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Abstract

We adapt a range of mainstream spatial econometric models to the four-component error term panel stochastic frontier framework to estimate the inefficiency of public hospitals in Queensland, Australia, and to investigate different channels of spatial effects in hospital performance. Our results demonstrate a statistically significant presence of the spatial dependence from the autoregressive dependent variable and the autocorrelated error term. Additionally, we observe a positive spillover effect of input factors, as well as some impacts from accounting for the spatial dependence on the inefficiency estimation. Specifically, the resulting inefficiency estimates from the spatial models turned out to be higher than those from the non-spatial model, yet the magnitude of difference is relatively modest, confirming the approximate validity of the non-spatial stochastic frontier approach for this data set.

Keywords: Stochastic frontier analysis, spatial model, inefficiency, hospital

JEL Codes: C24, C61, I11, I18

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1 Introduction

The performance of healthcare facilities, especially hospitals, has been an important aspect of public concern in many nations worldwide. Thus, improving efficiency in health systems is among the natural means to address the cost inflation and the unmet needs in delivering health services. As such, there has been a vast and growing body of literature on the productivity and efficiency of healthcare facilities, aiming at providing healthcare policymakers and managers with a clear picture of the state of (in)efficiency within their system. Such an insight may serve as an important prerequisite for any evidence-based policies to promote efficiency.

Besides examining the efficiency level of healthcare facilities, studies in this body of literature also focus on investigating possible sources of their efficiency differentials. Among these, there has been an increasing interest in studying the interaction between spatial contexts and hospital performance. This follows the recent tendency of decentralizing the governance of hospitals to a regional level. For example, after the National Health Reform Agreement in 2012 (Council of Australian Governments, 2011), public hospitals in Queensland, Australia, have been operated by 16 different Local Hospital Networks (also known as Hospital and Health Services), who are responsible for providing healthcare services to their local communities.

It is conjectured that operating in the same administrative context would cause a given hospital to be affected by the neighbor hospitals with regard to many aspects such as inputs, outputs, as well as the performance (Mobley et al., 2009; Brekke et al., 2011; Herwartz and Strumann, 2012; Gravelle et al., 2014; Cavalieri et al., 2020). More importantly, going beyond the effect of a common institutional setting, the performance of hospitals might be spatially dependent due to peer effects and spillover effects (Herwartz and Strumann, 2014; Cavalieri et al., 2020). For instance, peer effects may arise if hospitals engage in local competition for attracting patients, or recruiting doctors and nurses, or if hospitals act collectively in determining the level of output quality to provide to a local community. Moreover, the advances in medical diagnostics and treatments are more likely to spillover faster among hospitals that are closer in a network. Thus, besides controlling for institutional settings, it might be important to account for the spatial dependence structure in the efficiency analysis of hospitals.

Econometric modeling for spatial dependence has long been developed thanks to the seminal contributions of Cliff and Ord (1973, 1981) and the further generalizations and extensions of many others, including Kelejian and Prucha (1998, 1999); Lee (2003, 2004, 2007); Kelejian and Prucha (2004, 2007, 2010); Elhorst (2005); Fingleton (2008); Piras (2013); Baltagi et al. (2014), to mention a few. The strategies to incorporate spatial dependence center around the inclusion of a spatially lagged dependent variable, spatially lagged exogenous covariates, or a spatially autocorrelated error term (or their combinations) to an econometric model. These strategies have been recently adapted to the field of productivity and efficiency analysis to account for the spatial dependence in analyzing the performance of production units. For example, the spatial error stochastic frontier model developed by Druska and Horrace (2004) is an adaption of the spatial error dependence structure to the time-invariant fixed effects estimator of inefficiency of Schmidt and Sickles (1984). Meanwhile, for the spatial autoregressive stochastic frontier model and the spatial Durbin model developed in Glass et al. (2013, 2014, 2016), the spatial dependence is incorporated to efficiency analysis via the spatial weights on the dependent variable and exogenous regressors. In addition to the traditional approach, the spatial dependence structure can also be imposed via the inefficiency term as in Areal et al. (2012); Herwartz and Strumann (2014); Tsionas and Michaelides (2016); Orea and Álvarez (2019).

The utilization of spatial econometric models in hospital efficiency analysis, however, is relatively sparse. To the best of our knowledge, until recently, there have been only Herwartz and Strumann (2014) and Cavalieri et al. (2020), who attempted to account for the spatial effects in their studies of hospital efficiency in Italy and Germany, respectively. Herwartz and Strumann (2014) followed a two-stage data envelopment analysis approach, meanwhile Cavalieri et al. (2020) utilized a spatial stochastic frontier model. Both of these studies imposed the spatially dependent structure on the inefficiency term. Our study aims to complement these early attempts in the literature by employing a wide range of spatial stochastic frontier models, including spatial error stochastic frontier (SESF), spatial autoregressive stochastic frontier (SARSF), and spatial Durbin stochastic frontier (SDSF) to empirically investigate different channels of spatial effects in the performance of public hospitals.

In particular, utilizing the data on 104 public hospitals in Queensland, Australia, in the period from the financial year (FY) 2012/13 to FY 2016/17, we found significant spatial dependence, especially from the spatially autoregressive output and the spatially autocorrelated error term among the studied hospitals. Among the regressors, the principal inputs, involving the capital, medical labor, and expenditure of consumable supplies, exhibit statistically significant positive marginal effects on the hospital itself as well as positive spillover effects on the neighbor hospitals under a variety of spatial weighting schemes. The inefficiency levels estimated with our spatial models are slightly higher (and should be more accurate) than the estimates of the analogous non-spatial model.

The structure of our study is as follows. We first discuss the proposed spatial stochastic frontier models in Section 2. The data and variables used are described in Section 3. Section 4 discusses the results from the various fitted models and the corresponding inefficiency estimates. Finally, our concluding remarks are summarized in Section 5.

2 Spatial Stochastic Frontier Models

2.1 Non-spatial specifications

The canonical frameworks of stochastic frontier analysis (SFA) were independently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). In the subsequent decades, a variety of stochastic frontier models (SFMs) have been developed for efficiency analysis in various fields of study. One prominent avenue for the development of SFA lies in panel data modeling. Among others, the pioneer models proposed by Pitt and Lee (1981) and Schmidt and Sickles (1984) are dedicated to estimating individual inefficiency based on standard panel regressions. In further extensions, Cornwell et al. (1990), Kumbhakar (1990), and Battese and Coelli (1992) demonstrated a diverse array of approaches incorporating time-variant inefficiency in the panel data framework.[1]

Meanwhile, more advanced variants of panel data SFMs have been introduced in this vein. More recently, Greene (2005a,b) proposed the 'true fixed effect' and 'true random effect' models to disentangle the individual heterogeneity from the estimation of the time-variant inefficiency. Additionally, the four-component model proposed by Kumbhakar et al. (2014) (hereafter KLH14) and Colombi et al. (2014) further distinguished the transitory inefficiency and individual persistent inefficiency, which can be denoted as

$$
\begin{aligned}
y_{it} &= \beta_0 + x_{it}'\beta + s_i - \eta_i + v_{it} - u_{it},\ i = 1, \ldots, n;\ t = 1, \ldots, T, \\
s_i &\sim iidN(0, \sigma_s^2), \\
\eta_i &\sim iidN^+(0, \sigma_\eta^2), \\
v_{it} &\sim iidN(0, \sigma_v^2), \\
u_{it} &\sim iidN^+(0, \sigma_u^2),
\end{aligned}
\tag{1}
$$

where $x_{it} \in \Re_+^p$ and $y_{it} \in \Re_+$ represent the p inputs and the output of decision making unit (DMU) i at period t, respectively, β_0 is the constant term, and β is the vector of corresponding parameters for x_{it}. The time-variant inefficiency term and the idiosyncratic random error are represented by u_{it} and v_{it}, respectively. Other than the transitory terms, the persistent inefficiency of individual DMU is denoted as η_i, while the unobserved individual heterogeneity is considered as s_i. Besides, the heterogeneity and random error terms are assumed to be normally distributed, and the two inefficiency terms are assumed to follow half-normal distributions.

As suggested by Colombi et al. (2014), the above model (1) can be estimated with a single-stage maximum likelihood estimator. In contrast, the two-stage procedure introduced in KLH14, although less efficient, is easier in implementation and computation. Following KLH14, (1) can be transformed into

[1]For a comprehensive discussion in SFA, see Sickles and Zelenyuk (2019, Chapter 11-16) in a textbook style and more recent reviews by Kumbhakar et al. (2021a,b).

$$y_{it} = \beta_0^* + x_{it}'\beta + a_i + \varepsilon_{it}, \quad i = 1, \ldots, n;\ t = 1, \ldots, T, \tag{2}$$

where

$$\begin{aligned}
\beta_0^* &= \beta_0 - E(\eta_i) - E(u_{it}), \\
a_i &= s_i - \eta_i + E(\eta_i), \\
\varepsilon_{it} &= v_{it} - u_{it} + E(u_{it}),
\end{aligned} \tag{3}$$

and where $E(\eta_i) = \sqrt{2/\pi}\sigma_\eta$ and $E(u_{it}) = \sqrt{2/\pi}\sigma_u$ are the population means of the persistent and transitory inefficiency, respectively.

Accordingly, the transformed model (2) adheres to a standard panel data model, and hence can be first estimated with standard panel data estimators. In this study, we utilize the random effects regression. Subsequently, the predicted values of individual effect ($\widehat{a}_i$) and noise term ($\widehat{\varepsilon}_{it}$) can be deployed into the second-stage estimation in (3), utilizing a standard SFA containing the persistent and transitory inefficiency and random error, respectively. Consequently, the persistent and transitory inefficiency can be estimated following the Jondrow et al. (1982) method as $\widehat{\eta}_i = \widehat{E}(\eta_i|e_i)$ and $\widehat{u}_{it} = \widehat{E}(u_{it}|e_{it})$, where $e_i = s_i - \eta_i$ and $e_{it} = v_{it} - u_{it}$. Moreover, the persistent and transitory efficiency levels then can be approximated as $\widehat{\phi}_i = 1 - \widehat{E}(\eta_i|e_i)$ and $\widehat{\phi}_{it} = 1 - \widehat{E}(u_{it}|e_{it})$, respectively.[2]

In this paper, to explore the possible influence of spatial dependence on efficiency estimation, following the spatial stochastic frontier studies in the literature, e.g., Glass et al. (2012, 2016); Fuller and Sickles (2023), we deploy a set of spatial SFMs based on the KLH14 frameworks as discussed in the following subsection.

[2] Alternatively, the efficiency levels can be estimated in percentage terms as $\widehat{\phi}_i = \widehat{E}[\exp(-\eta_i)|e_i]$ and $\widehat{\phi}_{it} = \widehat{E}[\exp(-u_{it})|e_{it}]$, respectively (Battese and Coelli, 1988).

2.2 Spatial stochastic frontier

To account for the spatial dependence between the DMUs, the spatial error model (SEM) can be adapted to the four-component error term framework (Kumbhakar et al., 2014) as

$$\begin{aligned} y_{it} &= \beta_0^* + x_{it}'\beta + a_i + \psi_{it}, \quad i = 1,\ldots,n;\ t = 1,\ldots,T, \\ \psi_{it} &= \lambda \sum_{j=1}^{n} \omega_{ij}\psi_{jt} + \varepsilon_{it}, \end{aligned} \tag{4}$$

where y_{it}, x_{it}, β, a_i, and ε_{it} are defined as above. The disturbance is assumed to be i.i.d. and normally distributed, i.e, $\varepsilon_{it} \sim \text{iid}N(0, \sigma_\varepsilon^2)$. Meanwhile, the spatial autocorrelation disturbance ψ_{it} reflects the cross-sectional spatial dependence weighted by the matrix Ω, with a parameter λ. The $(n \times n)$ matrix Ω is the spatial weight between each pair of neighbor units, i.e.,

$$\Omega = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1n} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{n1} & \omega_{n2} & \cdots & \omega_{nn} \end{bmatrix}, \tag{5}$$

where the weight ω_{ij} $(i = 1,\ldots,n;\ j = 1,\ldots,n)$ is non-negative, which is predefined for the j^{th} neighbor unit to the i^{th} unit. Besides, Ω is row-standardized to unity, where the diagonal elements are zeros (by convention, meaning each area is not a neighbor to itself).

Other types of spatial models can also be considered for an adaption into an SFM framework. In a similar formulation as SEM, the spatial autoregressive model (SAR) reflects the spatial dependence by the cross-sectional effect of the spatial lag of the dependent variable instead of the spatial autocorrelation disturbance. Additionally to the spatial lag of the dependent variable, the spatial Durbin model (SDM) considers the effect of the spatial lag of independent variables. The SEM, among others, is a comprehensive representation of the spatial dependence (Glass et al., 2012). Nevertheless, if we intend to interpret the spillovers from/to the neighbors, the spatial errors are not interpretable. Instead, the spillovers in SAR or SDM can be interpreted as they are related to the independent or the dependent variables or both (Glass et al., 2016).[3]

Accordingly, the SAR model can also be adapted to a four-component error term stochastic frontier framework (SARSF), for example, using the specification with the spatially lagged dependent variable as

$$y_{it} = \beta_0^* + x_{it}'\beta + \gamma \sum_{j=1}^{n} \omega_{ij} y_{jt} + a_i + \varepsilon_{it}, \quad i = 1, \ldots, n;\ t = 1, \ldots, T, \tag{6}$$

and a stochastic frontier specification with the SDM (SDSF) can be stated as

$$y_{it} = \beta_0^* + x_{it}'\beta + \gamma \sum_{j=1}^{n} \omega_{ij} y_{jt} + \theta \sum_{j=1}^{n} \omega_{ij} x_{jt} + a_i + \varepsilon_{it}, \quad i = 1, \ldots, n;\ t = 1, \ldots, T. \tag{7}$$

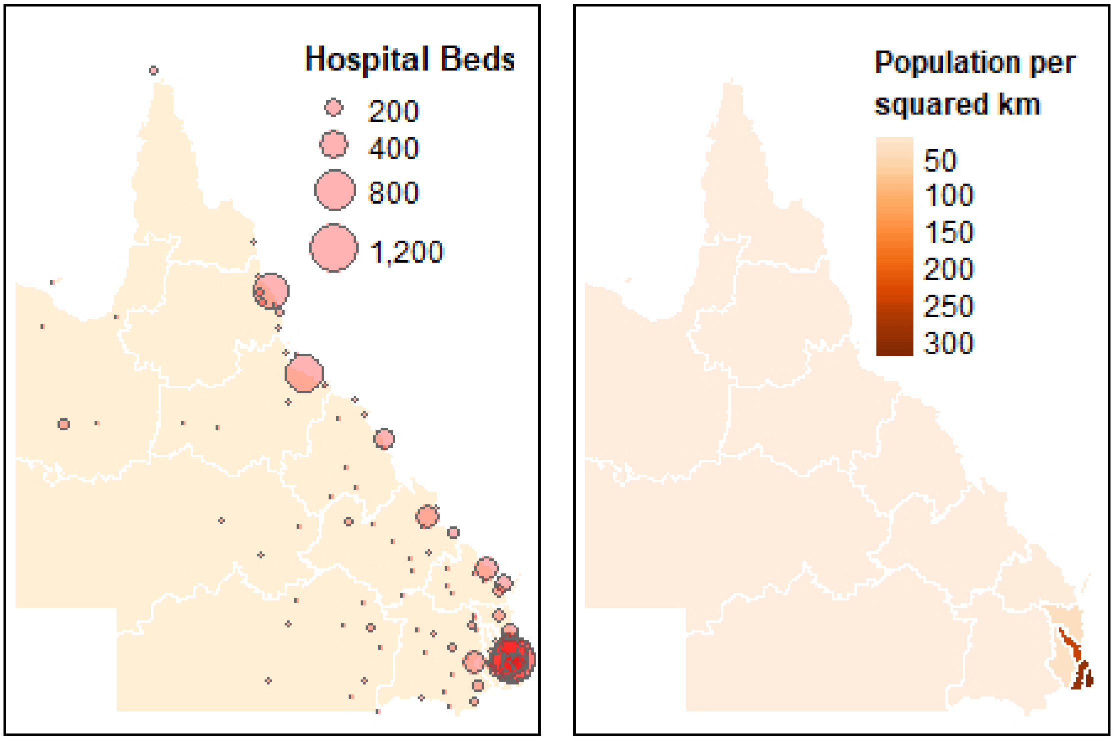
Similar to the SEM stochastic frontier (SESF), a weight matrix Ω is also predetermined to describe the spatial effect between neighbors. Meanwhile, more corresponding parameters need to be estimated instead of λ, i.e., the coefficient γ for the spatial lag of the dependent variable and the variable-specific coefficient θ for the spatial lag of the independent variables. With the estimated parameters, the inefficiency scores can be estimated accordingly, e.g., based on the KLH14 framework.[4]

In what follows, we apply the SEM, SAR, and SDM stochastic frontier models on the Queensland hospital data set with the weight matrix Ω constructed based on the geographical distance between hospitals.[5]

[3] The marginal effect of the independent variables in an SAR specification can be estimated as a direct (own) effect, an indirect (spillover) effect, and total effect (LeSage and Pace, 2009).

[4] As indicated in Glass et al. (2016), spatial models can be adapted to more SFMs. In the SF frameworks where a maximum likelihood estimator is applied, the spatial SFMs can also be estimated with maximum likelihood type estimators. Further, the individual inefficiency can be obtained through the Jondrow et al. (1982) method (e.g., Elhorst (2009); Glass et al. (2012, 2013, 2014, 2016)).

[5] See more discussions about different sets of spatial weights utilized in the study in Section (3.3).



(a) Hospital locations (b) Population density by HHS

Figure 1: Geographical distribution of public hospitals in our sample

3 Data and Variables

3.1 Data

In this study, we utilize a data set on 104 public hospitals in Queensland, Australia, in a period starting from the financial year (FY) 2012/13 to FY 2016/17, obtained from the Queensland Department of Health (Queensland Health). These hospitals are operated by 16 local Hospital and Health Services (HHSs), who were established in 2012 as a result of the National Health Reform Agreement.[6] As illustrated in Figure 1 , being consistent with the geographical distribution of population in Queensland, public hospitals in the state are distributed along the coastline, with a large cluster of hospitals and beds centering around Brisbane–the capital city of Queensland.

[6]Among the HHSs, 15 of them are in the scope of our study, who directly manage and operate public hospitals in defined local geographical areas. The remaining HHS is a specialist statewide HHS dedicated to caring for children and young people from across Queensland.

To model the production process of hospitals, we follow the common practice in the literature, especially studies undertaken in the Australian context, and use labor (containing medical and non-medical labor), expenditure, and the number of beds as hospital inputs, and an aggregation of outpatient and inpatient services as a hospital output.[7] In the following subsection, we provide a brief description of variables used in our study and refer interested readers to Nguyen and Zelenyuk (2021a) for more details.

Table 1: Descriptive statistics of Queensland public hospitals, FY 2012/13 to FY 2016/17

Variables	**Description**	**Mean**	**Std Dev**	**Min**	**Median**	**Max**
Input						
BEDS	Number of beds	99.67	196.48	3.00	21.00	1055.00
AGGMLABOR	Aggregated medical labor input	0.72	1.72	0.00	0.06	10.06
MEO	Salaried medical officers*	71.56	167.89	0.00	4.73	951.64
TNUR	Nurses*	210.44	463.34	2.27	24.76	2651.66
DHP	Diagnostic and health professionals*	50.88	137.38	0.00	2.18	914.20
AGGNMLABOR	Aggregated non-medical labor input	0.77	1.67	0.01	0.12	10.54
ACS	Administrative and clerical staff*	69.71	165.01	0.18	6.74	1187.09
OPCS	Other personal care staff*	12.19	30.20	0.00	1.41	201.30
DOS	Domestic and other staff*	63.93	127.54	0.00	14.32	900.16
SUPP	Consumable input**	12.40	33.60	0.03	0.48	327.00
DSUP	Drug supplies expenditure***	3.84	11.60	0.00	0.11	94.40
MSSUP	Medical and surgical supplies***	9.06	24.30	0.01	0.33	252.00
Output						
AGGOUT	Aggregated output	0.68	1.41	0.01	0.10	8.64
WEPISODES	Case-mix weighted episodes****	11.54	26.21	0.03	0.88	157.81
OUT	Number of outpatient visits****	100.95	191.88	1.25	20.38	1190.22

* *Full-time equivalent staff.*

** *Measured in AUD 1,000,000 and in constant price of FY2012/2013.*

*** *Measured in AUD 1,000,000.*

**** *Measured in 1,000s.*

[7] For example, see Hao and Pegels (1994); Burgess and Wilson (1996); Magnussen (1996); Harris et al. (2000); Grosskopf et al. (2001); Berta et al. (2010); Ferrier and Trivitt (2013); Nayar et al. (2013); Chowdhury and Zelenyuk (2016) for studies in the international context and Productivity Commission (2010); Chua et al. (2011); Nghiem et al. (2011); O'Donnell and Nguyen (2013); Nguyen and Zelenyuk (2021a,b,c); Nguyen et al. (2022a,b); Wang and Zelenyuk (2023) for studies in the Australian context.

3.2 Variables

The labor input is measured by full-time equivalent (FTE) medical and non-medical staff hours, each comprising three labor categories respectively.[8] These two labor measures are aggregated with the principal component analysis (PCA) based approach, proposed by Daraio and Simar (2007), respectively. Meanwhile, the hospital consumable input is measured by the expenditure on drug and medical supplies (in FY 2012/13 constant price), and the hospital capital input is proxied by the number of beds.

In our data set, we have two categories of hospital outputs, which are outpatient services (measured by the number of non-admitted occasions of service) and inpatient services (measured by the number of case-mix weighted inpatient episodes). To deal with multiple outputs in the SFA framework, we also utilize the Daraio and Simar (2007) approach to construct an aggregate measure of hospital output. The descriptive statistics of all variables are provided in Table 1.

3.3 Spatial weights

In this study, we construct the spatial weights based on geographical distances between hospitals using their geographic coordinates. Specifically, the spatial weights attached to a hospital i can be formulated as[9]

$$\omega_{ij} = \begin{cases} \dfrac{1}{[d(i,j)]^2}, & \text{if } j \in \mathscr{H}(i), \\ 0, & \text{if } j \notin \mathscr{H}(i), \end{cases} \tag{8}$$

where $d(i,j)$ is the geographical distance between hospital i and the peer hospital j, and $\mathscr{H}(i)$ is a set of neighbors of hospital i excluding itself, i.e., $i \notin \mathscr{H}(i)$. Generally, the squared inverse distance function (IDF) assigns a higher weight to the hospitals located in closer proximity.

Moreover, we consider four different approaches to identify the set of neighbors of hospital i,

[8] The medical staff contains: i.) medical officers, ii.) nurses, and iii.) diagnostic and health professionals, and the non-medical staff contains: i.) administrative and clerical staff, ii.) other personal care staff, and iii.) domestic and other staff.

[9] These weights then will be utilized to construct the spatial weight matrix Ω, where Ω is row-standardized to unity.

and denote the corresponding spatial weight matrices as Ω_1, Ω_2, Ω_3, and Ω_4, respectively. Firstly, we can impose no distance restrictions (without a cutoff distance) on the set of neighbors for hospital i, i.e., any other hospital in the sample can be its neighbor. In the second approach, we specify a cut-off distance to determine neighbors for hospital i, i.e., any hospital located within the cut-off distance to hospital i is considered as a neighbor of hospital i. Meanwhile, the cut-off distance in Ω_2 is determined as the minimal distance that guarantees each hospital in our sample has at least one neighbor. In the third approach, we specify $\mathscr{H}(i)$ with the k-nearest-neighbors (KNN) approach (i.e., $k = 5$) to identify a set of k nearest hospitals to hospital i. Finally, due to the consistency in management and fluidity of resources among the hospitals within the same network, in the fourth approach, $\mathscr{H}(i)$ is designated as the hospitals that are operated in the same HHS with hospital i. The first-order spatial links between hospitals based on these four approaches are represented in Figure 2.

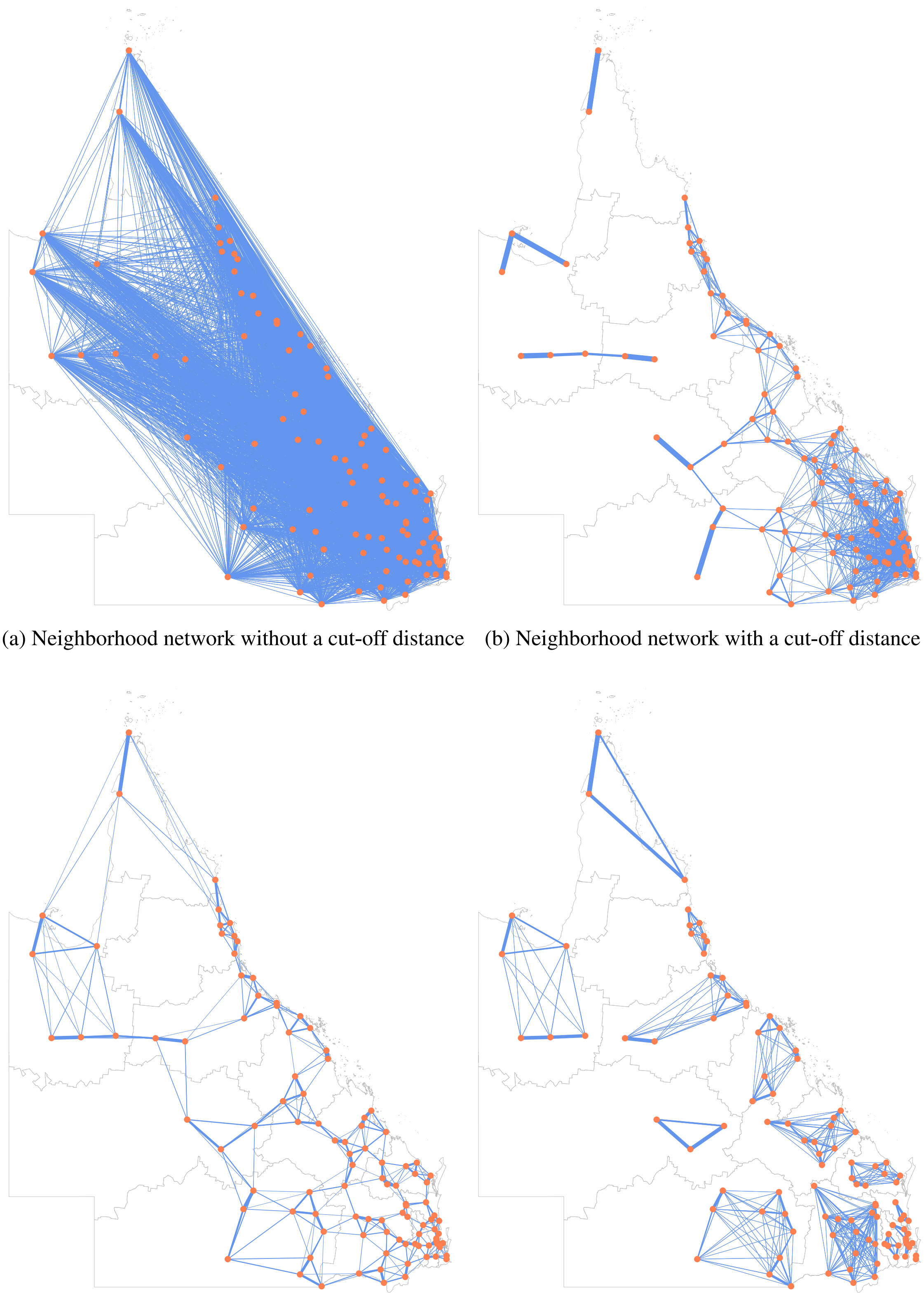
4 Results and Discussion

4.1 Frontier estimation

We deploy a linear-in-logarithms form of Cobb-Douglas production function with a time trend variable, i.e.,

$$\begin{aligned} \ln \text{AGGOUT} =& \beta_0^* + \beta_1 \ln \text{BEDS} + \beta_2 \ln \text{AGGMLABOR} + \beta_3 \ln \text{AGGNMLABOR} \\ & + \beta_4 \ln \text{SUPP} + \tau t + a_i + \varepsilon_{it}, \end{aligned} \tag{9}$$

based on which, the three spatial SF models (4), (6), and (7) are adapted and estimated with the four spatial weight matrices, respectively.



(a) Neighborhood network without a cut-off distance (b) Neighborhood network with a cut-off distance

(c) Neighborhood network with 5 nearest neighbors (d) Neighborhood network within the same HHS

Figure 2: Spatial links between hospitals using different approaches

Spatial error stochastic frontier model (SESF)

The estimated parameters of the four SESF models with corresponding weight matrices are reported in Table 2, alongside the benchmark non-spatial KLH14 model. Mild differences are observed among the estimations of the benchmark model and the four SESF models, incorporating different spatial weight methods. The estimated coefficients of all the input variables indicate positive associations with the output, which are statistically significant except that for the non-medical labor (ln AGGNMLABOR). The coefficients of the time variable demonstrate a statistically insignificant relationship between output and the time trend. Moreover, the coefficient of the spatial autocorrelation disturbance is positive among the four scenarios and is statistically significant in most cases. According to the Akaike information criterion (AIC) and Bayesian information criterion (BIC), the SESF employing the IDF weight matrix without a cutoff distance appears to be a more appropriate specification.

Spatial autoregressive stochastic frontier model (SARSF)

As illustrated in Table 3, the coefficients estimated for the production function in SARSF are akin to those for the SESF models, with respect to the value and statistical significance. The capital input (ln BEDS), medical labor input (ln AGGMLABOR), and the expenditure of consumable supplies (ln SUPP) are estimated to exhibit a positive relationship with the output of the hospitals. The spatial lag of the dependent variable is estimated to be positively correlated to the output among the four SARSF models, with a high level of statistical significance. This may imply the existence of the spatial dependence among the hospitals and hence the necessity of incorporating the spatial lag in the SFM. Meanwhile, the AIC and BIC values of the third model, employing the KNN weight matrix, are among the lowest.

Spatial Durbin stochastic frontier model (SDSF)

The estimation results of the SDSF models are summarized in Table 4, where the estimated coefficients of the independent variables are analogous to those in the above spatial SFMs. Mean-

Table 2: Coefficient estimates of benchmark and SESF models

Model		KLH14	SESF			
Weight matrix			SESF1	SESF2	SESF3	SESF4
Main function						
ln BEDS	β_1	0.465***	0.462***	0.460***	0.460***	0.461***
		(0.078)	(0.079)	(0.080)	(0.080)	(0.080)
ln AGGMLABOR	β_2	0.294***	0.285***	0.290***	0.285***	0.280***
		(0.053)	(0.056)	(0.056)	(0.056)	(0.057)
ln AGGNMLABOR	β_3	0.008	0.008	0.008	0.009	0.011
		(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
ln SUPP	β_4	0.187***	0.186***	0.183***	0.187***	0.190***
		(0.037)	(0.043)	(0.043)	(0.044)	(0.045)
t	τ	-0.008	-0.008	-0.008	-0.008	-0.008
		(0.008)	(0.010)	(0.009)	(0.009)	(0.009)
Constant	β_0^*	-5.468***	-5.472***	-5.413***	-5.482***	-5.523***
		(0.544)	(0.604)	(0.593)	(0.601)	(0.618)
Spatial function						
AC disturbance	λ		0.232***	0.075	0.122*	0.135**
			(0.075)	(0.067)	(0.065)	(0.060)
R^2		0.95	0.95	0.95	0.95	0.95
AIC			-25.56	-20.36	-23.14	-24.52
BIC			12.72	17.93	15.15	13.77

Notes: Standard errors clustered at individual hospital level are reported beneath corresponding coefficients.

** $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.*

AC: autocorrelated.

Table 3: Coefficient estimates of benchmark and SARSF models

Model		KLH14	SARSF			
Weight matrix			SARSF1	SARSF2	SARSF3	SARSF4
Main function						
ln BEDS	β_1	0.465***	0.426***	0.432***	0.432***	0.441***
		(0.078)	(0.077)	(0.077)	(0.076)	(0.077)
ln AGGMLABOR	β_2	0.294***	0.272***	0.275***	0.273***	0.275***
		(0.053)	(0.055)	(0.055)	(0.055)	(0.055)
ln AGGNMLABOR	β_3	0.008	0.005	0.006	0.005	0.007
		(0.035)	(0.033)	(0.034)	(0.034)	(0.034)
ln SUPP	β_4	0.187***	0.161***	0.168***	0.166***	0.169***
		(0.037)	(0.042)	(0.041)	(0.041)	(0.041)
t	τ	-0.008	-0.008	-0.007	-0.007	-0.007
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	β_0^*	-5.468***	-4.761***	-4.923***	-4.899***	-5.006***
		(0.544)	(0.667)	(0.616)	(0.620)	(0.615)
Spatial function						
AR dependent variables	γ		0.155***	0.118***	0.114***	0.095***
			(0.056)	(0.037)	(0.034)	(0.034)
R^2		0.95	0.95	0.95	0.95	0.95
AIC			-13.4	-13.51	-15.38	-9.92
BIC			67.42	67.31	65.44	70.90

Notes: Standard errors clustered at individual hospital level are reported beneath corresponding coefficients.

** $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.*

AR: autoregressive.

while, the coefficient of the autoregressive dependent variable (γ) is also statistically significant in a high confidence level when utilizing different weight matrices, which is aligned with the results observed in the SARSF models. Besides, all the coefficient estimates of the autoregressive independent variables (θ), are statistically insignificant among the four SDSF models. Analogously, the SDSF utilizing the KNN weight matrix is preferable according to the AIC and BIC criteria, aligning with the findings of the SARSF models. Nevertheless, it is worth noting that the AIC and BIC values of the models utilizing the same spatial model with different spatial weight matrices exhibit close proximity to one another.

Marginal effects of inputs

Following the evaluation approaches by LeSage and Pace (2009); Glass et al. (2016), the marginal effects of the input variables are reported in Table 5. Across the SARSF and SDSF models utilizing the four weight matrices, the capital (ln BEDS), medical labor (ln AGGMLABOR), and the expenditure (ln SUPP) mostly exhibit statistically significant positive effects on all the hospitals (total effect), primarily through the direct effect (to the respective hospitals themselves). The magnitude of the direct and total effects closely resemble each other across the models.

Besides, regarding the indirect effect, when utilizing the SARSF models, the capital, medical labor, and expenditure inputs also demonstrate a positive spillover effect on the neighbor hospitals, which are statistically significant at a 95 percent or higher confidence level. Meanwhile, in the SDSF models, all the inputs demonstrate statistically insignificant indirect effects with all the weight matrices.

Overall, the results indicate that the capital, medical labor, and expenditure inputs all play a vital role in shaping the output of the public hospital system in Queensland. More importantly, when incorporating the spatial autoregressive output, the inputs also provide positive spillover effects to the neighbor hospitals, although to a lower magnitude than the direct effect.

Table 4: Coefficient estimates of benchmark and SDSF models

Model		KLH14	SDSF			
Weight matrix			SDSF1	SDSF2	SDSF3	SDSF4
Main function						
ln BEDS	β_1	0.465***	0.437***	0.427***	0.433***	0.448***
		(0.078)	(0.077)	(0.077)	(0.076)	(0.078)
ln AGGMLABOR	β_2	0.294***	0.259***	0.269***	0.264***	0.247***
		(0.053)	(0.057)	(0.059)	(0.059)	(0.059)
ln AGGNMLABOR	β_3	0.008	0.004	0.007	0.004	0.009
		(0.035)	(0.033)	(0.033)	(0.034)	(0.033)
ln SUPP	β_4	0.187***	0.187***	0.181***	0.191***	0.210***
		(0.037)	(0.048)	(0.048)	(0.049)	(0.052)
t	τ	-0.008	-0.003	-0.003	-0.003	-0.004
		(0.008)	(0.009)	(0.009)	(0.008)	(0.009)
Constant	β_0^*	-5.468***	-3.069***	-4.378***	-4.188***	-4.069***
		(0.544)	(1.022)	(0.817)	(0.771)	(0.741)
Spatial function						
AR dependent variables	γ		0.255***	0.133**	0.159***	0.156***
			(0.069)	(0.061)	(0.057)	(0.051)
AR independent variables						
ln BEDS	θ_1		-0.019	0.088	0.041	-0.020
			(0.120)	(0.112)	(0.093)	(0.089)
ln AGGMLABOR	θ_2		0.073	0.012	0.047	0.086
			(0.109)	(0.062)	(0.074)	(0.075)
ln AGGNMLABOR	θ_3		-0.043	-0.018	-0.051	-0.055
			(0.094)	(0.065)	(0.066)	(0.061)
ln SUPP	θ_4		-0.129	-0.073	-0.082	-0.095*
			(0.078)	(0.064)	(0.058)	(0.055)
R^2		0.95	0.95	0.95	0.95	0.95
AIC			-11.19	-9.84	-13.21	-11.91
BIC			86.64	88.00	84.63	85.93

Notes: Standard errors clustered at individual hospital level are reported beneath corresponding coefficients.

** p < 0.10; ** p < 0.05; *** p < 0.01.*

AR: autoregressive.

Table 5: Marginal effects of spatial frontier models

Model	SARSF			SDSF		
	Direct	Indirect	Total	Direct	Indirect	Total
Weight matrix	Without a cutoff					
ln BEDS	0.430***	0.078**	0.508***	0.443***	0.111	0.553***
	(0.080)	(0.033)	(0.095)	(0.079)	(0.150)	(0.177)
ln AGGMLABOR	0.270***	0.048**	0.319***	0.261***	0.183	0.445***
	(0.055)	(0.020)	(0.063)	(0.057)	(0.146)	(0.160)
ln AGGNMLABOR	0.008	0.001	0.010	0.006	-0.049	-0.043
	(0.032)	(0.007)	(0.038)	(0.032)	(0.121)	(0.125)
ln SUPP	0.160***	0.028***	0.188***	0.182***	-0.105	0.077
	(0.042)	(0.011)	(0.044)	(0.046)	(0.092)	(0.095)
Weight matrix	With a cutoff					
ln BEDS	0.437***	0.057***	0.494***	0.434***	0.157	0.591***
	(0.079)	(0.022)	(0.091)	(0.079)	(0.114)	(0.150)
ln AGGMLABOR	0.274***	0.036***	0.309***	0.268***	0.054	0.321***
	(0.054)	(0.013)	(0.062)	(0.059)	(0.072)	(0.093)
ln AGGNMLABOR	0.009	0.001	0.010	0.009	-0.013	-0.004
	(0.033)	(0.005)	(0.037)	(0.032)	(0.071)	(0.080)
ln SUPP	0.167***	0.021***	0.188***	0.177***	-0.055	0.122
	(0.040)	(0.007)	(0.043)	(0.046)	(0.068)	(0.078)
Weight matrix	KNN					
ln BEDS	0.437***	0.055***	0.492***	0.441***	0.118	0.559***
	(0.079)	(0.020)	(0.090)	(0.078)	(0.098)	(0.136)
ln AGGMLABOR	0.272***	0.034***	0.305***	0.266***	0.100	0.366***
	(0.055)	(0.012)	(0.061)	(0.058)	(0.083)	(0.103)
ln AGGNMLABOR	0.008	0.001	0.008	0.004	-0.052	-0.047
	(0.033)	(0.004)	(0.037)	(0.033)	(0.074)	(0.083)
ln SUPP	0.165***	0.020***	0.184***	0.186***	-0.059	0.127*
	(0.040)	(0.006)	(0.042)	(0.047)	(0.060)	(0.069)
Weight matrix	HHS					
ln BEDS	0.446***	0.046**	0.492***	0.453***	0.051	0.504***
	(0.080)	(0.019)	(0.089)	(0.080)	(0.095)	(0.133)
ln AGGMLABOR	0.273***	0.028**	0.301***	0.251***	0.140*	0.391***
	(0.054)	(0.011)	(0.060)	(0.058)	(0.084)	(0.102)
ln AGGNMLABOR	0.010	0.001	0.012	0.009	-0.055	-0.046
	(0.033)	(0.004)	(0.036)	(0.032)	(0.067)	(0.076)
ln SUPP	0.167***	0.017***	0.184***	0.204***	-0.070	0.134**
	(0.040)	(0.006)	(0.042)	(0.049)	(0.054)	(0.063)

Notes: Standard errors clustered at individual hospital level are reported beneath corresponding coefficients.

** p < 0.10; ** p < 0.05; *** p < 0.01.*

Model selection

To incorporate appropriate spatially lagged effects, a range of diagnostic tests can be conducted to facilitate the selection process among the spatial SFMs. One stream is based on the modified Lagrange multiplier (LM) test for spatial error and spatial lag of the dependent variable by Bera and Yoon (1993). Following the simplified but robust procedures proposed by Anselin et al. (1996) and Elhorst (2014), we first conduct a series of LM tests, and the results are reported in Table 6. Across the four spatial weight matrices in a random effects model (aligning with the KLH14 model), the null hypotheses of the LM and robust LM tests of the spatial lag of error (i.e., $\lambda = 0$) are all rejected at a significance level of lower than 1%. Meanwhile, the robust LM tests of the spatial lag of the dependent variable indicate that the null hypotheses of $\gamma = 0$ cannot be rejected at a 1% significance level in most cases. Therefore, these tests suggest that the SESF model is preferable in this context compared to the SARSF model.

It is also worth noting that the selection between the two types of spatial dependence is limited in practice (Kelejian and Prucha, 1998). Besides, due to the unbiased coefficient estimates with the spatial lag of the dependent variable or the error term, SDM is also recommended in most cases by LeSage and Pace (2009). Consequently, in subsequent analysis, we will encompass all three spatial models, which also serves as an exploration into the adaption of the mainstream spatial models in the SFA paradigm. Nevertheless, the different influences illustrated later in the efficiency estimates still emphasize the necessity of the selection of spatial dependence prior to formulating policy implications.

4.2 Inefficiency estimation

The persistent and transitory inefficiency are estimated under the four-component error term framework as discussed in Section (2.1). The descriptive statistics of the inefficiency levels (in percentage) of the three spatial SFMs are summarized in Tables 7 and 8, where, as a benchmark, the inefficiency of the non-spatial KLH14 is also reported alongside.

When utilizing identical spatial SFM with different weight matrices, the persistent and tran-

Table 6: Test results for model selection

	Spatial lag of error				Spatial lag of dependent variable			
	LM		Robust LM		LM		Robust LM	
	LM	p-value	LM	p-value	LM	p-value	LM	p-value
Weight matrix								
Without a cut-off distance	17.3	0.0000	13.9	0.0002	6.0	0.0141	2.6	0.1046
With a cut-off distance	38.1	0.0000	28.9	0.0000	15.4	0.0000	6.2	0.0130
KNN	32.6	0.0000	25.0	0.0000	12.9	0.0003	5.4	0.0203
HHS	39.1	0.0000	34.4	0.0000	5.5	0.0187	0.8	0.3833

sitory inefficiency estimates are close to one another. More significant differences are observed among different spatial models. Generally, the total inefficiency levels estimated by SESF (i.e., with a mean level of about 29%) are slightly higher than the estimates of the original non-spatial model (i.e., mean level at around 27% vs. 29-31% for the spatial models). Furthermore, the estimates of inefficiency yielded by SARSF and SDSF are comparatively higher than the SESF estimates. Such a shift of the inefficiency levels demonstrates some importance of incorporating the spatial effects during the estimation, while also suggesting that the studies that have not done so for this data with the basic SFMs still reached fairly similar estimates. Meanwhile, the selection of the spatial effects may also introduce varying influences on the outcomes.

In our sample, the persistent inefficiency is the predominant contributor to the overall inefficiency across all the scenarios. This implies that the long-term performance of public hospitals in Queensland maintains an inherent and sustainable inefficiency level, even accounting for temporary shocks or random fluctuations.

As shown in Table 9, the correlations between the estimates of different spatial SFMs or between the same spatial model with different weight matrices are extremely high, which are mostly higher than 95%. The correlations between the estimates of the non-spatial KLH14 model and those of the spatial models are also notably high, which indicates the relatively higher inefficiency estimated by the spatial models may be due to an approximately ‘parallel’ shift of the inefficiency estimates of all the hospitals.

For a more intuitive illustration, the distribution and the tendency of the correlations of the

Table 7: Descriptive statistics for the estimated inefficiency levels

Models	Mean	Std Dev	Min	Q1	Median	Q3	Max
Persistent inefficiency							
KLH14	26.77%	12.72%	6.26%	18.17%	23.01%	33.60%	61.35%
SESF1	28.47%	14.04%	6.10%	18.19%	23.77%	37.28%	64.93%
SESF2	28.44%	14.01%	6.11%	18.21%	23.74%	37.19%	64.85%
SESF3	28.32%	13.93%	6.11%	18.21%	23.63%	36.92%	64.60%
SESF4	28.27%	13.90%	6.10%	18.22%	23.59%	36.81%	64.49%
SARSF1	30.74%	14.73%	7.58%	18.81%	27.10%	39.43%	68.93%
SARSF2	29.06%	13.98%	7.02%	18.03%	25.58%	36.73%	67.19%
SARSF3	29.34%	14.11%	7.16%	18.00%	25.39%	37.98%	67.78%
SARSF4	30.18%	14.99%	6.53%	17.86%	27.00%	39.88%	68.92%
SDSF1	29.65%	14.71%	6.50%	17.56%	26.84%	38.83%	68.55%
SDSF2	28.47%	13.61%	6.79%	18.06%	25.61%	36.36%	65.88%
SDSF3	28.32%	14.00%	6.33%	17.01%	24.93%	37.66%	66.86%
SDSF4	28.25%	14.34%	5.75%	16.77%	25.56%	37.57%	66.93%
Transitory inefficiency							
KLH14	0.20%	0.00%	0.19%	0.20%	0.20%	0.20%	0.20%
SESF1	0.16%	0.00%	0.16%	0.16%	0.16%	0.16%	0.16%
SESF2	0.19%	0.00%	0.19%	0.19%	0.19%	0.19%	0.20%
SESF3	0.20%	0.00%	0.19%	0.20%	0.20%	0.20%	0.20%
SESF4	0.17%	0.00%	0.16%	0.17%	0.17%	0.17%	0.17%
SARSF1	0.18%	0.00%	0.17%	0.18%	0.18%	0.18%	0.18%
SARSF2	0.20%	0.00%	0.20%	0.20%	0.20%	0.20%	0.21%
SARSF3	0.18%	0.00%	0.18%	0.18%	0.18%	0.18%	0.19%
SARSF4	0.18%	0.00%	0.18%	0.18%	0.18%	0.18%	0.19%
SDSF1	0.20%	0.00%	0.20%	0.20%	0.20%	0.21%	0.21%
SDSF2	0.17%	0.00%	0.16%	0.17%	0.17%	0.17%	0.17%
SDSF3	0.20%	0.00%	0.19%	0.19%	0.20%	0.20%	0.20%
SDSF4	0.19%	0.00%	0.18%	0.19%	0.19%	0.19%	0.19%

Table 8: Descriptive statistics for the total inefficiency level

Models	**Mean**	**Std Dev**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Total inefficiency							
KLH14	26.97%	12.72%	6.46%	18.37%	23.21%	33.80%	61.55%
SESF1	28.63%	14.04%	6.26%	18.35%	23.93%	37.45%	65.09%
SESF2	28.63%	14.01%	6.30%	18.40%	23.93%	37.39%	65.04%
SESF3	28.51%	13.93%	6.30%	18.41%	23.82%	37.11%	64.80%
SESF4	28.44%	13.90%	6.27%	18.38%	23.76%	36.97%	64.66%
SARSF1	30.92%	14.73%	7.76%	18.99%	27.28%	39.61%	69.12%
SARSF2	29.26%	13.98%	7.22%	18.24%	25.78%	36.93%	67.40%
SARSF3	29.52%	14.11%	7.34%	18.19%	25.57%	38.16%	67.97%
SARSF4	30.36%	14.99%	6.71%	18.04%	27.19%	40.06%	69.11%
SDSF1	29.85%	14.71%	6.70%	17.77%	27.05%	39.04%	68.76%
SDSF2	28.64%	13.61%	6.95%	18.23%	25.77%	36.52%	66.05%
SDSF3	28.52%	14.00%	6.53%	17.21%	25.12%	37.85%	67.06%
SDSF4	28.44%	14.34%	5.94%	16.96%	25.75%	37.76%	67.12%

inefficiency estimates are as shown in the estimated kernel density plots in Figure 3,[10] where the horizontal axis is the estimated inefficiency levels. The estimated densities of the inefficiency levels using different weight matrices but the same spatial model, as indicated by row, are mostly akin to each other. The densities of the inefficiency estimates of SESF are in a similar shape to that of the non-spatial KLH14, with a relatively higher inefficiency level. Meanwhile, the densities of the inefficiency estimates of SARSF and SDSF demonstrate a further enhanced concentration within the range of higher inefficiency levels in comparison to the non-spatial estimate.

Consequently, we conclude that there is some evidence that the spatial dependence is statistically significant among Queensland public hospitals. When ignoring the spatial dependence in an SFM framework, the inefficiency level tends to be underestimated compared to the results when incorporating a spatial SFM. On the other hand, the difference that we found is usually very modest, and to some extent depends on the particular spatial model applied, suggesting that a careful selection of the spatial effect is necessary from a wide range of possibilities.

[10]Estimated with Epanechnikov kernel and bandwidth selected with the Sheather and Jones (1991) method.

Table 9: Correlation matrix of individual inefficiency estimated by different models

	KLH14	SESF1	SESF2	SESF3	SESF4	SARSF1	SARSF2	SARSF3	SARSF4	SDSF1	SDSF2	SDSF3	SDSF4
KLH14	1.0000												
SESF1	0.9984	1.0000											
SESF2	0.9984	1.0000	1.0000										
SESF3	0.9986	1.0000	1.0000	1.0000									
SESF4	0.9987	1.0000	1.0000	1.0000	1.0000								
SARSF1	0.9467	0.9492	0.9493	0.9491	0.9490	1.0000							
SARSF2	0.9519	0.9537	0.9539	0.9537	0.9536	0.9962	1.0000						
SARSF3	0.9440	0.9458	0.9459	0.9457	0.9457	0.9954	0.9953	1.0000					
SARSF4	0.9598	0.9620	0.9621	0.9619	0.9617	0.9934	0.9925	0.9916	1.0000				
SDSF1	0.9658	0.9673	0.9674	0.9673	0.9672	0.9964	0.9954	0.9929	0.9945	1.0000			
SDSF2	0.9582	0.9596	0.9596	0.9595	0.9595	0.9958	0.9988	0.9941	0.9928	0.9968	1.0000		
SDSF3	0.9585	0.9589	0.9590	0.9590	0.9590	0.9936	0.9945	0.9971	0.9925	0.9966	0.9957	1.0000	
SDSF4	0.9778	0.9780	0.9780	0.9780	0.9780	0.9849	0.9866	0.9831	0.9936	0.9943	0.9894	0.9912	1.0000

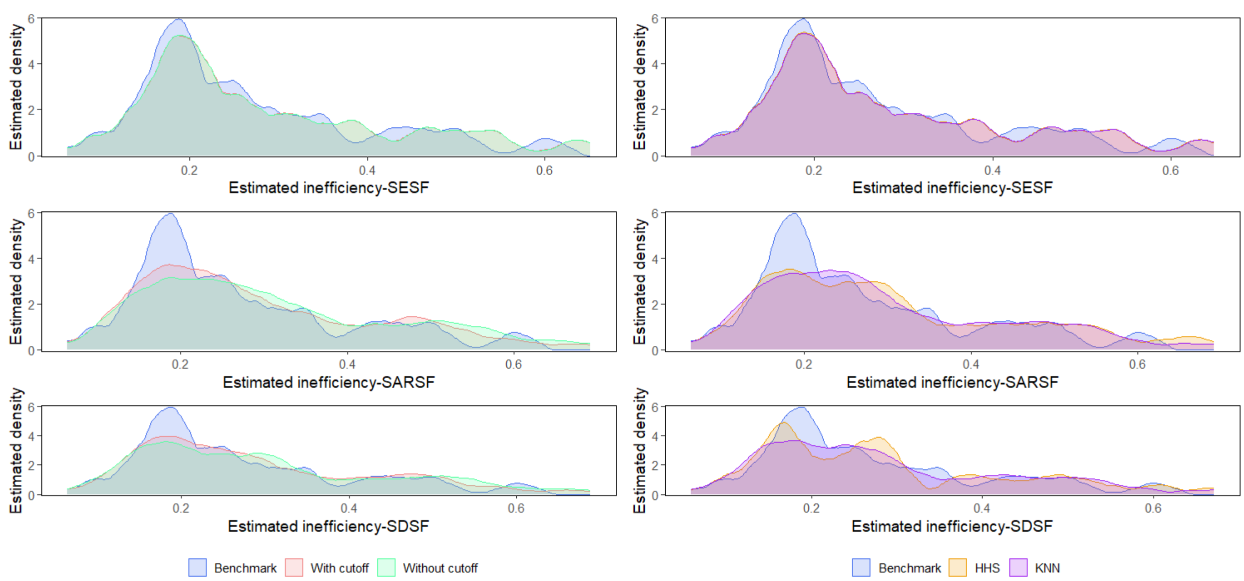


Figure 3: Estimated kernel density of inefficiency estimation of different models

5 Concluding Remarks

In this paper, we utilized spatial stochastic frontier analysis based on three mainstream spatial models, SEM, SAR, and SDM, adapted into the four-component error term framework, an advanced SFM in panel data settings. In the efficiency analysis of 104 Queensland hospitals from FY 2012/13 to FY 2016/17, the fitted models of the three spatial SFMs indicate the existence of statistically significant spatial dependence among the studied hospitals, especially from the autoregressive output variable and the autocorrelated error term. The capital input, medical labor input, and the expenditure of consumable supplies are prominent features among the regressors, exhibiting statistically significant direct marginal effects on the hospital itself as well as positive spillover effects on the neighbor hospitals under most of the spatial weighting schemes that we considered.

Moreover, the divergent inefficiency estimates of the spatial SFMs and the benchmark non-spatial KLH14 model further illustrate the necessity of conducting an appropriate spatial SFM in cases where the spatial dependence indeed impacts the performance of the production units. Although the influence of the spatial effects on the inefficiency estimates is evident, the difference observed is modest, and hence still confirming an approximate validity of the non-spatial stochastic frontier studies for this data.

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