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Efficiency assessment of primary care providers: A conditional nonparametric approach

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Abstract

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) and of hospital readmissions. The empirical results show that all the exogenous variables considered have a significant and negative effect on efficiency estimates.

Keywords: OR in health services, Efficiency, Data Envelopment Analysis, Environmental factors, Nonparametric analysis

JEL Codes: I12, C13, C14

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1. INTRODUCTION

The combination of growing care demands from an ageing population and the increasing pressures in public budgets as a consequence of the economic crisis has placed the objective of improving the effectiveness and efficiency of health systems at the center of the debate on the future of healthcare 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 *et al.*, 2004), primary care provision is receiving progressively more attention (Amado and 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 *et al.*, 2008).

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[1]See Hollingsworth (2003, 2008) or Worthington (2004) for an overview of studies on the measurement of efficiency in the health sector.

This paper contributes to the existing literature in the field by applying two extensions of the nonparametric approach to assess the performance of a set of primary care units (hereafter PCUs). Specifically, we combine the use of a transformation approach in the traditional DEA model to incorporate undesirable outputs and 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 (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 hospitalization rates for ambulatory care sensitive conditions (ACSCs) and hospital readmission rates. 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 *et al*., 2012) as well as in the environmental sector (Lu and Lo, 2007; Hua *et al*., 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, 1994). 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 *et al*., 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 outcomes and even of some inputs.

Therefore, in this paper we use the so-called *conditional nonparametric approach* (Cazals, 2002; Daraio and Simar, 2005; Daraio and Simar, 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 *et al*., 2006; Cherchye *et al*., 2010; De Witte and Rogge, 2011; Haelermans and De Witte, 2012; De Witte and Kortelainen, 2013; De Witte *et al*., 2013), banks and mutual funds (Daraio and Simar, 2005; 2006; Daouia and Simar, 2007; Blass *et al*., 2008; Badin *et al*., 2010), post offices (Cazals *et al*., 2008), public libraries (De Witte and Geys, 2011; 2013), regional welfare and environment (Halkos and Tzeremes, 2011a, Halkos and Tzeremes, 2013), local services (Rogge and De Jaeger, 2012; Verschelde and Rogge, 2012) and the water sector (De Witte and Marques, 2010a, 2010b; Carvalho and Marques, 2011; 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 health administrative districts in Greece (Halkos and Tzeremes, 2011b) and only continuous exogenous variables were considered. Therefore, we believe that this is the first study 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 nonparametric 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 and McLaughlin, 1989; Pina and Torres, 1992; Szczepura *et al.*, 1993). Subsequently, it has also been employed to assess the performance of general practitioners (Bates *et al.*, 1996), physicians (Chilingerian and Sherman, 1996, 1997) and primary care teams (Goñi, 1999).

All these studies use the so-called "*activity-oriented models*" in which the output of primary health care is approximated 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 does not directly link to outcomes in terms of improvement in population health.

Such criticisms show that it is necessary to consider not just activity-related but also quality-related indicators to properly measure primary health care output. However, the concept of quality is difficult to define, 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 (Donabedian, 1980; Campbell *et al*., 2000). Therefore, in the short list of studies using a nonparametric framework to incorporate quality measures into efficiency analysis it is possible to identify a variety of indicators used as proxies for this concept (Salinas-Jiménez and Smith, 1996; García *et al*., 1999; Rosenman and Friesner, 2004; Amado and Santos, 2009).

An indicator widely used as a measure of primary care quality and effectiveness is that of rates of hospital admission for ACSCs (Finegan *et al.* 2010; Schiøtz e*t al*., 2011; Pelone *et al.* 2012). 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 *et al*., 1999). Several empirical studies (Kringos *et al.,* 2013) and literature reviews (Rosano *et al*., 2012; Gibson *et al*., 2013) 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 expert opinions and particularly well suited to the views 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 *et al.,* 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 *et al.* 2012). As measures of integrated care, previous comparative and evaluation studies have included indicators such as unplanned hospital admissions, re-admissions and avoidable hospital admissions (Curry and Ham, 2010), 30-day readmission rates (Schiøtz e*t al*., 2011) and emergency hospital admissions (Bardsley *et al*., 2013). The main problem with all 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 socioeconomic factors such as age, health status and co-morbidities, deprivation and income level (Caminal *et al.,* 2004; Rosano *et al.*, 2012; Gibson *et al.*, 2013).

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 *et al.*, 2002; Kontodimopoulos *et al.*, 2007, Ramirez-Valdivia *et al.* 2010).

More recently, Kontodimopoulos *et al.* (2010) and Cordero *et al.* (2010; 2013) 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 (Muñiz, 2002) and four-stage model (Fried *et al.*, 1999), which adjust original input and output values to obtain 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 attempting to incorporate this information through a conditional nonparametric model.

3. METHODOLOGY

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 ($x \in \Re_+^p$) and outputs y ($y \in \Re_+^q$). The production technology is the set of all feasible input-output combinations:

$$\psi = \left\{ (x, y) \in \Re_+^{p+q} \mid x \text{ can produce } y \right\} \tag{1}$$

Given that the set ψ 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 $\psi(x_i, y_i)$, which under the free disposability of inputs and outputs, can be written as:

$$\psi(xi, yi) = \left\{ (x, y) \in \Re_+^{p+q} \middle| x \geq x_i; y \leq y_i \right\} \tag{2}$$

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. Following the notation provided by Daraio and Simar (2007a), this estimator $\hat{\psi}_{DEA}$ can be defined as[2]:

$$\hat{\psi}_{DEA} = \left\{ (x, y) \in \Re_+^{p+q} \middle| y \leq \sum_{i=1}^{n} \gamma_i y_i; x \geq \sum_{i=1}^{n} \gamma_i x_i, \text{ for } (\gamma_1, ..., \gamma_n) \right.$$

$$\left. \text{s.t.} \sum_{i=1}^{n} \gamma_i = 1; y_i \geq 0, i = 1, ..., n \right\} \tag{3}$$

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

$$\hat{\lambda}_{DEA}(x_0, y_0) = \sup \left\{ \lambda \middle| (x_0, \lambda y_0) \in \hat{\psi}_{DEA} \right\} \tag{4}$$

This production describes a production process which transforms conventional inputs 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.

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[2] This definition represents the case of variable returns to scale (VRS) according to the model introduced by Banker *et al.* (1984). The constant returns to scale model developed by Charnes *et al.* (1978) can also be applied when the equality constraint ($\sum_{i=1}^{n} \gamma_i = 1$) is omitted from the equation.

3.1. 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 *et al*., 1997), and this complicates the estimation of the DEA standard efficiency scores using Equation (2), because these bad outputs cannot be simply incorporated as another conventional output[3].

In the literature, several approaches are proposed for handling undesirable factors in DEA models[4], but there is no clear standard protocol (Sheel, 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 outcomes in terms of the units identified as efficient and in terms of the targets set for inefficient units (Dyson *et al*., 2001; Sahoo *et al*., 2011).

Färe *et al*. (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[5]. These approaches have been widely applied in the field of environmental performance measurement, where the presence of undesirable outputs is frequent[6]. 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

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[3] The presence of negative values in data can cause similar problems. See Cheng *et al*. (2013) for details.
[4] See Hua and Bian (2007) or You and Yan (2011) for an extended review of these methods.
[5] Weak disposability assumes that it is costly to reduce undesirable outputs because it increases the inputs or decreases desirable outputs at the same time (Yang *et al.*, 2008).
[6] See Zhou *et al*. (2008) for a review of studies using this approach.

incompatible with the methodology presented above as well as the extension used to deal with external factors[7].

Among the methods transforming the data, which do not need to modify the standard axioms of the technology (free disposability is assumed), there are also different options. The first possibility would be either to treat the negative or undesirable outputs as inputs (Dyckhoff and Allen, 2001, Korhonen and Luptacik, 2004), or to invert the value of the original variables (Lovell *et al*., 1995). However, these methods do not truly reflect the real production process or lose an invariant to 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 and 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 take this decision cautiously. Moreover, due to strong convexity constraints, it can only be solved under variable returns to scale (Silva Portela *et al*., 2004), so our empirical analysis should be performed using the BCC model (Banker *et al*., 1984).

3.2. *The incorporation of external factors using a conditional approach*

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 centre truly

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[7] See Podinovski and Kuosmanen (2011) for details.

reflects the portion of the production process for which that centre is itself responsible (Muñiz, 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[8]. 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 and Wilson, 2007; McDonald, 2009)[9]. 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 and Wilson, 2007). However, this two-stage approach still has a major weakness, since it requires a restrictive separability condition between the input–output space and the space of external or environmental factors. This is often unrealistic, since those factors usually affect the probability of being more or less efficient (Badin *et al.*, 2010). One model in which the two-stage approach is valid was proposed by Banker and Natarajan (2008), but this heavily depends on quite restrictive and unrealistic assumptions about the production process, as described in Simar and Wilson (2011).

More recently, the specific literature devoted to exogenous (environmental) factors and their influence on efficiency has advanced significantly with the development of a more general and appealing full nonparametric conditional approach based on a probabilistic definition of the frontier (Daraio and Simar, 2005, 2007a, 2007b). In order to explain the conditional efficiency approach, it is necessary to introduce some basic concepts developed by Cazals *et al.* (2002). These authors proposed an alternative probabilistic formulation to the production process, denoted by $H_{XY}(x, y)$, which represents the probability of dominating a unit operating at level *(x, y)*:

$$H_{XY}(x, y) = \Pr(X \leq x, Y \geq y) \tag{5}$$

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[8] See Fried *et al.* (2008) for an overview.
[9] In a slight variation on this approach, Fried *et al.* (1999, 2002) regress radial and non-radial slacks on environmental variables.

This probability function can be further decomposed as follows:

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

$$S_{Y|X}(Y \geq y \mid X \leq x)F_X(X \leq x) = S_{Y|X}(y \mid x)F_X(x) \qquad (6)$$

where $S_{Y|X}(y \mid x)$ 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 been 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:

$$\hat{\lambda}(x,y) = \sup\{\lambda \mid S_Y(\lambda y \mid x) > 0\} = \sup\{\lambda \mid H_{XY}(x, \lambda y) > 0\} \qquad (7)$$

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

$$\hat{H}_{XY,n}(x,y) = \frac{1}{n}\sum_{i=1}^{n} I(x_i \leq x, y_i \geq y) \qquad (8)$$

$$\hat{S}_{Y,n}(y \mid x) = \frac{\hat{H}_{XY,n}(x,y)}{\hat{F}_{X,n}(x)} = \frac{\hat{H}_{XY,n}(x,y)}{\hat{H}_{XY,n}(x,0)} \qquad (9)$$

where *I(-)* is an indicator function. Using the plug-in rule, the conditional DEA estimator (which relies on the convexity assumption of ψ) for the output-oriented efficiency score can be obtained by solving the linear program involved by:

$$\hat{\lambda}_{DEA}(x,y) = \sup\{\lambda \mid \hat{S}_{Y,n}(\lambda x \mid y) \in \hat{\psi}_{DEA}\} \qquad (10)$$

In this context, Cazals *et al*. (2002) and, subsequently, Daraio and Simar (2005; 2007a; 2007b) suggested that the presence of additional external factors $Z \in \Re_+^k$ can be incorporated into the analysis by conditioning the production process to a given value of $Z = z$. This conditional function can be defined as:

$$H_{XY|Z}(x, y|z) = \Pr(X \leq x, Y \geq y|Z = z) \qquad (11)$$

The function $H_{XY|Z}(x, y|z)$ 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:

$$H_{XY|Z}(x, y|z) = \Pr(Y \geq y|x \leq x, Z = z) \Pr(X \leq x, Z = z)$$

$$= S_{Y|X,Z}(Y \geq y|X \leq x, Z = z)F_X(X \leq x; Z = z)$$

$$= S_Y(y|x, z)F_X(x|z) \qquad (12)$$

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

$$\hat{\lambda}(x, y|z) = \sup\{\lambda > 0 | S_{Y|XZ}(\lambda y|X \leq x, Z = z) > 0\} \qquad (13)$$

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 $Z = z$):

$$\hat{S}_{Y,n}(y|x, z) = \frac{\sum_{i=1}^{n} I(x_i \leq x, y_i \geq y)K_{\hat{h}}(z, z_i)}{\sum_{i=1}^{n} I(x_i \leq x)K_{\hat{h}}(z, z_i)} \qquad (14)$$

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[10]. 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

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[10] The estimation of conditional full frontiers does not depend on the chosen kernel but only on the selected bandwidth.

unordered) along with continuous variables extending the ideas proposed by Racine and Li (2004), Hall et al. (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 ($K_{\hat{h}}$) and substitute it for $K_{\hat{h}}$ in equation 14. Subsequently, the conditional estimator $\hat{\lambda}(x, y|z)$ can be obtained by plugging in the new $\hat{S}_{Y,n}(y|x, z)$ in equation 13.

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 ($K_{\hat{h}}(z, z_i) = h^{-1}K((Z - z_i)/h)$ 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[11].

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 ($Q^z = \hat{\lambda}(x, y|z) / \hat{\lambda}(x, y)$) 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 $\lambda(x, y|z)$ will be much smaller than $\lambda(x, y)$ 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 $\lambda(x, y|z)$ will be smaller than $\lambda(x, y)$ for large values of Z (Daraio and Simar, 2005).

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[11] 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.

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 bootstrap tests proposed by Racine (1997) and Racine *et al.* (2006), which can be interpreted as the nonparametric equivalent of standard t-tests in ordinary least squares regression.

4. DATA AND VARIABLES

The aim of the present study is to analyse the efficiency of PCUs in the public Basque Health Service. In the Basque Country, with a population of approximately 2.2 million inhabitants, a public organization (Osakidetza) provides universal and comprehensive health care 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 132 PCUs (with on average 1,500 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 health care 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 its geographical area.

Resources at the disposal of PPCs for the accomplishment of their mission to maintain and improve the health status of the population under their responsibility care can be divided into four main categories: labour (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 and Dyson, 2008).

Output indicators have been selected following the criterion that they reflect the role of primary care, focused 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 with the healthcare system and guiding them throughout the different healthcare settings and services. According to this, two output indicators were selected: hospitalisation rates for ACSCs and the rates of re-admissions to hospital 30 days after discharge (in both cases counting only one per person). Both of these indicators are solidly supported by the literature (as seen in Section 2) and represent undesirable outputs.

Exogenous variables have been selected in accordance with evidence in the literature (seen in Section 2), and our own findings (Orueta *el al*., 2013) on the factors influencing health care outcomes, and 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 *et al.* (1991) and well-known all over the world[12]. 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 *et al.*, 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 16–29 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 1,200 inhabitants per tract), which are classified into quintiles, thus the variable is categorical.

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[12] This instrument enables the classification of individuals into a hundred of mutually exclusive groups according to their diagnosis, age and sex; such categorization offers a measure of health care needs and expected costs. .

All inputs and outputs 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, the values of both variables were multiplied 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. Descriptive statistics of inputs, outputs and exogenous variables

Variables	Role	Mean	SD	Min	Max
Number of GPs per PCU per 10,000	Input	6.53	2.69	3.78	33.08
Number of nurses per PCU per 10,000 inhabitants	Input	6.32	1.26	3.78	12.52
Number of prescriptions per PCU per 10,000 inhabitants	Input	166,522.3	48,998.9	62,064.6	55,5171.5
Hospitalizations due to ACSC per PCU per 10,000 inhabitants	Output	389.95	41.43	213.00	474.22
Re-admissions in 30 days per PCU per	Output	432.68	23.85	307.30	487.39
Percentage of population above 65	Exogenous (continuous)	19.55	3.99	4.31	29.24
Morbidity rate	Exogenous (continuous)	1.03	0.13	0.65	1.38
Deprivation index	Exogenous (discrete)	3.07	1.25	1.00	5.00

Source: PREST dataset

5. RESULTS

The results of the efficiency estimations for both unconditional and conditional models using VRS and an output orientation are summarized in Table 2. Focusing on the performance of PCUs without controlling for exogenous variables (unconditional model), we note that the mean efficiency score is 1.116, with only 10 PCUs being considered efficient. Therefore, one could suppose that inefficient units could still

improve their performance by almost 12% on average to achieve the efficiency levels of the best practices. However, this initial assessment does not take into account the characteristics of the population served by each primary care unit, so these initial efficiency scores may not adequately represent their level of efficiency.

Once we include the three exogenous indicators (two continuous and one discrete) in the estimation of the conditional efficiency model, more than half of the units become efficient. 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 line with this, the margin for improvement is notably reduced, since the average level of efficiency decreases to 1.0251.

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, these values do not imply that the influence of the variables is not significant as we demonstrate above.

Table 2. Efficiency estimates and bandwidths

	Min	Median	Mean	Max	SD	Efficient units
Unconditional eff.	1.0000	1.1157	1.1160	1.5196	0.0765	10 (7.5%)
Conditional eff.	1.0000	1.0000	1.0251	1.3246	0.0532	74 (56%)
Bandwidth Dep. Index	0.0000	0.3171	0.3767	0.1948	0.7928	-
Bandwidth % > 65 years	0.1086	2.6950	1.00E+07	3.07E+07	1.99E+08	-
Bandwidth Morb. Index	0.009	0.1378	2.61E+05	1.03E+06	7.11E+06	-

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.

Table 3. Nonparametric significance test

Variable	p-value
Deprivation index	0.084*
Percentage of people over 65 years	< 2E-16***
Morbidity index	0.035**
R^2	0.309

** denotes statistical significance at 5%

 * denotes statistical significance at 10%

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, 2007), 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 (Figure 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 *et al.*, 2013), 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.

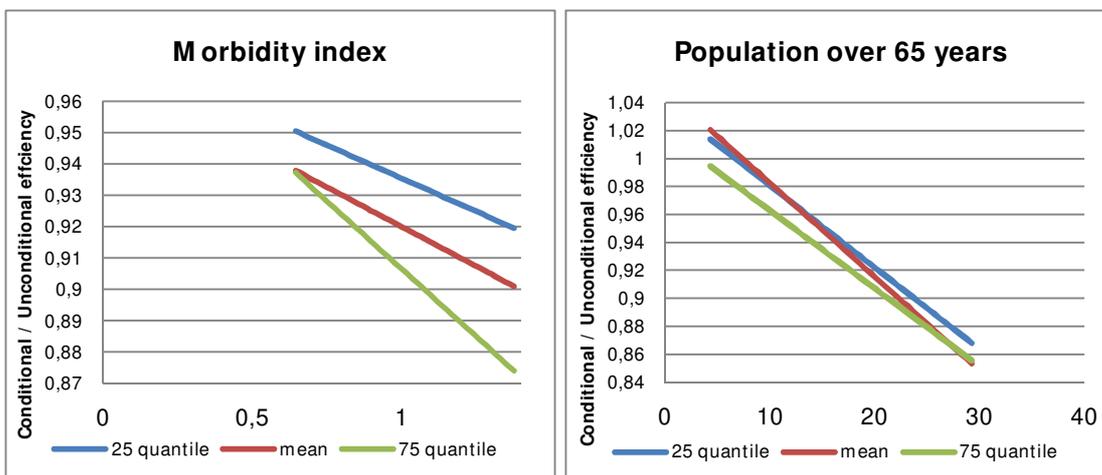Figure 1. Effects of continuous Z variables on PCU efficiency scores

Figure 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 for the highest level (5). This can be explained by the existence of a low number of units with these values, which implies that most of them are considered as efficient in the conditional model, where the reference set is smaller.

Figure 2. Effect of the discrete variable on PCU efficiency score
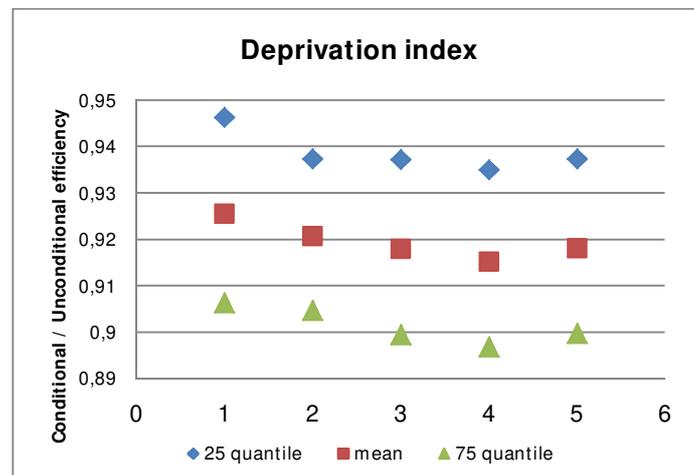
6. CONCLUSIONS

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 environmental variables required by traditional approaches 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 in the health sector.

Further, the variables selected to represent the outcomes of the evaluated units can be interpreted as undesirable outputs according to the structure of the production process.

For this, we have needed to use an extension of the traditional DEA model 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 more solid performance indicators, in particular, hospitalization rates for ACSCs and hospital re-admission rates. In addition, the study population is adjusted for health status through a morbidity index (based on ACGs), which is a sophisticated measure validated in our context (Orueta *et al.*, 2006). The population 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.*, 2013). 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. Specifically, hospitalisation rates for ACSCs might also depend on differences in quality of outpatient specialist care and admission policies between hospitals (Muecke, 2010), and hospital re-admission rates could also depend on the quality of inpatient care at the first hospital admission. Finally, it has to be considered that the deprivation index is not assessed at the individual level so it could also represent an ecological fallacy.

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