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Using COVID-19 mortality to select among hospital plant capacity models: An exploratory empirical application to Hubei province

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ABSTRACT

This contribution defines short- and long-run output- and input-oriented plant capacity measures and evaluates them relative to convex and nonconvex technologies. By applying these different plant capacity concepts, the authors seek to measure the use of existing capacities, as well as the evolution and build-up of extra hospital capacity in the Chinese province of Hubei during the outbreak of the COVID-19 epidemic in early 2020. Furthermore, medical literature has established that mortality rates increase with high capacity utilization rates, an insight that this study leverages to select the most plausible of eight plant capacity concepts. The preliminary results indicate that a relatively new, input-oriented plant capacity concept correlates best with mortality.

1. Introduction

The COVID-19 epidemic that started in the Chinese province of Hubei in December 2019 quickly became a pandemic of almost unprecedented scale, with devastating medical, socioeconomic, and psychological consequences. Without a vaccine or cure, various containment measures were the only policy options (for an early evaluation of such policies, see Yoo and Managi 2020)).

Despite early warnings in medical literature about real or potential epidemics and pandemics, economists were ill-prepared to respond to the virus. Until the recent emergence of COVID-19, almost no economics literature addressed epidemics or pandemics (cf. Fan et al., 2018). With the unfolding of the pandemic, a surge in publications occurred, addressing a wide variety of socioeconomic research topics. Examples include descriptions and analyses of macroeconomic and industrial policy instruments (e.g., Baldwin and Weder di Mauro, 2020) and examinations of the impact of demand and supply shocks on inequality (Blundell et al., 2020). Newly developed multidisciplinary studies include Nakamura and Managi's (2020) use of global spatial and mapping information to study the impact of three air travel restriction scenarios on changes in the risk of importation and exportation of COVID-19. To the best of our knowledge, we provide the first use of

nonparametric frontier methods to measure the plant capacity of hospitals in the Chinese province of Hubei since the outbreak began.

In economics literature, the notion of output-oriented plant capacity has been informally defined as "the maximum amount that can be produced per unit of time with existing plant and equipment, provided that the availability of variable factors of production is not restricted" (Johansen (1968, p. 362)). Färe et al. (1989a) and Färe et al. (1989b) published relevant articles and provided a formal definition according to a nonparametric frontier framework. Their measure of plant capacity utilization leverages data about observed inputs and outputs, using two output-oriented efficiency measures. Their work also prompted a series of empirical applications in diverse sectors, such as of fisheries (e.g., Felthoven, 2002; Tingley and Pascoe, 2005) and health care (e.g., Karagiannis, 2015; Magnussen and Rivers Mobley, 1999)), as well as banking (Sahoo and Tone, 2009) and a macroeconomic application to trade barriers (Badau, 2015).

Other than some minor methodological refinements—including the integration of the plant capacity notion into a decomposition of the Malmquist productivity index (e.g., De Borger and Kerstens, 2000)—no major methodological innovations related to the plant capacity concept emerged for about two decades. Then, two major innovations occurred in quick succession. First, Cesaroni et al. (2017) defined a new

input-oriented concept of plant capacity utilization, using a pair of input-oriented efficiency measures with the same nonparametric frontier framework. Second, in 2019, the same authors defined new long-run (LR) output- and input-oriented plant capacity concepts that allow for changes in all input dimensions simultaneously, rather than requiring separate changes in the variable inputs. Their definition resulted in a reinterpretation of plant capacity concepts that focuses on changes in variable inputs alone as short-run (SR) concepts. The combination of both innovations provides empirical practitioners with four distinct concepts: output-oriented versus input-oriented plant capacity concepts, and SR versus LR plant capacity concepts.

Furthermore, Kerstens et al. (2019a) argue and empirically illustrate that traditional output-oriented plant capacity utilization is unrealistic, because the amounts of variable inputs needed to reach maximum capacity outputs may not be available at either the firm or industry level. In response to this so-called attainability issue, as identified by Johansen (1968), Kerstens et al. (2019a) defined a new type of attainable output-oriented plant capacity utilization that limits the availability of variable inputs. The main problem then is to define the true limits of the availability of variable inputs; the entire issue of attainability also applies to LR plant capacity concepts.

In view of these methodological issues surrounding the longstanding output-oriented plant capacity utilization notion, our first research question pertains to whether input-oriented plant capacity concepts perform better or worse than output-oriented plant capacity concepts, as well as whether SR plant capacity concepts perform better or worse than LR plant capacity concepts.[1] The axiom of convexity could exert a potentially vast impact on such technology-based empirical analyses (e. g., Tone and Sahoo, 2003). Walden and Tomberlin (2010) offer the first empirical illustration of the effect of convexity on the output-oriented plant capacity. Then Cesaroni et al. (2017) empirically compare output- and input-oriented plant capacity concepts and show that convexity has a powerful influence on both concepts in practice. Kerstens et al. (2019a) also empirically illustrate the impact of convexity on both traditional and attainable output-oriented plant capacity concepts.

However, most researchers tend to ignore the potential impact of convexity on the cost function, seemingly due to a property in its outputs that tends to be ignored. The cost function is nondecreasing and convex (C) in the outputs when the technology is convex (see Jacobsen, 1970); otherwise, the cost function is nonconvex (NC) in the outputs. Most empirical studies fail to put this property to a test. Kerstens et al. (2019b) empirically compare the four plant capacity concepts (output-oriented versus input-oriented, SR versus LR) with a series of cost-based capacity utilization measures. Two key conclusions emerge. First, input-oriented plant capacity notions tend to lend themselves more naturally to comparisons with cost-based capacity notions than do output-oriented plant capacity concepts. Second, convexity makes a difference for both technical and economic capacity notions. Notably, cost-based capacity utilization measures are not options for our analysis, because they require input price information, and our data lack such information. Thus, as a second research goal, we aim to document the impact of convexity and nonconvexity on the empirical fit of the four plant capacity concepts.

The empirical testing ground for our two main research questions is the outbreak of the COVID-19 pandemic in the Chinese province of Hubei in late 2019 and early 2020. Confronted with an unknown virus,

Chinese authorities faced a huge logistical challenge in efficiently using and improving, to the extent possible, existing hospital capacity in the Hubei province to treat a surging number of patients. Strains on hospital capacity are associated with increased mortality and worsened health outcomes (see, e.g., the survey by Eriksson et al. (2017)). We use this relationship, known from medical literature, to shed light on our research questions, grounded in economic literature, about which SR plant capacity concepts provide a better fit with the empirical data obtained in reference to this pandemic.

Chinese authorities not only faced the challenge of optimally exploiting existing hospital capacities, but they also had to find ways to create new, extra capacities using temporary makeshift hospitals. Because such build-up of new capacity requires an alternative modeling strategy, we propose that LR plant capacity concepts are particularly well suited for capturing the creation of new hospital capacity. The COVID-19 pandemic offers a unique testing ground for determining whether LR plant capacity concepts are viable.

Our study is structured as follows: Section 2 begins with a literature review of plant capacity concepts in the medical sector; it briefly explores medical literature on the relationship between capacity utilization and mortality. Section 3 then defines the technology and efficiency measures needed to establish the four focal plant capacity concepts, then provides detailed definitions of output-oriented and input-oriented SR and LR plant capacity concepts and a discussion of nonparametric frontier specifications, to estimate the various plant capacity concepts. Section 4 details data from Hubei province, because the quality of the data conditions our inferences. Section 5 presents our empirical results, and Section 6 concludes.

2. Hospital plant capacity and mortality: A brief, candid literature review

2.1. Plant capacity in hospitals: Economic literature

We know of few studies devoted to analyzing plant capacity in the hospital sector. In chronological order, Färe et al. (1989b) started by analyzing hospitals in Michigan. Next, Magnussen and Rivers Mobley (1999) compare Norwegian and Californian hospitals, and Kerr et al. (1999) analyze Northern Irish acute hospitals. Valdmanis et al. (2004) focus on plant capacity in Thai public hospitals; Valdmanis et al. (2010) compute state-wide hospital capacity in Florida, whereas Valdmanis et al. (2015) report on Florida's public health departments. Karagiannis (2015) analyzes Greek public hospitals, and Arfa et al. (2017) report findings on public hospitals in Tunisia. These eight studies are somewhat further analyzed for our purposes below.

In some methodological variations, Kang and Kim (2015) also develop a cost-based frontier capacity concept for regional public hospitals in South Korea, and Arfa et al. (2017) propose a dual approach to the traditional output-oriented plant capacity concept that includes information on relative shadow prices of certain inputs. Finally, Valdmanis et al. (2015) list bootstrapped plant capacity results to avoid bias due to single point estimates. Yet a persistent, critical, methodological issue is the choice of a returns to scale assumption when defining the frontier technology. Although it is not implied in Johansen's (1968) informal definition, Färe et al. (1989a) and Färe et al. (1989b) impose constant returns to scale on the technology. Adopting their example, three studies that report only plant capacity under constant returns to scale: Kerr et al. (1999), Valdmanis et al. (2004), and Valdmanis et al. (2010).

However, the application of constant returns to scale presupposes that the hospital sector is in a long-run, zero-profit competitive, equilibrium. This condition is unlikely for any sector in general (see Scarf,

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[1] In exploiting the relationship between efficiency measures and goodness-of-fit measures used for hypothesis testing (see Färe and Grosskopf (1995)), the comparison of efficiency measures (or combinations of efficiency measures, such as plant capacity measures) computed relative to two nonparametric frontier models amounts to a test of the null hypothesis distinguishing both models involved.

1994; Tone and Sahoo, 2003).[2] Furthermore, there is overwhelming evidence that there are increasing returns to scale and economies of scale in the hospital sector at large (see a survey by Giancotti et al. (2017)). This evidence explains the phenomenon of hospital mergers as well as policies aimed at expanding larger hospitals and restructuring/closing smaller hospitals. Therefore, in our analysis, we consistently impose flexible or variable returns to scale on the frontier specifications of the technology, in line with both Johansen's (1968) informal definition and the other four studies we cited previously. That is, prior studies employ the SR output-oriented plant capacity concept and maintain the axiom of convexity in technology. Our study is the first to analyze the SR input-oriented plant capacity concept and the LR plant capacity concept in the hospital sector. Furthermore, we are the first to test for the impact of convexity on plant capacity measurement in the hospital sector.

2.2. Hospital capacity and mortality: Economic and medical literature

Among the vast literature that applies efficiency and productivity analyses, using frontier technologies, to hospitals and other medical care facilities (see, e.g., the surveys by Hollingsworth (2003), Pelone et al. (2015), and Rosko and Mutter (2011)), some of them control for quality of care and mortality, but little conclusive evidence pertains to the relationship between efficiency, productivity, and their components on the one hand and the quality of care and mortality on the other hand. Similarly, in wider economic and operations management literature, we find little clear-cut evidence of a relationship between healthcare operational decisions and mortality (for a recent survey, see Singh et al. (2019)). Kuntz et al. (2015) offer some evidence, using department-level bed occupancy rates. They document, at the hospital level, a highly nonlinear effect of occupancy on mortality and identify tipping points after which mortality increases rapidly as occupancy levels increase. In a related study of the differential behavior of public and private hospitals with regard to limits on capacity utilization, Yang et al. (2020) document "cream skimming," such that Australian private hospitals transfer complex patients to public hospitals to accommodate non-complex patients and free up their capacity.

Medical literature also provides somewhat more substantial evidence that mortality correlates strongly with high capacity utilization and high occupancy rates, at the levels of individual diseases (e.g., Ross et al., 2010), departments (e.g., intensive care units [ICUs], Iapichino et al. (2004)), and hospitals (e.g., Madsen et al., 2014). Despite heterogeneous measures of capacity strain applied to in ICU versus non-ICU settings, a systematic review by Eriksson et al. (2017) indicates that hospital capacity strain in highly developed countries is associated with increased patient mortality in 9 of 12 studies in ICU settings and 18 of 30 studies overall. They report other worsened health outcomes too. Thus,

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[2] Scarf (1994, pp. 114–115) criticizes the possibility of a constant returns to scale technology as follows: "Both linear programming and the Walrasian model of equilibrium make the fundamental assumption that the production possibility set displays constant or decreasing returns to scale; that there are no economies associated with production at a high scale. I find this an absurd assumption, contradicted by the most casual of observations. Taken literally, the assumption of constant returns to scale in production implies that if technical knowledge were universally available we could all trade only in factors of production, and assemble in our own backyards all of the manufactured goods whose services we would like to consume. If I want an automobile at a specified future date, I would purchase steel, glass, rubber, electrical wiring and tools, hire labor of a variety of skills on a parttime basis, and simply make the automobile myself. I would grow my own food, cut and sew my own clothing, build my own computer chips and assemble and disassemble my own international communication system whenever I need to make a telephone call, without any loss of efficiency. Notwithstanding the analysis offered by Adam Smith more than two centuries ago, I would manufacture pins as I needed them."

sufficiently robust medical evidence exists to predict a positive relationship between capacity utilization and mortality.

We use ex post real data from the COVID-19 pandemic as it developed in the Chinese province of Hubei province in early 2020 to test for the relationship between mortality and measures of plant capacity utilization levels in eight models. We employ both SR and LR output-oriented and input-oriented plant capacity concepts that reflect both C and NC conditions.

Two somewhat related approaches also appear in prior literature. First, Moghadas et al. (2020) uses an epidemiological model to simulate the COVID-19 outbreak in the United States and its grave challenges to ICU capacity, leading to exacerbated case fatality rates. In that model, self-isolation policies appear to delay the epidemic peak, creating more time to mobilize an expansion of hospital capacity. Rather than taking an ex ante approach, we undertake an ex post analysis of the compatibility of mortality, using frontier-based plant capacity utilization measures. Second, within the frontier literature, Valdmanis et al. (2010) compute SR output-oriented plant capacity at the hospital level for the entire population of the state of Florida, as part of an emergency preparedness plan. Starting from a scenario of patient evacuations from Miami, as a result of a major hurricane event, they assess whether hospitals close to the affected market could absorb excess patient flow. However, this scenario analysis does not rely on real emergency data, so it cannot provide a valid test of the proposed models. Instead, we adopt the methodological framework that we describe in the next section use to measure various models of plant capacity utilization.

3. Methodology

3.1. Definition of production technology

In this section, we introduce some basic notations and define the hospital production technology. According to the theory of axiomatic production, homogeneously observed units determine the shape of the production possibility set, according to some minimal set of production assumptions (Färe et al. (1994)). If we assume a multiple-input, multiple-output production technology, such that decision-making units (DMUs) consume N types of inputs (x) to produce M types of outputs (y), then the production possibility set or production technology T is given by:

$$T = \left\{ (x, y) \in \mathbb{R}_+^{N+M} : x \text{ can produce } y \right\} \tag{1}$$

We must impose regularity conditions on the input and output data (Färe et al. (1994, 44–45)): (1) Each producer uses nonnegative amounts of each input to produce nonnegative amounts of each output; (2) there is an aggregate production of positive amounts of every output, and an aggregate utilization of positive amounts of every input; and (3) each producer employs a positive amount of at least one input to produce a positive amount of at least one output.

The production technology also can be represented by an output set $P(x)$ that indicates all possible output combinations that can be produced by at most a given level of inputs:

$$P(x) = \left\{ y \in \mathbb{R}_+^M : (x, y) \in T \right\} \tag{2}$$

Alternatively, this technology can be represented by an input set $L(y)$ that denotes all possible input combinations that can produce at least a given level of outputs. The input correspondence therefore can be formally defined as follows:

$$L(y) = \left\{ x \in \mathbb{R}_+^N : (x, y) \in T \right\} \tag{3}$$

The technology also satisfies several widely adopted economic assumptions. These general axioms usually are imposed on the production possibility set (Färe et al., 1994) as follows:

$A_1 : (0, 0) \in T$ and if $(0, y) \in T$ then $y = 0$.

$A_2 : T$ is closed.

$A_3 :$ For each input $x \in \mathbb{R}_+^N$, T is bounded. $\qquad$ (4)

$A_4 :$ If $(x, y) \in T$, then $(\tilde{x}, \tilde{y}) \in T$ for all $(-\tilde{x}, \tilde{y}) \leq (-x, y)$.

$A_5 : T$ is convex.

Assumption A_1 implies that inactivity is feasible and, conversely, that there is no free lunch (i.e., outputs cannot be generated without inputs). Assumption A_2 states that unlimited quantities of outputs cannot be produced from finite quantities of inputs, whereas Assumption A_3 implies that production plans located on the efficient frontier belong to the technology. Assumption A_4 implies free (strong) disposability of inputs and outputs: given outputs can be produced from more inputs than necessary or given inputs can produce fewer outputs than currently produced. Finally, Assumption A_5 requires a convex production technology. More detailed discussions are available in, for example Färe et al. (1994).

In some cases, we adopt the assumption that the technology is convex. However, we explicitly test for the validity of this assumption. That is, we do not seek to maintain all these axioms simultaneously in our empirical analysis.[3] Furthermore, we do not add a specific returns to scale assumption and instead adopt a flexible or variable returns to scale hypothesis.

In the SR, inputs can be grouped into fixed and variable parts: $x = (x^f, x^v)$ with $N = N_v + N_f$. The fixed part, which indicates that the inputs cannot be varied in a short period, is denoted by $x^f \in \mathbb{R}_+^{N_f}$. The variable part can vary in relation to the quantity of outputs produced; it is denoted by $x^v \in \mathbb{R}_+^{N_v}$.

In line with Färe et al. (1889b: 127), we define an SR technology $T^f = \{(x^f, y):$ there exists some x^v, such that (x^f, x^v) can produce at least $y\}$, along with the corresponding input set $L^f(y) = \{x^f : (x^f, y) \in T^f\}$ and output set $P^f(x^f) = \{y : (x^f, y) \in T^f\}$. This distinction between fixed and variable inputs sharpens the conditions placed on the input and output data. According to Färe et al. (1989a: 659–660), each fixed input is used by some producer, and each producer uses some fixed input. The following conditions also apply: Each variable input is used by some producer; each producer uses some variable input. Furthermore, the output set $P = \{y : \exists x : (x, y) \in T\}$ denotes the set of all possible outputs regardless of the needed inputs. Finally, $L(0) = \{x : (x, 0) \in T\}$ is the input set compatible with a zero output level. Cesaroni et al. (2019) provide more details on these special technology definitions, and their Figs. 1 to 4 explicitly clarify the various technology definitions.

3.2. Distance functions and efficiency measures

Distance functions provide an equivalent representation of production technologies and position observations with regard to the boundary of production possibilities sets. When an observation is at the boundary of technology, then it is technically efficient. However, if an observation is positioned below this boundary, then it is technically inefficient, and its performance can be improved.

Traditionally, there are two ways to increase the technical efficiency of a production activity: maximizing outputs for given inputs or minimizing inputs for given outputs. Maximizing output efficiency yields a revenue interpretation, whereas minimizing input efficiency yields a cost interpretation (e.g., Färe et al. (1994)). Distance functions are related to efficiency measures. In the remainder of this contribution, we focus on output- and input-oriented efficiency measures.

In line with Färe et al. (1994), we formulate the radial output efficiency measure as:

$$DF_{output}(x, y) = \max\{\theta \in \mathbb{R}_+ : \theta y \in P(x)\}, \qquad (5)$$

where θ is a measure of technical efficiency, indicating the maximum proportional expansion of outputs that can be achieved at a given level of inputs. This score is larger than or equal to unity $DF_{output}(x, y) \geq 1$; an efficient DMU is located on the production frontier $DF_{output}(x, y) = 1$, and an inefficient unit is situated in the interior of the production possibility set $DF_{output}(x, y) > 1$.

Similarly, the radial input efficiency measure can be defined as:

$$DF_{input}(x, y) = \min\{\lambda \in \mathbb{R}_+ : \lambda x \in L(y)\}, \qquad (6)$$

where λ indicates the possible proportional decrease in inputs for a given level of outputs. This ratio is situated between zero and unity $0 < DF_{input}(x, y) \leq 1$; the best practice is situated on the frontier $DF_{input}(x, y) = 1$, and an inefficient unit is found below the boundary of the input set $0 < DF_{input}(x, y) < 1$.

Denoting the radial output efficiency measure of the output set $P^f(x^f)$ by $DF_{output}^f(x^f, y)$, we can define this efficiency measure as $DF_{output}^f(x^f, y) = \max\{\theta : \theta \geq 0, \theta y \in P^f(x^f)\}$. Next, we denote $DF_{output}(y) = \max\{\theta : \theta \geq 0, \theta y \in P\}$. In contrast with the traditional radial output efficiency measure (5), this proposed efficiency measure $DF_{output}(y)$ does not depend on a particular input vector x. Therefore, this new measure effectively can choose the level of inputs needed to maximize θ.

We must offer some particular definitions too: First, we need a sub-vector input efficiency measure $DF_{input}^{SR}(x^f, x^v, y) = \min\{\lambda : \lambda \geq 0, (x^f, \lambda x^v) \in L(y)\}$ that aims only to reduce the variable inputs. Second, we need a similar sub-vector input efficiency measure $DF_{input}^{SR}(x^f, x^v, 0) = \min\{\lambda : \lambda \geq 0, (x^f, \lambda x^v) \in L(0)\}$ that reduces variable inputs only but is evaluated relative to this input set with a zero-output level.

3.3. Short-Run plant capacity utilization

We can define SR output-oriented plant capacity utilization $PCU_{output}^{SR}(x, x^f, y)$ by a ratio of output efficiency measures between a normal production technology $DF_{output}(x, y)$ and an identical technology that has no constraints on the use of variable inputs $DF_{output}^{SR}(x^f, y)$, as in Färe et al. (1989a) and Färe et al. (1989b):

$$PCU_{output}^{SR}(x, x^f, y) = \frac{DF_{output}(x, y)}{DF_{output}^{SR}(x^f, y)}, \qquad (7)$$

where $DF_{output}(x, y)$ and $DF_{output}^{SR}(x^f, y)$ are output efficiency measures relative to technologies that include or exclude the variable inputs, respectively. According to the approach and terminology introduced by Färe et al. (1989a), we can obtain an SR output-oriented decomposition:

$$DF_{output}(x, y) = DF_{output}^{SR}(x^f, y) PCU_{output}^{SR}(x, x^f, y), \qquad (8)$$

where we decompose $DF_{output}(x, y)$ into a biased plant capacity measure $DF_{output}^{SR}(x^f, y)$ and an unbiased measure $PCU_{output}^{SR}(x, x^f, y)$, depending on whether we ignore inefficiency or adjust for it (see also Cesaroni et al. (2019)). The unbiased measure is the ratio between the maximum possible quantity of outputs produced by a given level of inputs $DF_{output}(x, y)$ and the maximum quantity of outputs produced by a given level of fixed inputs, but with any quantity of variable inputs within the observed empirical range of the data $DF_{output}^{SR}(x^f, y)$. Because $1 \leq DF_{output}(x, y) \leq DF_{output}^{SR}(x^f, y)$, we note that $0 < PCU_{output}^{SR}(x, x^f, y) \leq 1$.

In line with Cesaroni et al. (2017), we also define SR input-oriented plant capacity utilization $PCU_{input}^{SR}(x, x^f, y)$ by a ratio of input efficiency measures, evaluated relative to a production technology targeting only at reducing variable inputs $DF_{input}^{SR}(x^f, x^v, y)$ and an identical technology

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[3] For example, the strongly disposable C technology with variable returns to scale does not satisfy inaction (e.g., when the zero input and zero output data point (0, 0) is included in the sample); see our subsequent discussion.

with a level of null outputs $DF_{input}^{SR}(x^f, x^v, 0)$:

$$PCU_{input}^{SR}(x, x^f, y) = \frac{DF_{input}^{SR}(x^f, x^v, y)}{DF_{input}^{SR}(x^f, x^v, 0)}, \tag{9}$$

where $DF_{input}^{SR}(x^f, x^v, y)$ and $DF_{input}^{SR}(x^f, x^v, 0)$ are input efficiency measures aimed at reducing variable inputs for a given level of outputs or null outputs, respectively.[4] Following Cesaroni et al. (2019), we also propose an SR input-oriented decomposition, as follows:

$$DF_{input}^{SR}(x^f, x^v, y) = DF_{input}^{SR}(x^f, x^v, 0) \, PCU_{input}^{SR}(x, x^f, y), \tag{10}$$

where $DF_{input}^{SR}(x^f, x^v, 0)$ is a biased measure, and $PCU_{input}^{SR}(x, x^f, y)$ is an unbiased measure of input-oriented plant capacity utilization. This unbiased measure is the ratio between the minimum use of variable inputs for producing a given level of outputs $DF_{input}^{SR}(x^f, x^v, y)$ and the minimum quantity of variable inputs for initiating the production process $DF_{input}^{SR}(x^f, x^v, 0)$. Because $0 < DF_{input}^{SR}(x^f, x^v, 0) \le DF_{input}^{SR}(x^f, x^v, y) \le 1$, we know that $PCU_{input}^{SR}(x, x^f, y) \ge 1$.

The combination of SR output- and input-oriented and biased and unbiased plant capacity utilization yields four measures in total. Table 1 summarizes these four measures of SR plant capacity utilization.

3.4. Long-Run plant capacity utilization

In the LR, all inputs can be regarded as variable inputs, because decision-making units have sufficient time to adjust input utilizations. Thus, fixed and variable inputs no longer need to be treated differently. Cesaroni et al. (2019) introduce a measure of LR output-oriented plant capacity utilization, given as:

$$PCU_{output}^{LR}(x, y) = \frac{DF_{output}(x, y)}{DF_{output}^{LR}(y)}, \tag{11}$$

where $DF_{output}(x, y)$ and $DF_{output}^{LR}(y)$ are output efficiency measures relative to a standard production technology and a technology without any constraints on availability of inputs. Note that the numerators in (9) and (11) are identical. Cesaroni et al. (2019) propose the following decomposition of this LR output-oriented measure:

$$DF_{output}(x, y) = DF_{output}^{LR}(y) PCU_{output}^{LR}(x, y), \tag{12}$$

where $DF_{output}^{LR}(y)$ and $PCU_{output}^{LR}(x, y)$ are biased and unbiased output-oriented measures of LR plant capacity utilization, respectively. This unbiased measure is the ratio between the maximum possible quantity of outputs produced by a given level of inputs $DF_{output}(x, y)$ and the maximum quantity of outputs produced by any quantity of inputs within the observed empirical range of the data $DF_{output}^{LR}(y)$. Because $1 \le DF_{output}(x, y) \le DF_{output}^{LR}(y)$, $PCU_{output}^{LR}(x, y)$ is situated between 0 and

Table 1
Measurements of SR plant capacity utilization.

	Measure	Notation	Interval
Output-oriented	Biased	$DF_{output}^{SR}(x^f, y)$	$[1, +\infty)$
	Unbiased	$PCU_{output}^{SR}(x, x^f, y)$	$(0,1]$
Input-oriented	Biased	$DF_{input}^{SR}(x^f, x^v, 0)$	$(0,1]$
	Unbiased	$PCU_{input}^{SR}(x, x^f, y)$	$[1, +\infty)$

unity.

Similarly, Cesaroni et al. (2019) define the LR input-oriented measure of plant capacity utilization as:

$$PCU_{input}^{LR}(x, y) = \frac{DF_{input}^{LR}(x, y)}{DF_{input}^{LR}(x, 0)}, \tag{13}$$

where $D_{input}^{LR}(x, y)$ and $D_{input}^{LR}(x, 0)$ are input efficiency measures estimated with a given level of outputs or at the level of null outputs, respectively. The decomposition of this LR input-oriented measure is given as:

$$DF_{input}^{LR}(x, y) = DF_{input}^{LR}(x, 0) PCU_{input}^{LR}(x, y), \tag{14}$$

where $DF_{input}^{LR}(x, 0)$ and $PCU_{input}^{LR}(x, y)$ are biased and unbiased input-oriented measures of LR plant capacity utilization, respectively. This unbiased measure is the ratio between the minimum possible use of inputs for a given level of outputs $DF_{input}^{LR}(x, y)$ and the minimum usage of inputs to initiate the production process. Because $0 < DF_{input}^{LR}(x, 0) \le DF_{input}^{LR}(x, y) \le 1$, $PCU_{input}^{LR}(x, y)$ is greater than unity.

The combination of LR output- and input-oriented and biased and unbiased plant capacity utilization yields four measures in total. Table 2 summarizes the four measures of LR plant capacity utilization. For a graphical illustration of all SR and LR plant capacity concepts, see Figs. 1, 3, and 4 in Cesaroni et al. (2019).

3.5. Nonparametric frontier estimation

We compute plant capacity concepts using deterministic nonparametric frontier technologies.[5] That is, using input–output vectors denoted by (x_k, y_k), we can construct the empirical technology $(k = 1, ..., K)$, with the key assumptions of strong input and output disposability, convexity, and flexible or variable returns to scale (Färe et al., 1994). We then define the corresponding piecewise linear frontier technology as:

$$T_{VRS}^{Convex} = \left\{ (x, y) : \sum_{k=1}^{K} z_k x_k \le x, \sum_{k=1}^{K} z_k y_k \ge y, \sum_{k=1}^{K} z_k = 1, z \ge 0 \right\}, \tag{15}$$

where z is an activity vector with non-negative elements. The convexity constraint ensures that linear combinations of the observed production plans are feasible. By relaxing the latter C assumption, we obtain an NC production frontier:

$$T_{VRS}^{Nonconvex} = \left\{ (x, y) : \sum_{k=1}^{K} z_k x_k \le x, \sum_{k=1}^{K} z_k y_k \ge y, \sum_{k=1}^{K} z_k = 1, z \in \{0, 1\} \right\}, \tag{16}$$

where z is the activity vector with binary integer elements. Cesaroni et al. (2019) and Kerstens et al. (2019b, Appendix B) provide further details of the underlying programming problems for computing plant

Table 2
Measurements of LR plant capacity utilization.

	Measure	Notation	Interval
Output-oriented	Biased	$DF_{output}^{LR}(y)$	$[1, +\infty)$
	Unbiased	$PCU_{output}^{LR}(x, y)$	$(0,1]$
Input-oriented	Biased	$DF_{input}^{LR}(x, 0)$	$(0,1]$
	Unbiased	$PCU_{input}^{LR}(x, y)$	$[1, +\infty)$

[4] Note that Sahoo and Tone (2009) introduce another input-oriented notion plant capacity utilization based on SR technology (T^f), using both radial and non-radial efficiency measures. Its relationship with the SR input-oriented plant capacity utilization concept remains to be explored.

[5] Plant capacity notions are difficult to estimate using traditional parametric specifications. See Felthoven (2002) for an example.

capacity measures in Tables 1 and 2 above relative to technologies (15)–(16). We also refer readers to Figs. 1–3 in Kerstens et al. (2005) for a graphical illustration of the difference between C and NC production frontiers in the context of an SR output-oriented plant capacity concept.

For panel data, we have various options for how to treat the time dimension when reconstructing the production frontier (e.g., Tulkens and Vanden Eeckaut, 1995). We discuss two relevant options for our empirical analysis. First, the intertemporal frontier approach constructs a single production frontier according to all observations available in the entire observation period. Second, the sequential frontier approach constructs a production frontier at each particular point in time, using the observations that accrue from a first time period to some particular point in time (Diewert, 1980). The sequential frontier is always smaller than or equal in size to the intertemporal frontier, except for in the last time period when the two frontiers coincide exactly (see Tulkens and Vanden Eeckaut (1995): 479)).

The ramifications of the choice between approaches for efficiency measurement and plant capacity measurement are simple. Because the sequential frontier is always smaller than or equal to the intertemporal frontier, the amount of inefficiency should be smaller under the sequential frontier than under the intertemporal frontier. In particular, input-oriented efficiency measures under a sequential frontier are larger than or equal to the same efficiency measures under an intertemporal frontier, whereas output-oriented efficiency measures under a sequential frontier are smaller than or equal to the same efficiency measures under an intertemporal frontier. However, plant capacity utilization measures—defined as ratios of two efficiency measures—cannot be ranked; thus, the data determine whether plant capacity utilization under a sequential frontier is smaller than, equal to, or larger than the same concept under an intertemporal frontier. For an example of the sequential frontier approach in a plant capacity utilization context, see Färe et al. (1989a).

3.6. Results

As previously mentioned, we use SR plant capacity concepts to assess the efficient use of existing hospital capacity in Hubei province and test their correlation with mortality. Then we use LR plant capacity concepts to assess the build-up of new hospital capacity. We now turn to a discussion of available data to implement these different plant capacity models.

4. Data and model specifications

To analyze plant capacity utilization for hospitals, we select Hubei province in China as our sample. The Hubei province was the first region in China affected by the COVID-19 epidemic outbreak.[6] Several types of hospitals treated patients differently, according to their symptoms. At the individual hospital level, each hospital had some diversity in terms of staff and patients; that is, production technologies were slightly heterogeneous. By defining the hospital production technology at the city level, we can better ensure the validity of our assumption of a homogeneous production technology. We considered 17 main cities in Hubei province in our investigation: Wuhan, Huanggang, Xiaogan, Jingmen, Xianning, Jingzhou, Suizhou, Xiangyang, Shiyan, Ezhou, Huangshi, Yichang, Enshi, Xiantao, Tianmen, Qianjiang, and Shennongjia. We collected data from three main sources: see the Appendix A for details of the sample. The sample covers eight weeks in 2020, from 19 January to 15 March, during the COVID-19 epidemic, which represents the total time span of the epidemic in Hubei province according to available information.

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[6] The exact location of the outbreak remains controversial. The only certainty is that Hubei province is the area of the first large-scale transmission of the COVID-19 virus in China.

Table 3
Average Inputs and Outputs (in 1000 persons, January–March 2020).

	Week	Personnel	Beds	Patients	Cured	Death
1	Jan 19–Jan 25	710.47	371.72	0.96	0.04	0.05
2	Jan 26–Feb 1	710.47	371.72	8.60	0.14	0.24
3	Feb 2–Feb 8	710.47	394.82	24.79	1.26	0.49
4	Feb 9–Feb 15	739.91	394.82	49.02	4.18	0.82
5	Feb 16–Feb 22	739.91	394.82	45.99	9.67	0.75
6	Feb 23–Feb 29	752.90	394.82	32.96	15.89	0.41
7	Mar 1–Mar 7	752.90	394.82	19.71	13.82	0.23
8	Mar 8–Mar 15	752.90	394.82	9.61	10.08	0.11

In line with Hollingsworth (2003), Pelone et al. (2015), and Rosko and Mutter (2011), we define hospital production technology at the city level according to two types of inputs and one type of output. The inputs for hospitals are (1) personnel and (2) beds available for all patients. The personnel input consists of main medical staff, such as licensed doctors, registered nurses, pharmacists, and other technical staff. Beds available are a kind of capital stock, reflecting hospital operations. Our single output is the number of COVID-19 patients. We also have information on the number of cured COVID-19 patients and the number of deaths from COVID-19. Table 3 displays averages for the two inputs and the single output, as well as cured and deceased patients, for each of the eight weeks.

Because population sizes and densities are relatively smaller in Tianmen, Qianjiang, and Shennongjia, we combined their data to avoid the problem of zero output at the beginning of the observation period. Zero output would violate the regularity conditions we detailed previously for the input and output matrices spelled out above on page 9. This combination reduces the number of cities analyzed from 17 to 15.

The single output is the number of patients infected by COVID-19 or who had COVID-19 symptoms. Note that diagnosing patients in these early weeks of the epidemic may have been difficult, and some errors in classification are likely. According to medical rules in China, all infected persons must be inpatients. With no vaccine and no established curative treatment, patients end their hospitalization periods either cured or deceased. The mortality rate is the ratio of COVID-19 deaths to the total number of COVID-19 patients.

The case definition adopted by the Chinese authorities initially was narrow; it gradually broadened to allow detection of more cases as knowledge increased (Tsang et al., 2020). However, to the best of our knowledge, the data we use reflect the same case definition throughout the observation period.

Note also that data on personnel and beds are available for all patients, but we have information on COVID-19 patients only in our single output. Thus, we have no information on other patients under treatment during these eight weeks. To avoid bias in our estimates of the various plant capacity concepts, we must assume that the proportion of COVID-19 patients to other patients is about the same for all cities in our sample, at any given time period. Aggregation at the city level mitigates any eventual deviations from this hypothesis at the underlying hospital level. All hospitals also were obliged to follow very similar strategies in response to this medical emergency, including separating COVID-19 patients from other patients, creating unique logistics chains, canceling non-urgent interventions, and dismissing patients to free up capacity, etc. (e.g., Cao et al., 2020; Gagliano et al., 2020).

During an epidemic, it is important to exploit existing hospital capacity as much as possible. If capacity is insufficient to cope with peak demand, then it is crucial to build up extra capacity as soon as possible. To model the exploitation of existing capacity, SR plant capacity concepts are suitable, whereas LR plant capacity concepts are needed to capture the extension of existing capacity and the build-up of new capacity. New capacity often comes from makeshift (shelter) hospitals or the temporary conversion of existing buildings. Zhou et al. (2020), for example, describe the conversion of schools and convention centers into hospitals. Hospital administrators and policy makers may face difficult
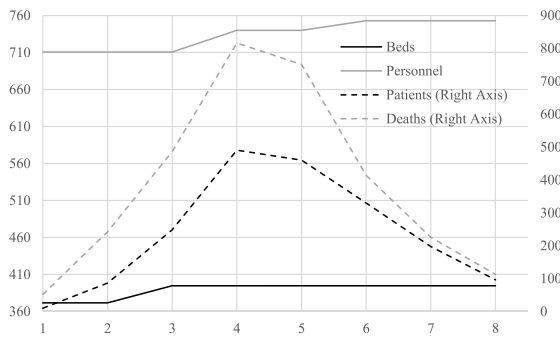
Fig. 1. Evolution of Inputs, Output, and Deaths over Time
Notes: Units of Beds and Personnel are in 1000 persons; units of patients and deaths are in 100 persons and per person, respectively.

choices in managing SR and LR decisions to optimize hospital operations involving both existing and new capacities.

The eight previously mentioned studies that use the SR output-oriented plant capacity concept specify some forms of fixed and variable inputs. In our study, we choose fixed and variable inputs pragmatically by looking at the evolution of both inputs over time. As shown in Fig. 1, the number of beds remains constant in the initial two weeks, then starts to increase from the third week onwards, as makeshift hospitals became put into use (e.g., Fire God Mountain hospital and Thunder God Mountain hospital in Wuhan). The number of medical staff remains constant in the initial first three weeks and then starts increasing in the fourth week. Thus, beds are more variable than medical staff in our sample. Furthermore, after week 4, both inputs become variable and change in numbers, clearly marking the LR period. Therefore, the first three weeks represent the SR period, during which beds are a variable input, and personnel is a fixed input. Because of the sequential buildup of inputs over time, we prefer to adopt a sequential frontier approach (see Section 3.5) to handle our balanced panel.

Medical staffing often is regarded as a fixed input, because professional qualifications or certifications are prerequisites. It is difficult to supplement medical staff in the SR, so the Chinese central government was forced to transfer medical personnel from other provinces to Hubei to increase the supply during the fourth and sixth weeks. Although we have information on various personnel qualification for the first three weeks, we cannot differentiate medical staff reinforcements. Therefore, we use aggregate personnel as a single fixed input. We gather data on the number of bed expansions and personnel reinforcements from Xinhua-Net, an official media department of the Chinese central government. The Appendix A describes the data in detail.

Finally, Fig. 1 shows that both numbers of COVID-19 patients and deaths increased rapidly and reached a turning point at week 4. Thereafter, we observe a slow decline in patients and deaths, but the number of personnel continues to increase, reaching a peak during week 6. These data indicate that the epidemic situation improved, before LR capacity achieved its maximum level.

Finally, we specify the a priori relationship between convex (C) and nonconvex (NC) plant capacity concepts. Kerstens, Sadeghi, and Van de Woestyne (2019, p. 704) specify, in their Propositions 3.1 and 3.2, the relationships among all biased and unbiased plant capacity concepts. With regard to biased plant capacity concepts, the C output-oriented concepts always are larger than or equal to the NC concepts, whereas the C input-oriented concepts always are smaller than or equal to the NC concepts. With regard to unbiased plant capacity concepts, the C output-oriented and input-oriented concepts can be smaller, equal to, or larger than the NC concepts; thus, ranking is not possible.

Because we have only one output and one variable input in our sample, we specify two more relationships in Proposition 1.

Proposition 1:

(a) Under a single variable input, $DF_{input}^{SR}(x^f, x^v, 0)$ is identical under C and NC.

(b) Under a single output, $DF_{output}^{LR}(y)$ is identical under C and NC.

Proof. Trivial: The empirical results suffice.

5. Empirical results

In the SR, we include 45 observations (15 cities over 3 weeks) in a sequential frontier estimation of SR plant capacities. The first two horizontal parts of Table 4 present the descriptive statistics for these SR plant capacity measures.[7] We can decompose technical efficiency scores into biased and unbiased plant capacity measures, according to equations (8), (10), (12), and (14). Technical inefficiency is substantial, even under NC. For biased output-oriented measures of SR plant capacity utilization, the average values are 5.18 and 3.71 under C and NC technologies, respectively. Notably, the result of the biased input-oriented SR plant capacity measures is 0.36 on average, and in line with Proposition 1, it is identical for C and NC technologies. The average values of unbiased output-oriented (input-oriented) SR plant capacity measures are 0.83 (3.09) and 0.81 (3.44) under C and NC technologies, respectively. These numbers are more modest, because technical inefficiency has been eliminated.

For LR plant capacity measures, we compute the results over the entire sample of 120 observation (15 cities over 8 weeks), using a sequential frontier. Table 4 contains the descriptive statistics in the last two horizontal parts, which indicate even more substantial technical inefficiency. The results of biased LR output-oriented plant capacity measures are identical under C and NC technologies, as follows from Proposition 1. Moreover, the results of biased LR input-oriented plant capacity measures under C and NC technologies are approximately equal, but this result is a coincidence. The average values of unbiased output-oriented (input-oriented) LR plant capacity measures are 0.18 (2.19) and 0.12 (2.35) under C and NC technologies, respectively: these values are smaller than the biased values, because technical inefficiency has been removed.

Overall, these descriptive statistics demonstrate that C and NC results differ substantially (see also Walden and Tomberlin, 2010; Cesaroni et al., 2017; Kerstens et al., 2019a). Otherwise, there is little evidence with regard to the pertinence of input-oriented versus output-oriented and SR versus LR plant capacity concepts; they seem to measure somewhat different realities. Because technical inefficiency is substantial, we no longer have any reason to analyze biased plant capacity measures, because they are not free of technical inefficiency.

Our next focus is the evolution of some of the previously discussed elements over the course of the eight weeks of the pandemic. Fig. 2 presents the evolution of LR technical efficiency measures under a sequential approach at the aggregate province level. It clearly shows that output-oriented efficiency measures trace a U-shaped curve, such that inefficiency is lowest in the middle of the pandemic and increasing near the beginning and the end. This U-shape is most pronounced under convexity and has extremely high inefficiencies near the end. Both C and NC input-oriented efficiency measures reveal an inverted U-shape, but otherwise present a similar trend.

At the city level, we select Wuhan to investigate the evolution of LR plant capacity over time in more detail. This city was the most severely affected by COVID-19 in China. As Fig. 3 shows both output-oriented plant capacity measures under C and NC technologies are equal to unity; hospitals operate at full capacity all the time. The input-oriented measures of plant capacity utilization reveal a stepwise, increasing evolution. Personnel reinforcements in weeks 4 and 6 clearly are picked

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[7] The estimation results with an intertemporal approach are available in Appendix B.

Table 4

Descriptive statistics for decomposition of plant capacity utilization under a sequential approach.

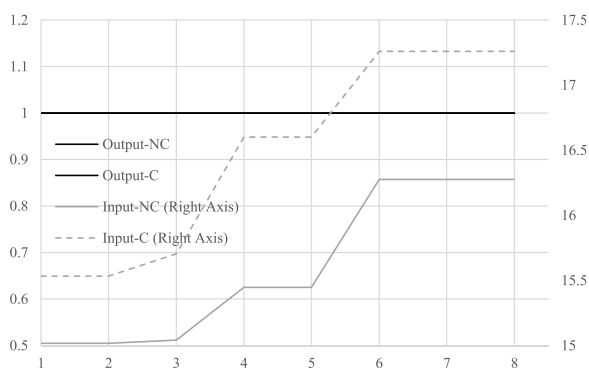| Technology	Convex	Nonconvex	Convex	Nonconvex	Convex	Nonconvex
SR Output-oriented	$DF_{output}(x,y)$		$DF_{output}^{SR}(x^f,y)$		$PCU_{output}^{SR}(x,x^f,y)$	
Mean	4.30	2.98	5.18	3.71	0.83	0.81
St. Dev.	12.38	8.60	13.92	8.60	0.18	0.25
Max	84.71	59.00	95.25	59.00	1.00	1.00
Min	1.00	1.00	1.00	1.00	0.36	0.26
SR Input-oriented	$DF_{input}^{SR}(x^f,x^v,y)$		$DF_{input}^{SR}(x^f,x^v,0)$		$PCU_{input}^{SR}(x,x^f,y)$	
Mean	0.62	0.70	0.36	0.36	3.09	3.44
St. Dev.	0.32	0.30	0.29	0.29	4.53	4.47
Max	1.00	1.00	1.00	1.00	21.12	21.12
Min	0.14	0.14	0.05	0.05	1.00	1.00
LR Output-oriented	$DF_{output}(x,y)$		$DF_{output}^{LR}(y)$		$PCU_{output}^{LR}(x,y)$	
Mean	10.82	2.87	168.28	168.28	0.18	0.12
St. Dev.	24.57	5.86	425.27	425.27	0.24	0.24
Max	225.56	59.00	3050.00	3050.00	1.00	1.00
Min	1.00	1.00	1.00	1.00	0.00	0.00
LR Input-oriented	$DF_{input}^{LR}(x,y)$		$DF_{input}^{LR}(x,0)$		$PCU_{input}^{LR}(x,y)$	
Mean	0.63	0.71	0.51	0.52	2.19	2.35
St. Dev.	0.31	0.30	0.31	0.31	3.86	3.62
Max	1.00	1.00	1.00	1.00	17.26	16.28
Min	0.21	0.21	0.06	0.06	1.00	1.00
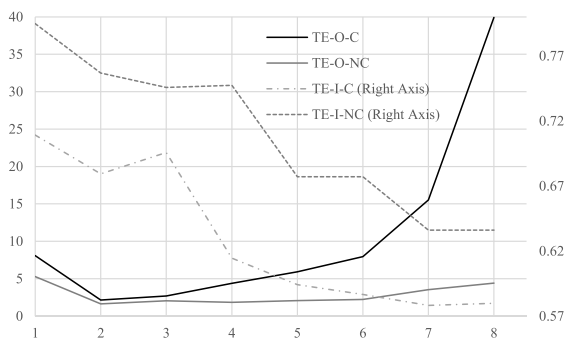
Fig. 2. Evolution of Technical Efficiency Measures at the Aggregate Province under a Sequential Approach

Notes: TE-O denotes the output-oriented LR technical efficiency measure, computed by $DF_{output}(x,y)$, and TE-I denotes the input-oriented LR technical efficiency measure, computed by $DF_{input}(x,y)$.

up by this input-oriented plant capacity concept, and they translate into greater capacity utilization.

We conducted regression analysis to assess the impact of SR and LR measures of plant capacity utilization on mortality rate. First, we tested the effect of SR capacity measures in a simple model, using ordinary least squares (OLS), because only three weeks of observations were available. The dependent variable was mortality rate and the

independent variables were technical efficiency or a plant capacity measure and a constant intercept. We considered both variables in logarithmic format. Note that our three-week samples normally contained 45 observations, but we ignored some cities with zero mortality rates at the beginning of the observation period, so only 28 observations remained. The first two horizontal parts of Table 5 present the SR regression results, while the last two horizontal parts contain the LR regression results.

With regard to the SR analysis, all coefficients are insignificant, possibly as a result of the insufficient sample size of 28 observations. For the LR analysis, we tested the effect of capacity measures on mortality rates in a fixed-effect panel model, using a sample of 120 observations. Again, we ignored cities with a zero-mortality rate at the start of the period, resulting in 92 observations. With regard to technical inefficiency, we observe a positive effect for the NC LR input-oriented technical efficiency measure: the higher the technical efficiency, the

Fig. 3. Unbiased LR PCU Measures for Wuhan with a Sequential Approach.

Table 5

Relationships among mortality rate, technical efficiency, and plant capacity utilization with a sequential approach.

Technology	Convex	Nonconvex	Convex	Nonconvex
Indep. Var.	$DF_{output}(x,y)$		$PCU_{output}^{SR}(x,x^f,y)$	
Observations	28	28	28	28
R^2	0.002	0.001	0.003	0.025
Coefficient	0.052	−0.069	0.204	−0.335
Constant	−4.147***	−4.094***	−4.075***	−4.210***
Indep. Var.	$DF_{input}^{SR}(x^f,x^v,y)$		$PCU_{input}^{SR}(x,x^f,y)$	
Observations	28	28	28	28
R^2	0.012	0.022	0.066	0.075
Coefficient	0.169	0.286	0.224	0.249
Constant	−4.030***	−4.012***	−4.301***	−4.359***
Indep. Var.	$DF_{output}(x,y)$		$PCU_{output}^{LR}(x,y)$	
Observations	92	92	92	92
R^2	0.012	0.001	0.008	0.019
Coefficient	−0.101	−0.048	0.130	0.113
Constant	−4.371***	−4.478***	−4.199***	−4.151***
Indep. Var.	$DF_{input}^{LR}(x,y)$		$PCU_{input}^{LR}(x,y)$	
Observations	92	92	92	92
R^2	0.033	0.051	0.030	0.057
Coefficient	0.649	0.706**	0.602	0.708**
Constant	−4.109***	−4.179***	−4.720***	−4.845***

Notes: The independent variable is the mortality rate. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

higher the mortality. We observe a significant positive sign between the mortality rate and the NC LR unbiased input-oriented measure of plant capacity utilization too, such that higher plant capacity utilization increases mortality. This finding validates conjectures of medical literature. Moreover, the value of the R-square for NC technology is marginally higher than that for C technology.

The regression analysis thus reveals several insights. First, NC LR input-oriented technical efficiency correlates with high mortality. This result is in line with findings pertaining to cost efficiency (which includes input-oriented technical efficiency) and mortality, as reported by Rosko and Mutter (2011). Second, as indicated in extant medical literature, higher NC LR input-oriented plant capacity utilization rates seem to increase mortality. Third, there is no similarly positive relationship for the SR input-oriented plant capacity utilization concept; this result requires further research and confirmation.

6. Conclusions

We begin our presentation by summarizing all known existing studies on the measurement of plant capacity in the hospital sector. Next, we explore economics and medical literature that provides evidence about the relationship between capacity utilization and mortality. In turn, we provide detailed definitions of SR and LR output- and input-oriented plant capacity measures and evaluate four plant capacity concepts relative to C and NC technologies, yielding eight different models.

We use these plant capacity concepts to measure the evolution and build-up of hospital capacity in the Chinese province of Hubei during the outbreak of the COVID-19 epidemic over eight weeks in early 2020. After describing our limited data, we compute eight different models according to this small sample. We use the finding that mortality rates increase as capacity utilization rates increase to select the most plausible of the eight plant capacity concepts.

Our empirical analysis leads to three main conclusions. First, in line with prior studies, the descriptive statistics of technical efficiency and plant capacity measures reveal that C and NC results differ substantially. Second, the regression analysis results indicate that LR NC input-oriented technical efficiency seems to correlate with high mortality. Third, in line with medical literature, our results show that high levels of LR nonconvex input-oriented plant capacity utilization increase mortality. Overall, the relatively recent input-oriented plant capacity concepts challenge older output-oriented plant capacity concepts. In substantiating concerns about the attainability of traditional output-oriented plant capacity concepts, our findings should lead applied researchers to reflect more carefully on the proper choice of plant capacity concept.

Our study has a series of important limitations that may shape the agendas of future research. First, our sample is very small, and the three weeks available for computing the SR concepts are particularly limited. Thus, we call for testing of these same plant capacity notions on more substantial samples. Second, the data are imperfect in that they do not supply information on COVID-19 beds and COVID-19 personnel exclusively. Also, the absence of information on personnel categories of the reinforcements is regrettable. Thus, more detailed studies are necessary to corroborate our preliminary and potentially fragile findings.

Author statement

Kerstens K.: Conceptualization, Methodology, Writing - Original Draft, Review & Editing. **Shen Z.:** Methodology, Data curation, Software, Writing - Original Draft, Review & Editing.

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Supplementary materials

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