Innovative Applications of O.R.

Efficiency assessment of primary care providers: A conditional nonparametric approach

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A R T I C L E   I N F O

Article history:
Received 29 November 2013
Accepted 21 June 2014
Available online 3 July 2014

Keywords:
OR in health services
Efficiency
Data envelopment analysis
Environmental factors
Nonparametric analysis

A B S T R A C T

This paper uses a fully nonparametric approach to estimate efficiency measures for primary care units incorporating the effect of (exogenous) environmental factors. This methodology allows us to account for different types of variables (continuous and discrete) describing the main characteristics of patients served by those providers. In addition, we use an extension of this nonparametric approach to deal with the presence of undesirable outputs in data, represented by the rates of hospitalization for ambulatory care sensitive condition (ACSC). The empirical results show that all the exogenous variables considered have a significant and negative effect on efficiency estimates.

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1. Introduction

The combination of growing care demands from an ageing population and the existing difficulties associated with budget restrictions has placed the objective of improving the effectiveness and efficiency of health systems at the center of the debate on the future of health care in Europe (European Commission, 2010). In this context, there has been a growing interest in measuring efficiency in the health sector. Although most of the empirical work has been focused on hospitals (Steinmann, Dittrich, Karmann, & Zweifel, 2004), primary care provision is receiving progressively more attention (Amado & Dyson, 2008). In fact, primary and community-based care is called on to play a pivotal role in the search for an overall more efficient organization of healthcare (Ham, 2010).

Modeling the production technology of primary care providers is a difficult task. The final output, which should capture the impact of the services on current and future health status of patients, cannot be directly measured or clearly identified. On the one hand, patients’ health status depends on many other factors, besides activities by primary care providers, and on the other hand, there may be a delay before particular primary care services are seen to have an effect on health. Hence, intermediate products related with final outputs are normally used as proxies. This strategy is not straightforward either, however, as primary care providers deliver multiple services, whose impact on health improvement is difficult to disentangle and/or may even be questionable in some cases.

In this context, the use of a nonparametric approach, and particularly data envelopment analysis (DEA), has become very popular in empirical studies, since it can easily handle multiple dimensions of performance and is less vulnerable to the misspecification problems that can affect econometric models.1 Furthermore, multiple extensions of this technique have been developed in the literature to facilitate its adaptation to different frameworks (Emrouznejad, Parker, & Tavares, 2008).

This paper contributes to the existing literature in the field by applying several extensions of the nonparametric approach to assess the performance of a set of primary care units (hereafter PCUs) in a Spanish region. First, we use a transformation approach in the traditional DEA model to incorporate undesirable outputs. Second, we adopt the robust order-m approach (Cazals, Flores, & Simar 2002) to avoid potential problems due to the presence of atypical observations or noise in the data. Finally, we use a conditional approach to include the effect of both continuous and discrete environmental variables.

The potential existence of undesirable (bad) outputs in a production process was already mentioned in the seminal work

by Koopmans (1951). These undesirable outputs are prominent in the energy and environmental context in the form of pollution emissions or waste in resources, but they can also appear in health care services (e.g., adverse effects of drugs). In such cases, the aim of units should be to minimize these outputs rather than maximize them. However, in the standard DEA model, decreases in outputs are not allowed\(^2\) (only inputs being allowed to decrease); thus, it would be necessary to transform the original data or change the production technology in order to take into account the presence of these factors. In the current study, the undesirable factors will be represented by the hospitalization rates for ambulatory care sensitive conditions (ACSCs). In order to include them in a DEA model we use the extension developed by Seiford and Zhu (2002), since this is the method that fits better with the assumed production technology. This model has been used previously in the health (Hu, Qi, & Yang, 2012) as well as in the environmental sector (Hua, Bian, & Liang, 2007; Lu & Lo, 2007).

In addition to the problem of dealing with undesirable outputs in data, we need to bear in mind that the performance of primary care providers can also be affected by exogenous or environmental variables, which in the context of our study are represented mainly by the characteristics of the patients served by each unit (Lezzoni, 1997). As these variables, unlike the inputs and the outputs, are not under the control of the decision making units (in our case, the PCUs), we need to include them in our efficiency analysis in a different way. For that purpose, many different approaches can be used (see Cordero, Pedraja, and Salinas (2008) for an overview); however, the validity of these traditional models is limited, because they need to assume the separability condition between the input–output space and the space of external factors environmental variables. This is not realistic for the health sector, where the characteristics of the population are clearly related to the volume of outputs and even of some inputs. Therefore, in this paper we use the so-called conditional nonparametric approach (Cazals et al., 2002; Daraio & Simar, 2005, 2007a), which avoids the restrictive separability assumption required by traditional approaches in order to provide meaningful results. This method was designed for continuous variables only, but we are interested in considering also discrete variables (in particular, a measure of deprivation), so we apply an extension of this methodology developed by De Witte and Kortelainen (2013) to include both types of exogenous variables.

The conditional approach has become very popular in the recent literature on efficiency measurement. Hence, it is possible to find studies using this approach to measure the efficiency of units operating in a wide range of settings including the education sector (Bonaccorsi, Daraio, & Simar, 2006; Cherchye, De Witte, Oghe, & Nicaise, 2010; De Witte & Kortelainen, 2013; De Witte & Rogge, 2011; De Witte, Rogge, Cherchye, & van Puyenbroeck, 2013; Haelermans & De Witte, 2012), banks and mutual funds (Badin, Daraio, & Simar, 2010; Blass, Da Silva, & Miranda, 2008; Daouia & Simar, 2007; Daraio & Simar, 2005, 2006), post offices (Cazals, Dudley, Flores, Patel, & Rodriguez, 2008), public libraries (De Witte & Geys, 2011, 2013), regional welfare and environment (Halkos & Tzeremes, 2011a, 2013), local services (Rogge & De Jaeger, 2012; Verschelde & Rogge, 2012) and the water sector (Carvalho & Marques, 2011; De Witte & Marques, 2010a, 2010b; Vidoli, 2011). However, to the best of our knowledge, this methodology has only been applied previously in the health sector to measure the efficiency of Greek health administrative districts (Halkos & Tzeremes, 2011b) and Portuguese hospitals (Ferreira & Marques, 2014), considering only continuous exogenous variables. Therefore, we believe that this is the first attempt using this approach to estimate efficiency measures of primary care organizations and considering both continuous and discrete environmental variables.

In the literature, there are few previous studies where the presence of both undesirable outputs and exogenous factors are considered simultaneously in a DEA framework. Hua et al. (2007) developed a non-radial output-oriented DEA considering both types of variables in a model to estimate the ecological efficiency of paper mills in China. Yang and Pollitt (2009) assess the performance of Chinese coal-fired power plants combining four different traditional models to incorporate uncontrollable variables into DEA with one approach to deal with undesirable factors. More recently, Halkos and Tzeremes (2013) use a conditional directional distance function approach for measuring regional environmental efficiency, although they opt for transforming the technology of production to adapt it to the presence of undesirable outputs.

The rest of the paper is organized as follows. The next section provides a brief literature review about previous studies attempting to measure efficiency of primary care providers. Section 3 presents the methodology employed in our study with a detailed explanation of the approaches we use to incorporate both undesirable outputs and environmental variables into the estimation of efficiency measures of PCU performance. Section 4 describes the dataset and the variables used in our analysis and Section 5 summarizes the main results. Finally, conclusions are set out in Section 6.

2. Literature review

As we mentioned in the previous section, most studies carried out in the context of primary health care have opted to use a non-parametric approach. Since the pioneering work by Nunamaker (1983) on nursing service efficiency, multiple applications used this technique to estimate efficiency measures of primary care units (Huang & McLaughlin, 1989; Pina & Torres, 1992; Szczepura, Davies, & Fletcher, 1993). Subsequently, it has also been employed to assess the performance of general practitioners (Bates, Baines, & Whynes, 1996), physicians (Chilingerian & Sherman, 1996, 1997) and primary care teams (Goji, 1999).

All these studies use the so-called “activity-oriented models” in which the output of primary health care is measured by the activity levels of the health units being analyzed, in particular, by their recorded number of visits or consultations. However, the use of these proxies of primary health care output is clearly vulnerable to criticism, since the number of visits does not provide any information about the quality of care being provided, and thus it does not directly include other outcomes of the production process related to the improvement of patients’ health status (e.g. preventable deaths or blood pressure control).\(^3\)

Such criticisms show that it is necessary to consider quality-related indicators to properly measure primary health care output. Actually, the AQA, a consortium of physician professional groups, insurance plans and others, has adopted a principle that measures can only be labeled as “efficiency of care” if they incorporate a quality indicator (AQA, 2007). Unfortunately, the concept of quality is difficult to define and measure, since it not only encompasses technical aspects reflecting the capacity of medical staff to diagnose and treat medical problems, but also patients’ perceptions of the service delivered (Campbell, Roland, & Butow, 2000; Donabedian, 1980). Therefore, in the short list of studies using non-parametric methods to incorporate quality measures into the measurement of efficiency it is possible to identify a variety of

\(^2\) In theory, the outputs can be decreased, but with a positive cost.

\(^3\) Hussey et al. (2009) provide an excellent review of the literature about health care efficiency measures.
indicators used as proxies for this concept (Salinas-Jiménez & Smith, 1996; García, Marcello, Serrano, & Urbina, 1999; Amado & Dyson, 2009; Amado & Santos, 2009; Collier, Collier, & Kelly, 2006; Rosenman & Friesner, 2004; Wagner, Shmaksh, & Novak, 2003).

An indicator widely used as a measure of primary care quality and effectiveness is that of rates of hospital admission for ACSCs (Finegan, Gao, Pasquale, & Campbell, 2010; Pelone et al. 2012; Schiøtz et al., 2011). The conditions chosen are those for which timely and effective primary care could be expected to reduce the risk of admission to hospital by preventing the onset of illness, controlling an acute episode of illness or better long term management (Giuffrida, Gravelle, & Roland, 1999). Several empirical studies (Kringos, Boerma, Van der Zee, & Groenewegen, 2013) and literature reviews (Gibson, Segal, & McDermott, 2013; Rosano, Abo Loha, & Falvo, 2012) support the (negative) association between access and quality of primary care and hospitalization rates for ACSCs. The role of primary care in avoiding hospitalizations for ACSCs is supported by views on point of view of primary care professionals of their own role in the healthcare system. This role would be focused around primary prevention, early detection and monitoring of acute episodes, and monitoring of chronic conditions (Caminal, Starfield, Sánchez, Casanova, & Morales, 2004). Likewise, care coordination and integration are aspects of primary care performance that are of particular interest in a context where chronic patients represent most of the interactions with the healthcare system (Ham, 2010; Nuño, Coleman, Bengoa, & Sauto, 2012). The main problem with these indicators is that they cannot be used in a standard DEA model, because they represent undesirable targets.

Particularly, in making an efficiency assessment of PCUs these variables can have on the performance of health care providers. The conditions chosen are those for which timely and effective primary care could be expected to reduce the risk of admission to hospital by preventing the onset of illness, controlling an acute episode of illness or better long term management (Giuffrida, Gravelle, & Roland, 1999). Several empirical studies (Kringos, Boerma, Van der Zee, & Groenewegen, 2013) and literature reviews (Gibson, Segal, & McDermott, 2013; Rosano, Abo Loha, & Falvo, 2012) support the (negative) association between access and quality of primary care and hospitalization rates for ACSCs. The role of primary care in avoiding hospitalizations for ACSCs is supported by views on point of view of primary care professionals of their own role in the healthcare system. This role would be focused around primary prevention, early detection and monitoring of acute episodes, and monitoring of chronic conditions (Caminal, Starfield, Sánchez, Casanova, & Morales, 2004). Likewise, care coordination and integration are aspects of primary care performance that are of particular interest in a context where chronic patients represent most of the interactions with the healthcare system (Ham, 2010; Nuño, Coleman, Bengoa, & Sauto, 2012). The main problem with these indicators is that they cannot be used in a standard DEA model, because they represent undesirable targets for the evaluated units, so we need to adapt the model used to their presence as we explain in Section 3.

Another way of increasing the accuracy of the model specification is to consider the influence that external or environmental variables can have on the performance of health care providers. Particularly, in making an efficiency assessment of PCUs these variables are mainly the characteristics of the population demanding care. Many previous studies recommend adjusting for case mix when making comparisons between healthcare organizations on the basis of hospitalization rates for ACSCs (Finegan et al., 2010), which are also found to be influenced by other clinical and socio-economic factors such as age, health status and co-morbidities, deprivation and income level (Caminal et al., 2004; Gibson et al., 2013; Rosano et al., 2012).

However, there is little in the primary health care performance literature on the approach of considering these environmental factors. Actually, most of the studies that have attempted to incorporate this information have been limited to performing a second-stage analysis in order to identify potential explanatory factors of inefficient behavior, but they have not incorporated the effect of these variables into the efficiency scores (Zavras, Tsakos, Economou, & Kyriopoulos, 2002; Kontodimopoulos, Moschovakis, Aletras, & Niakas, 2007; Ramirez-Valdivia, Maturana, & Salvo-Garrido, 2010).

More recently, Kontodimopoulos, Papathanasiou, Tountas, and Niakas (2010) and Cordero, Crespo, and Murillo (2010) estimated corrected efficiency scores including information about the characteristics of the population covered by each primary care center using two traditional approaches such as the three-stage model (Muiriz, 2002) and four-stage model (Fried, Schmidt, & Vaisisawarg, 1999), which adjust original input and output values obtained from a measure of managerial inefficiency that controls for the effect of exogenous factors. However, as we mentioned in the previous section, there have not been previous empirical studies incorporating this information through a conditional nonparametric model.

### 3. Methodology

#### 3.1. The production process

Following most previous studies in the health sector, we use a nonparametric approach to measure the efficiency of PCUs. Introducing the basic notation used in this paper, we consider a production process where units are characterized by a set of inputs $x \in \mathbb{R}^n_+$ and outputs $y/y \in \mathbb{R}^q_+$. The production technology is the set of all feasible input–output combinations:

$$\psi = \{(x, y) \in \mathbb{R}^{n+q}_+ | x \text{ can produce } y\}$$  \hspace{1cm} (1)

Given that the set $\psi$ cannot be observed as well as the efficiency scores, it has to be estimated from a random sample of production units denoted by $X = \{(x_i, y_i)|i = 1, ..., n\}$. Since the pioneering work of Farrell (1957), multiple approaches have been developed to achieve this goal. In this framework, an observed production unit $(x_i, y_i)$, defines an individual production possibility set $\psi_i = \psi(x_i)$, which under the free disposability of inputs and outputs, can be written as:

$$\psi_i(x, y) = \{(x, y) \in \mathbb{R}^{n+q}_+ | x \geq x_i; y \leq y_i\}$$  \hspace{1cm} (2)

Within this framework, the DEA estimator is the most common in the literature since it does not rely on a restrictive hypothesis on the data generating process. This estimator $\hat{\psi}_{DEA}$ can be defined as:

$$\hat{\psi}_{DEA} = \left\{ (x, y) \in \mathbb{R}^{n+q}_+ | y \leq \sum_{i=1}^{n} y_i x_i; X \geq \sum_{i=1}^{n} x_i y_i \right\} \text{ for } (y_1, \ldots, y_n)$$

s.t. $\sum_{i=1}^{n} y_i = 1; \ y_i \geq 0; \ i = 1, \ldots, n$ \hspace{1cm} (3)

The estimator of the output efficiency scores for a given $(x_0, y_0)$ can be obtained by solving a simple linear program:

$$\lambda_{DEA}(x_0, y_0) = \sup \left\{ \hat{\lambda} | x_0 \lambda y_0 \in \hat{\psi}_{DEA} \right\}$$  \hspace{1cm} (4)

where $\lambda_{DEA} = 1$ denotes an efficient unit, while $\lambda_{DEA} > 1$ implies that the unit is inefficient. However, this estimator presents some significant drawbacks due to its deterministic nature: (1) statistical inference is not possible due to its deterministic nature; (2) it is very sensitive to the presence of outliers and measurement errors in data and (3) it experiences dimensionality problems due to their slow convergence rates.

In order to overcome those problems, Cazals et al. (2002) introduced the robust order-$m$ estimation, which is based on evaluating the efficiency of observations relative to a partial frontier that envelops only $m > 1$ observations randomly drawn from the sample. This procedure is repeated $B$ times resulting in multiple measures from which the final order-$m$ efficiency measure is computed as the simple mean. Specifically, the order-$m$ efficiency score can be derived from Eq. (5):

$$\lambda_m = E \left[ \min_{1 \leq i \leq m} \left\{ \max_{1 \leq j \leq q} \left( \frac{x_j}{y_j} \right) \right\} \right] \left| y_i \geq y \right.$$  \hspace{1cm} (5)

This estimator allows us to compare the efficiency of an observation with that of $m$ potential units that have a production larger or equal to $y$. As it does not include all the observations, it is less sensitive to outliers, extreme values or noise in the data. As $m$ increases, the expected order-$m$ estimator tends to the DEA efficiency score ($\lambda_{DEA}$). For acceptable $m$ values, normally the efficiency scores will present values higher than unity, which indicates that $\lambda_{DEA}$ is not a reasonable measure of efficiency.
units are inefficient, as outputs can be increased without modifying the level of inputs. When \( \theta < 1 \), the evaluated observation can be labeled as super-efficient, since the order-\( m \) frontier exhibits lower levels of outputs than the unit under analysis. This is not possible in the traditional nonparametric framework where by construction \( \lambda \geq 1 \).

The production process can also be defined by using an alternative probabilistic formulation following the notation introduced by Cazals et al. (2002) and Daraio and Simar (2005). According to this criterion, the production process can be described by the joint probability measure of \((X, Y)\) denoted by \( H_{XY}(x, y) \), which represents the probability of dominating a unit operating at level \((x, y)\):

\[
H_{XY}(x, y) = \Pr(X \leq x, Y \geq y)
\]

(6)

This probability function can be further decomposed as follows:

\[
H_{XY}(x, y) = \Pr(Y \geq y | X \leq x) \Pr(X \leq x) = S_{YX}(y | X \leq x) F_X(x)
\]

(7)

where \( S_{YX}(y | x) \) represents the conditional function of \( Y \) and \( F_X(x) \) the cumulative distribution function of \( X \). Therefore, the output oriented technical efficiency measure can also be defined as the proportionate increase in outputs required for the evaluated unit to have a zero probability of being dominated at the given input level:

\[
\lambda(x, y) = \sup \{ \lambda | S_Y(y | x) > 0 \} = \sup \{ \lambda | H_{XY}(x, y) > 0 \}
\]

(8)

In order to estimate efficiency scores using this probabilistic formulation, the empirical distribution functions \( \hat{H}_{XY}(x, y) \) and \( \hat{S}_{YX}(y | x) \) must replace \( H_{XY}(x, y) \) and \( S_{YX}(y | x) \) respectively. These empirical analogs are represented by the following expressions:

\[
\hat{H}_{XY}(x, y) = \frac{1}{n} \sum_{i=1}^{n} I(X_i \leq x, Y_i \geq y)
\]

(9)

\[
\hat{S}_{YX}(y | x) = \frac{\hat{H}_{XY}(x, y)}{F_X(x)} = \frac{\hat{H}_{XY}(x, y)}{\hat{H}_{XY}(x, 0)}
\]

(10)

where \( I(\cdot) \) is an indicator function. Using the plug-in rule, the conditional DEA estimator (which relies on the convexity assumption of \( \psi \)) for the output-oriented efficiency score can be obtained as:

\[
\lambda_{\text{DEA}}(x, y) = \sup \{ \lambda | \hat{S}_{YX}(y | x) \in \Psi_{\text{DEA}} \}
\]

However, if we are interested in using a partial frontier approach, the order-\( m \) efficiency measure would be defined as the expected value of the minimum of \( m \) random variables drawn from the distribution of \( X \) : \( \lambda_m(x, y) = \int_0^1 \left[ 1 - (1 - S_{YX}(y | x))^m \right] du \). Similarly to DEA, it is possible to obtain the order-\( m \) efficiency measure by applying the conditional estimator:

\[
\lambda_{\text{m,DEA}}(x, y) = \int_0^1 \left[ 1 - (1 - \hat{S}_{YX}(y | x))^m \right] du
\]

(11)

Using one of these two alternative ways of describing the production process we could estimate any model in which conventional inputs are transformed into conventional outputs. However, in the context of our study the technology must also allow for the production of undesirable factors and the potential effect of external or environmental variables on results. The following subsections are devoted to the analysis of these two aspects within a nonparametric framework.

3.2. Dealing with undesirable outputs

Efficiency measurement usually relies on the idea that inputs have to be minimized and outputs have to be maximized. This means that, for each evaluated unit, more output and less input imply a higher degree of efficiency, which is also implicitly assumed in DEA models. However, in some cases, the production function may also contain undesirable outputs that need to be minimized (Chung, Fare, & Grosskopf, 1997), and this complicates the estimation of the DEA standard efficiency scores using Eq. (2), because these bad outputs cannot be simply incorporated as another conventional output.

In the literature one can find different approaches to integrate undesirable factors in DEA models, but there is no clear standard protocol (Scheel, 2001). The proposed models can be roughly divided into two groups. The first is based on the concept of weak disposability reference technology and allows for using the original data. The second is based on data translation and the utilization of traditional DEA models. It is worth noting that the use of these alternative approaches often leads to different results in terms of the units identified as efficient and in terms of the targets set for inefficient units (Dyson et al., 2001; Sahoo, Luptacik, & Mahlberg, 2011).

Färe, Grosskopf, Lovell, and Pasurka (1989) proposed the first non-linear DEA program in which desirable outputs are increased and undesirable outputs are decreased using a hyperbolic output efficiency measure. Subsequently, Färe and Grosskopf (2004) suggested an alternative approach for treating the undesirable factors involving the use of a directional distance function to estimate efficiency scores based on weak disposability of undesirable outputs. These approaches have been widely applied in the field of environmental performance measurement, where the presence of undesirable outputs is frequent. Indeed, the weak disposable reference technology is also referred to as an environmental DEA technology. We decided not to use this methodology in our study because it would imply the introduction of new axioms (weak disposability of outputs) that would be incompatible with the methodology presented above as well as the extension used to deal with external factors.

Among the methods proposed for transforming the data, which do not need to modify the standard axioms of the technology (free disposability is assumed), there are different options. The first possibility would be either to treat the negative or undesirable outputs as inputs (Dyckhoff & Allen, 2001; Korhonen & Luptacik, 2004), or to invert the value of the original variables (Lovell, Pastor, & Turner, 1995). However, these methods do not truly reflect the real production process and the scale and intervals of original variables are affected by the data transformation.

To overcome these shortcomings, Seiford and Zhu (2002) developed a methodology based on a monotone decreasing transformation by multiplying each undesirable output by \(-1\) and then find a proper translation vector to let all negative undesirable outputs be positive. In particular, they proposed that a sufficiently large positive scalar constant number \( (K) \) be added to the reciprocal additive transformation of the undesirable output to ensure that the final new value would be isotonic.

We selected this method to treat the undesirable output factors in our study as it can truly reflect the real production process and is invariant to the data transformation within the DEA model (Lovell & Pastor, 1995). A problem then arises from the fact that the method is sensitive to the choice of the constant value: an overly large value can dominate the data and modify the structure of the efficient frontier, while selecting a small value reduces the effect of the translation on results. Therefore, we must make this decision cautiously. Moreover, due to strong convexity constraints, it can only be solved under variable returns to scale (Silva Portela, 2004).
Environmental factors that are not under the control of the primary care provider need to be considered in evaluation of the provider since such factors are a potential source of inefficiency. An evaluation of a health care facility should explicitly include this information to ensure that the efficiency score finally assigned to the center truly reflects the portion of the production process for which the unit is itself responsible (Muniz, 2002).

Recent years have seen the development of different ways to incorporate the effect of external factors or environmental variables into the production process in estimating efficiency scores through DEA. The most widely used approach is a two-stage procedure, where initial efficiency scores are estimated using a standard DEA model and then they are regressed on the environmental variables (Simar & Wilson, 2007; McDonald, 2008).1 Most studies using this approach in the second stage estimation have employed either Tobit regression or ordinary least squares. Unfortunately, usual inference on the obtained estimates of the regression coefficients is not possible, so it is necessary to use a bootstrap-based procedure to obtain more reliable results (Simar & Wilson, 2007). However, this two-stage approach still has a major weakness, since it requires a two-stage approach instead of using the expression:

\[
H_{XY}(x,y|z) = \Pr(x \leq x, y \geq y|z=z) \]

The function \(H_{XY}(x,y|z)\) represents the probability of a unit operating at level \((x,y)\) being dominated by other units facing the same environmental conditions \(z\). This can also be decomposed into:

\[
H_{XY}(x,y|z) = \Pr(Y \geq y|x \leq x, Z=z) \Pr(X \leq x, Z=z) \\
= S_{Y|x}(y|z)F_X(x|x;Z=z) \\
= S_{Y}(y|x,z) F_X(X|Z=z) 
\]

Therefore, the output efficiency measure can be analogously defined as:

\[
\lambda_m(x,y|z) = \sup \{ \lambda > 0 | S_{Y|x}(y|z)F_X(x|x;Z=z) > 0 \} 
\]

The conditional order-\(m\) efficiency measure can be defined using the expression:

\[
\lambda_m(x,y|z) = \int_0^\infty [1 - (1 - \tilde{S}_{XY}(uv|z,x))^m] du 
\]

However, the estimation of \(S_{Y}(y|x,z)\) is more difficult than the unconditional case, because we need to use smoothing techniques for the exogenous variables in \(z\) (due to the equality constraint \(Z=z\):

\[
\tilde{S}_{Y|z}(y|x,z) = \frac{\sum_{i=1}^n I(x_i \leq x, y_i \geq y)K_y(z,z_i)}{\sum_{i=1}^n I(x_i \leq x)K_y(z,z_i)} 
\]

Therefore, this approach relies on the estimation of a nonparametric kernel function to select the appropriate reference partners and a bandwidth parameter \(h\) using some bandwidth choice method. This would be straightforward if all the \(Z\) variables are continuous, but it is more complicated if we have mixed data (continuous and discrete variables) as in our empirical study. For that purpose, De Witte and Kortelainen (2013) recently proposed a model to smooth any type of discrete variable (ordered and unordered) along with continuous variables extending the ideas proposed by Racine and Li (2004). Hall, Racine, and Li (2004) and Li and Racine (2007). Basically, this approach consists of multiplying three different multivariate kernel functions (one for each type of variable) to obtain a generalized product kernel function \(K_{xy}(z)\) and substitute it for \(K_{xy}\) in Eq. (14). Subsequently, the conditional estimators \(\hat{\lambda}(x,y|z)\) and \(\hat{\lambda}_m(x,y|z)\) can be obtained by plugging in the new \(\tilde{S}_{Y|z}(y|x,z)\) in Eqs. (13) and (14) respectively.

Given that our dataset only contains continuous and ordered discrete variables, we adapt this methodology to a simpler case with only two multivariate kernel functions. Following De Witte and Kortelainen (2013), we employ the Epanechnikov kernel function \(K_{xy}(z) = h^{-1}K(z-z_i/h)\) for continuous variables and the Li and Racine (2007) discrete kernel function for ordered discrete variables. Regarding the estimation of the bandwidth parameters, we follow the data-driven selection approach developed by Badin et al. (2010), which can be easily adapted to the case of mixed environmental variables.13

Finally, this conditional approach allows us to evaluate the direction of the effect of exogenous variables on the production process by comparing conditional with unconditional measures. In particular, when \(Z\) is continuous and univariate, Daraio and Simar (2005, 2007a) suggest using a scatter plot of the ratio between these measures \((Q^z = \frac{\hat{\lambda}_m(x,y|z)}{\hat{\lambda}_m(x,y)}) \) against \(Z\) and its smoothed nonparametric regression line. In an output-oriented conditional model, an increasing regression line will indicate that \(Z\) is favorable to efficiency whereas a decreasing line will denote an unfavorable effect. In the former case, the environmental variable operates as a sort of extra input freely available, and consequently the value of \(\lambda_m(x,y|z)\) will be much smaller than \(\lambda_m(x,y)\) for small values of \(Z\) than for large values of \(Z\). In the latter case, the environmental variable can be interpreted as an extra undesired output to be produced, which requires the use of more inputs, and thus \(\lambda_m(x,y|z)\) will be smaller than \(\lambda_m(x,y)\) for large values of \(Z\) (Daraio & Simar, 2005).

In addition, it is also possible to investigate the statistical significance of \(Z\) explaining the variations of \(Q\). For that purpose, we use local linear least squares for regression estimation and then we apply the nonparametric regression significance test proposed by Li and Racine (2004) and Racine and Li (2004), which smooths both continuous and discrete variables. Specifically, we test the significance of each of the continuous and discrete variables using

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11 In a slight variation on this approach, Fried et al. (1999) and Fried, Lovell, Schmidt, and Yaisawarng (2002) regress radial and non-radial slacks on environmental variables.
12 The estimation of conditional full frontiers does not depend on the chosen kernel but only on the selected bandwidth.
13 In the case of an ordered discrete variable, we assure that the performance of each unit is compared only to those in the same category (i.e., the same value of discrete variable) by forcing the bandwidth to be zero for the variable in question.
It is old, a morbidity index and a deprivation indicator. The morbidity sponds to the period between September 2009 and August 2010.

These include measures of age, health status and socioeconomic status of the population being served by each PCU. Data put. These are similar across PCUs and that there are few non-health professionals, pharmaceuticals and other medical products, infrastructure and technology. Assuming that in the Basque public health sector available infrastructure and medical technology are similar across PCUs and that there are few non-health professionals directly involved in patient care at the primary care level, we propose using the following input variables in our empirical study: number of GPs, number of nurses and number of prescriptions per PCU, which correspond to those most commonly used in the literature (Amado & Dyson, 2008).

As an output indicator we are interested in variables that can reflect the role of primary care on health promotion and education, disease prevention, early diagnosis and timely treatment. Primary care also plays a key role in ensuring the comprehensiveness and continuity of patient care, being patients' first point of contact within the healthcare system and guiding them throughout the different healthcare settings and services. According to this, we have selected the hospitalization rates for ACSCs (counting only one per person), which is solidly supported by the literature (as seen in Section 2) and represent an undesirable output.

Exogenous variables have been selected in accordance with evidence in the literature (see in Section 2) and our own findings (Orueta et al., 2013) on the effects influencing the health care output. These include measures of age, health status and socioeconomic status of the population being served by each PCU. Data originate from the database of the Basque Country population stratification program (PREST) (Orueta et al., 2013), and correspond to the period between September 2009 and August 2010. In particular, we use the percentage of population above 65 years old, a morbidity index and a deprivation indicator. The morbidity index used is based on Adjusted Clinical Groups (ACGs), a case-mix system developed by Starfield, Weiner, Mumford, and Steinwachs (1991) and well-known all over the world. It is defined as a measure of “disease burden” of individuals and populations and, in our case, it was estimated as the ratio between the expected number of visits for a group of patients (in our case, the ones served by a PCU) and the mean observed for the whole population (Tucker, Weiner, Hongfield, & Parton, 1996). The deprivation indicator was constructed from variables such as the percentage of manual workers, the unemployment and temporary employment rates and low levels of educational attainment for the whole population and also for young people (inhabitants between 16 and 29 years of age) (Domínguez et al., 2008). It is based on census tract, the smallest geographical unit into which population census data can be divided (around 1200 inhabitants per tract), which are classified into quintiles, thus the variable is categorical.

The values of variables have been adjusted by 10,000 inhabitants in order to avoid potential distortions due to the existence of significant differences in the size of the PCUs. Likewise, the original values of the (undesirable) output variables have been transformed using the method proposed by Seiford and Zhu (2002). Following this model, we multiplied the values of the variable by \(-1\) and, subsequently, we subtracted the value obtained from a large enough parameter, which in our case was set at a value \(K = 500\). Table 1 provides a brief summary of the main descriptive statistics of variables used in the analysis.

### Table 1

<table>
<thead>
<tr>
<th>Variables</th>
<th>Role</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of GPs per PCU per 10,000 inhabitants</td>
<td>Input</td>
<td>6.53</td>
<td>2.69</td>
<td>3.78</td>
<td>33.08</td>
</tr>
<tr>
<td>Number of nurses per PCU per 10,000 inhabitants</td>
<td>Input</td>
<td>6.32</td>
<td>1.26</td>
<td>3.78</td>
<td>12.52</td>
</tr>
<tr>
<td>Number of prescriptions per PCU per 10,000 inhabitants</td>
<td>Input</td>
<td>166,522</td>
<td>48,998</td>
<td>62,064</td>
<td>555,171</td>
</tr>
<tr>
<td>Hospitalizations due to ACSC per PCU per 10,000 inhabitants</td>
<td>Output</td>
<td>389.95</td>
<td>41.43</td>
<td>213.00</td>
<td>474.42</td>
</tr>
<tr>
<td>Percentage of population above 65</td>
<td>Exogenous (continuous)</td>
<td>19.55</td>
<td>3.99</td>
<td>4.31</td>
<td>29.24</td>
</tr>
<tr>
<td>Morbidity rate</td>
<td>Exogenous (continuous)</td>
<td>1.03</td>
<td>0.13</td>
<td>0.65</td>
<td>1.38</td>
</tr>
<tr>
<td>Deprivation index</td>
<td>Exogenous (discrete)</td>
<td>3.07</td>
<td>1.25</td>
<td>1.00</td>
<td>5.00</td>
</tr>
</tbody>
</table>

### 4. Data and variables

The aim of the present study is to analyse the efficiency of the 132 existing PCUs in the public Basque Health Service using data from year 2010. In the Spanish region of Basque Country, with a population of approximately 2.2 million inhabitants, a public organization (Osakidetza) provides universal and comprehensive healthcare services (primary, specialized and mental care), free of charge at the point of service, to all residents. Primary care is provided through group practices, organized in PCUs (with on average 1500 registered patients per general practitioner) spread across the region both in urban and rural areas. Each resident is registered with a GP, who plays a gate-keeping role regarding access to other healthcare services of the system (except for emergency services, which can be directly accessed by patients). There are ten acute hospitals in the Basque Health Service, each of them acting as referral hospitals for outpatient and inpatient care for a set of PCUs in geographical area.

Resources at the disposal of PCUs for the accomplishment of their mission to maintain and improve the health status of the population can be divided into four main categories: labor (health and non-health professionals), pharmaceuticals and other medical products, infrastructure and technology. Assuming that in the Basque public health sector available infrastructure and medical technology are similar across PCUs and that there are few non-health professionals directly involved in patient care at the primary care level, we propose using the following input variables in our empirical study: number of GPs, number of nurses and number of prescriptions per PCU, which correspond to those most commonly used in the literature (Amado & Dyson, 2008).

As an output indicator we are interested in variables that can reflect the role of primary care on health promotion and education, disease prevention, early diagnosis and timely treatment. Primary care also plays a key role in ensuring the comprehensiveness and continuity of patient care, being patients' first point of contact within the healthcare system and guiding them throughout the different healthcare settings and services. According to this, we have selected the hospitalization rates for ACSCs (counting only one per person), which is solidly supported by the literature (as seen in Section 2) and represent an undesirable output.

### 5. Results

The results of the efficiency estimations for both unconditional and conditional models are summarized in Table 2. In both cases, we estimate the robust order-m model using an output orientation \(\lambda_m\). Regarding the value of the parameter \(m\), which determines the sample size for comparisons, we followed the criterion established by Daraio and Simar (2005) based on selecting the value for which the decrease in super-efficient observations stabilizes. In our case, this value corresponds to \(m = 10\). For statistical inference, we use 200 bootstrap replications.

Focusing on the performance of PCUs without controlling for exogenous variables (unconditional model), we note that the mean performance score is \(\lambda_m = 1.1709\). Therefore, one could suppose that inefficient units could still improve their performance by almost 17% on average to achieve the efficiency levels of the best practices. Likewise, it is possible to identify seven units with an efficiency score below 1, which can be identified as the best performers in the sample. These super efficient PCUs are performing better than the average 10 units they are benchmarked with.

The main problem of this initial assessment is that it does not take into account the environment under which units are operating, so the estimated performance scores may not adequately represent their level of efficiency. Therefore, the next step consists of...
of estimating the conditional efficiency model which allows us to control for heterogeneity among the characteristics of the population served by each primary care unit.

Once we include the three exogenous indicators (two continuous and one discrete) in the estimation of the conditional efficiency model, the number of efficient units increases notably (almost 50% of units become efficient or superefficient) and, therefore, the median value of the distribution of results decreases to $\frac{\lambda_m(x, y | z)}{1}$. This result derives from the fact that now each unit is only compared with those operating in a similar environment, so the reference set is smaller. In addition, we can identify three super efficient units $(\lambda_m < 1)$, which can be considered as the best performers among all the evaluated units.

Table 2 also includes the summary statistics for bandwidth estimates, which present a reasonable average value for the discrete variable (deprivation index) and very high average and maximum values for the two continuous variables. At this point, it should be noted that the high values can be attributed to some outlying maximum scores. Nevertheless, according to these values, the influence of the variables is significant as we demonstrate above.

In order to test the influence of the exogenous variable, we regress the ratio between conditioned and unconditioned efficiency scores on the environmental variables using the local linear estimator described in Section 3.2. Table 3 presents the p-values of the significance tests proposed by Li and Racine (2004) and Racine and Li (2004), which suggest that all the variables have a significant impact on PCU performance, although the level of significance is slightly lower for the deprivation index.

As we are interested in identifying the effect of the exogenous variables, we analyze the values of the ratio against the $Z$ variables. Hence, following the principles established by Daraio and Simar (2005, 2007a), we first observe the partial regression scatter plots for both continuous variables, considering their median value and, respectively, their first and third quartiles to capture the heterogeneity among units (Fig. 1). Since we are examining an output oriented case, a decreasing regression line indicates that the environmental variable is unfavorable to PCU efficiency. This evidence confirms the result we expected and is in line with some previous studies (see Cordero, Crespo, & Murillo, 2014), since the performance of units is frequently worse when the levels of morbidity and the percentage of older adults in the population (proxies for a poor health status) are higher.

Fig. 2 also illustrates the partial regression plot for the discrete ordered variable (Deprivation index). In this case, the result observed is similar, since the variable has an unfavorable effect on the level of efficiency, although there is an unexpected favorable increase between the level 1 and 2 and for the highest level (5). This can be explained by the existence of a low number of units in the extremes of the distribution, which implies that most of them are considered as efficient in the conditional model, where the reference set is smaller.
6. Conclusions

This paper uses a recently developed conditional nonparametric approach to estimate efficiency measures for a set of Spanish primary care units incorporating the effect of different types of environmental factors (continuous and discrete) representing the characteristics of the population served by these providers. This method allows us to avoid the restrictive separability assumption between the input–output space and the space of external factors and thereby provide meaningful results. In addition, this methodology makes it possible to determine the statistical significance and the direction of the effect of the exogenous variables. To the best of our knowledge, this is the first empirical study using this method to measure efficiency in primary health care.

Further, the variables selected to represent the outcome of the evaluated units can be interpreted as undesirable variables according to the structure of the production process. For this, we have needed to use an extension of the traditional nonparametric models to transform the original values of those variables and estimate valid measures of performance for the evaluated units.

Other strengths of the study are that it includes all the primary care organizations of the public Basque Health Service. Moreover, instead of only considering activity-related indicators, it uses a more solid performance indicator represented by hospitalization rates for ACSCs. In addition, the study population is adjusted for characteristics of the population served by these providers. This is also adjusted for age and for the socio-economic level of the area of residence.

The empirical results show that all the environmental variables considered have a significant and negative effect on the performance of primary health care providers, which is in line with the results obtained in the scarce previous literature using traditional semi-parametric approaches (Cordero et al., 2014). Among the limitations of this study, it should be noted that the output measures used might not only depend on performance by PCUs, but could also be influenced by other factors. For example, hospitalization rates for ACSCs might also depend on differences in quality of out-patient specialist care and admission policies between hospitals (Muecke, 2010). Finally, it has to be considered that the deprivation index is not assessed at the individual level so it could also represent an ecologic fallacy.

Acknowledgements

The authors would like to thank Professors Mika Kortelainen and Kristof De Witte for providing us with the routines for estimating the efficiency scores and bandwidths as well as for displaying plots using R codes. They would also like to thank Santiago Esnaola and his team for providing data on deprivation indices in the Basque Country.

References


