited; Patients cannot receive continuous healthcare services and they still need to visit hospitals in person after receiving online virtual diagnosis. |
provided via technological devices, patients could save accommodation and transportation expenditures.

Note: The authors compiled the table based on a previous published paper and policy review.

Table 3 Average Efficiency Scores of Hospitals

| Hospital                  | Efficiency score (VRS) | Efficiency score (CRS) | Scale efficiency score |
|---------------------------|------------------------|------------------------|------------------------|
| Mean efficiency score of IC hospitals | 0.957                  | 0.875                  | 0.916                  |
| Mean efficiency score of AI | 1                      | 1                      | 1                      |
| Mean efficiency score of CI | 0.949                  | 0.85                   | 0.900                  |
| Mean efficiency score of VI | 1                      | 1                      | 1                      |
| Mean efficiency score of non-IC hospitals | 0.790                  | 0.739                  | 0.765                  |
| Mean efficiency score of all hospitals | 0.810                  | 0.755                  | 0.783                  |

Table 4 Descriptive Statistics for the Matched Sample of Hospitals (Mean)

| Variable | Before-match | After-match | P-value | Before-match | After-match | P-value |
|----------|--------------|-------------|---------|--------------|-------------|---------|
|          | Non-IC       | IC          |         | Non-IC       | IC          |         |
|          | (Mean(SD))   | (N=176)     | (N=24)  | (Mean(SD))   | (N=23)     | (N=23)  |
| WHC=0    | 140 (79.5)   | 13 (54.2)   | 0.013   | 15 (65.2)    | 13 (56.5)  | 0.763   |
| WHC=1    | 36 (20.5)    | 11 (45.8)   | <0.001  | 8 (34.8)     | 10 (43.5)  | 0.786   |
| RMA      | 10.40 (12.20)| 23.83 (43.44)| 0.001   | 19.67 (28.18)| 24.45 (44.31)| 0.664 |
| ROPA     | 5.05 (5.10)  | 5.41 (6.80) | 0.756   | 4.87 (7.78)  | 5.54 (6.93)| 0.758   |
| NAPP     | 3.80 (3.99)  | 2.84 (3.01) | 0.258   | 2.61 (2.52)  | 2.91 (3.06)| 0.717   |
| NAPN     | 1.52 (2.64)  | 6.00 (8.06) | <0.001  | 4.35 (5.64)  | 4.91 (6.19)| 0.749   |
| TNS      |              |             |         |              |             |         |

Table 5 Balance Diagnostics of Matched Sample (SD)
|        | Before (%) | After (%) | Reduction (%) |
|--------|------------|-----------|---------------|
| RMA    | 49.803     | 9.622     | 80.680        |
| WHC    | 55.986     | 17.889    | 68.047        |
| TNS    | 74.683     | 9.501     | 87.278        |
| NAPP   | 6.005      | 12.862    | -114.188      |
| NAPN   | 27.167     | 15.397    | 43.325        |
| ROPA   | 42.081     | 17.009    | 59.580        |
| Mean   | 42.621     | 13.713    | 37.454        |

Note: The reduction of the standardized difference equals to the ratio of (absolute standardized difference before matching - absolute standardized difference after matching) to absolute standardized difference before matching.

Table 6 The Impact of Different Factors on the Inefficiency Score of Hospitals Using Tobit Regression
### Table 7 The influence of IC on Output and Input Variables

|               | Model 1 (VRS)          |               | Model 2 (VRS)          |               |
|---------------|------------------------|---------------|------------------------|---------------|
|               | Est. (Std. Error)      | t-value       | Pr>|t|       | 95%CI          | Est. (Std. Error) | t-value       | Pr>|t|       | 95%CI          |
| Intercept     | 0.218 (0.145)          | 1.499         | 0.134                  | [0.067, 0.502]| 0.485           | 3.174         | 0.002**     | [0.186, 0.785]|
| IC            | -0.592 (0.215)         | -2.756        | 0.006**                | [-1.012, -0.171]| -0.538          | -3.390        | 0.001***    | [-0.848, -0.227]|
| RMA           |                        |               |                        |               | -19.490         | -1.573         | 0.116       |                |
|               |                        |               |                        |               | (12.388)        |               |            |                |
| WHC           | -0.337 (0.162)         |               |                        |               | -0.543          | -3.065        | 0.002**     | [-0.088, -0.19]|
| TNS           | -0.054 (0.018)         |               |                        |               | -0.169          | -3.026        | 0.003**     | [-0.278, -0.19]|
| NAPP          | -0.169 (0.056)         |               |                        |               | 0.003           | 0.744         | 0.457       | [0.010, 0.155]|
| ROPA          |                        |               |                        |               | 0.354           | 3.658         | 0.000***    | [0.165, 0.544]|
| NAPN          |                        |               |                        |               | -0.4729         | -2.783        | 0.005**     | [-0.806, -0.140]|
|               |                        |               |                        |               | (0.169)         |               |            |                |

|               | Est. (Std. Error)      | t-value       | Pr>|t|       | 95%CI          | Est. (Std. Error) | t-value       | Pr>|t|       | 95%CI          |
| Intercept     | 0.422 (0.121)          | 3.483         | 0.000***               | [0.184, 0.658]| 0.460           | 2.930         | 0.003**     | [0.152, 0.767]|
| IC            | -0.433 (0.175)         | -2.469        | 0.014*                 | [-0.776, -0.089]| -0.423          | -2.847        | 0.004**     | [-0.715, -0.132]|
| RMA           | 0.894 (6.571)          |               | 0.002                  | [13.773]       | 0.136           | 0.892         |            |                |
| WHC           | -0.179 (0.163)         |               |                        |               | -1.100          | 0.271         |            | [-0.498, 0.140]|
| TNS           | -0.024 (0.014)         |               |                        |               | -1.747          | 0.081         |            | [-0.051, 0.003]|
| NAPP          | -0.083 (0.031)         |               |                        |               | -2.682          | 0.007**       | [0.144, -0.022]|
| ROPA          | 0.002 (0.003)          |               |                        |               | 0.445           | 0.656         |            | [-0.005, 0.008]|
| NAPN          | 0.199 (0.077)          |               |                        |               | 2.572           | 0.010**       | [0.047, 0.351]|
|               | -0.584 (0.138)         | -4.231        | 0.000***               | [-0.854, -0.313]| -0.768          | -5.563        | 0.000***    | [-1.039, -0.498]|

Note: Signif. codes: ‘***’ ≤ 0.001; ‘**’ ≤ 0.01; ‘*’ ≤ 0.05
### Table

| Dependent variable | Estimate (Std.Error) | t-value | Pr(>|t|) | 95%CI             |
|--------------------|----------------------|---------|----------|------------------|
| **Output variable**|                      |         |          |                  |
| ND                 | 19179 (8766)         | 2.188   | 0.034*   | [1511.749, 36845.56] |
| BUD                | 229088 (86403)       | 2.651   | 0.011*   | [54955.40, 403221.4] |
| NIA                | 19246 (8763)         | 2.196   | 0.033*   | [1584.254, 36906.88] |
| NOV                | 237400 (153958)      | 1.542   | 0.130    | [-72882.971, 547682.4] |
| NEV                | 53604 (21171)        | 2.532   | 0.015*   | [10936.58, 96271.92] |
| AVFP               | -470 (2300)          | -1.074  | 0.289    | [-7105.227, 2164.915] |
| ARH                | 361001 (258554)      | 1.396   | 0.170    | [-160081.04, 882083.0] |
| NS                 | 6432 (3689)          | 1.743   | 0.088    | [-1003.135, 13866.44] |
| **Input variable** |                      |         |          |                  |
| NP                 | 165.70 (71.34)       | 2.322   | 0.025*   | [21.912, 309.480] |
| NAMS               | -1.2416 (1.217)      | -1.020  | 0.313    | [-3.694, 1.211] |
| NN                 | 344.4 (141.4)        | 2.435   | 0.019*   | [59.401, 629.469] |
| NOE                | 129.34 (64.04)       | 2.020   | 0.050*   | [0.265, 258.412] |
| NB                 | 649.3 (236.4)        | 2.747   | 0.009**  | [172.932, 1125.676] |
| OO                 | 334981 (262901)      | 1.274   | 0.209    | [-194861.68, 864823.9] |

Note: Signif. codes: ‘***’ ≤ 0.001; ‘**’ ≤ 0.01; ‘*’ ≤ 0.05

### Figures

#### Figure 1

Integration of Health-care Institutions in China. Note: The author visualized the structure of Chinese IC based on policy review. Chinese IC includes: 1) Vertical integration among different types of healthcare institutions or aged-care institution; 2) Horizontal integration among the healthcare institutions and aged-care institutions.
Figure 2

Common Support

Figure 3

Balance Diagnostics of Matched Sample (Mean)
Figure 4

Balance Diagnostics of Matched Sample (SD)