Assessing the level of happiness across countries: A robust frontier approach

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Assessing the level of happiness across countries: A robust frontier approach

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Abstract

In this paper we propose an innovative approach based on life satisfaction to estimate efficiency measures for individuals considering how they convert their resources into higher levels of happiness. We use an extension of the conditional nonparametric robust approach which allows us to consider a mixed set of individual and institutional variables that can affect the levels of life satisfaction. Our empirical analysis includes data about 31,854 individuals from 26 OECD countries participating in the last wave of the World Values Survey. Results obtained indicate that the most efficient individuals in achieving happiness tend to live in northern and central European countries whereas the less efficient individuals are found, in average, in Asian transitional economies. In addition, it is also found that most of the traditional determinants of wellbeing (e.g. age, marital status, religion or unemployment) also have a significant impact on efficiency measures.

Key words: Efficiency, Happiness, Cross-country analysis, nonparametric.

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1. Introduction

The pursuit of happiness is inherent to the human condition. Everybody is interested in attaining the maximum level of wellbeing, thus studying the causes of human happiness has been one of the main concerns in disciplines like philosophy, sociology or psychology. More recently, this topic of research has also become very popular in the economic literature, where the so-called *happiness economics* has experienced a remarkable expansion during the last two decades (Kahneman and Krueger, 2006, Clark *et al.*, 2008)[1]. As a result, numerous articles regarding the identification of determinants of subjective wellbeing have been published in the most prestigious economic journals (See Dolan *et al.*, 2008, for a detailed review of this literature). Although the methodological approaches used in those studies differ in detail, most of them are based on defining an equation where the dependent variable is a measure of the absolute level of wellbeing and statistical inference techniques are used to identify explanatory variables significantly associated to this happiness indicator (Powdthavee, 2010).

In this paper, we aim to contribute to this literature by developing an innovative approach to estimate relative measures of happiness based on the efficiency demonstrated by individuals to convert the resources they have at their disposal into wellbeing. This approach has so far been scarcely explored in the happiness literature and, to the best of our knowledge, the work of Binder and Broeckel (2012) represents the only previous study using what they called the "happiness efficiency" approach. These authors consider that an individual is a "*locus of production of happiness*" that is dependent upon its available set of resources. Within this framework, individuals' happiness or satisfaction is the result of combining certain resources, so increasing these inputs in the individual production process would lead to higher outcomes in terms of satisfaction, happiness or subjective wellbeing. Nevertheless, if there are inefficiencies at the individual conversion process of resources into wellbeing it would be possible to increase the efficiency with which individuals reach their levels of happiness, increasing the levels of perceived wellbeing given a certain set of resources or, alternatively, attaining current levels of happiness with fewer resources. In this context, the objective

[1]The literature on happiness economics bases on individuals' self-reported data about satisfaction with life, happiness or subjective wellbeing. It is noteworthy that satisfaction with life is a component, in addition to positive and negative effects, of subjective wellbeing (Diener, 1984). Although recognizing differences in these constructs, throughout the paper we will use the words happiness, satisfaction and (subjective) wellbeing indistinctly. In any case, the focus of our study is on life satisfaction.

of this paper is twofold. First, we aim to analyze the efficiency with which individuals convert their resources into wellbeing, thus focusing on measures of relative happiness (i.e. the levels of happiness achieved given a certain set of resources). Second, we explore what individual and environmental variables influence the efficiency with which resources are converted into happiness, either fostering this conversion process or showing an unfavorable effect on happiness efficiency.

The main contribution of this research is to adapt the traditional concepts developed in the efficiency analysis literature to the estimation of individual efficiency measures based on the level of happiness declared by individuals. For that purpose, it becomes necessary to construct an efficient boundary represented by the best performers in transforming their resources into higher levels of satisfaction. The distance between individual efficiency scores and the frontier would hence represent the level of inefficiency shown by individuals in terms of subjective wellbeing. In order to estimate this frontier we use a fully nonparametric framework, which implies that we do not impose any a priori specification on the functional form of the production technology. Our model bases on the popular Data Envelopment Analysis (DEA) literature (Charnes *et al.*, 1978), although we adapt it to the robust order-*m* technique proposed by Cazals *et al.* (2002) to mitigate the effects of potential outliers or errors in data. Specifically, we estimate efficiency measures for each individual considering his/her level of life satisfaction and the main factors affecting this condition such as income, education and health status.

A second contribution of the paper comes from testing whether some individual and institutional factors identified in the happiness literature as predictors of the absolute levels of wellbeing have also a significant impact on relative happiness efficiency measures. This is possible by adapting our model to a conditional nonparametric framework (Daraio and Simar, 2005, 2007a, 2007b). The conditional approach has become very popular in the recent literature on efficiency measurement. However, to the best of our knowledge, this methodology has not been previously applied to measure the efficiency of individuals in the search of happiness. The major advantage of this approach is that it avoids the restrictive separability condition required by traditional methods like the two-stage model, which implies to assume that the background variables do not have an impact on the input and output mix and, therefore, on the frontier of the efficiency scores. This is really a strong assumption, which is difficult to maintain in the context of our study since one would expect that some personal variables considered in the analysis, such as gender, age, marital status or the number of kids, might be associated to subjective wellbeing and even to some inputs (e.g. age could be linked to the health status or being unemployed might determine the level of income, with health and income conditioning the levels of perceived wellbeing). Although this methodology was originally designed for continuous variables only, we are interested in also considering discrete variables (categorical and dummies), so we apply an extension of this methodology developed by De Witte and Kortelainen (2013) to include both types of background or environmental variables.

In order to illustrate the usefulness of the proposed approach, we present an empirical analysis using international data from the last wave of the World Values Survey (2005-06 WVS), which allows us to compare relative levels of life satisfaction across countries. This dataset is a global research project designed to provide a comprehensive measurement of all major areas of human concern, from religion or politics to economic and social life. It also includes data related to perceived well-being, including variables such as life satisfaction and the level of happiness. The data is collected by interviewing representative national samples of individuals using an extensive questionnaire about multiple aspects of life. The available dataset includes information about individuals from developed and non developed countries; however, in our empirical study we consider only OECD countries in order to maintain a certain level of homogeneity among observations. As a result, our dataset covers individuals from 26 developed countries.

The remainder of this paper is structured as follows: Section 2 provides a brief review of the previous literature on the determinants of subjective wellbeing. Section 3 presents some arguments supporting the model proposed to measure efficiency in this framework. Section 4 describes the methodology and Section 5 explains the main characteristics of the dataset and the variables used in this study. Section 6 presents the obtained results and relates them to the existing literature. Finally, the paper ends with some concluding remarks in Section 7.

2. Literature Review

The study of subjective wellbeing has received increasing attention in the economic literature in recent decades[2]. The literature on happiness economics bases on the concept of subjective wellbeing (SWB), which can be derived from the responses provided by individuals to questions about their current level of happiness or their satisfaction with their lives (Frey and Stutzer, 2002). Although the validity of these measures was initially questioned, recent evidence has proved their reliability (Krueger and Schkade, 2008), so it is common to find this variable in international and national surveys.

Most empirical research on the determinants of wellbeing bases on a simple additive function in which the measure of SWB depend on a range of individual, economic, socio-demographic and institutional factors. Thus, the empirical analysis usually estimates an equation of this type:

$$SWB_i = \alpha + \sum_n \beta_n X_{n,i} + \varepsilon_i \qquad (1)$$

where i refers to the individual, SWB is a measure of perceived wellbeing, X_n is a set of explanatory variables, such as income and other socio-demographic and individual characteristics, β_n are the parameters to be estimated and ε is a random term.

The treatment of the dependent variable varies across studies. In some cases, it is considered as a cardinal indicator whilst others respect the strict order of the data and treat the real level of life satisfaction as a latent variable using an ordered logit or probit (Ferrer-i-Carbonell and Frijters, 2004). This can then be estimated by examining within-person deviations from means when only cross sectional data is available, although the use of panel data is becoming more frequent in recent analyses; in this case, it is possible to control for time-invariant individual effects, such as the personality of individuals.

The existing evidence suggests that there are some key factors strongly associated to SWB. Most of the happiness economic literature has focused on the relationship

[2] Extensive reviews on the 'happiness economics' literature can be found in Bruni and Porta (2007), Frey (2008), or Dolan *et al*. (2008).

between income and subjective wellbeing, pointing to a strong positive effect of income on wellbeing. However, this relationship is not straightforward: on average, individuals with higher levels of income seem to enjoy higher levels of subjective wellbeing, although the levels of wellbeing do not tend to increase as a society becomes richer[3]. When studying the relationship between income and life satisfaction it is usual to introduce some control variables in the analysis, such as the health status or the educational level. Whereas there is a strong consensus on the positive effects of health on perceived wellbeing (Veenhoven, 2008, Blanchflower and Oswald, 2011), the evidence on the impact of education on subjective wellbeing is mixed. At first, education positively correlates with subjective wellbeing, but when income and occupational status are controlled for, the effects of education narrow down (Argyle, 1999, Blanchflower and Oswald, 2004a). The empirical evidence thus suggests that the positive correlation between education and subjective wellbeing works, at least in part, through indirect variables such as health, income, employment or social status (Hartog and Oosterbeek, 1998, Heliwell, 2003).

Other individual characteristics or socio-demographic variables that have proved to be significantly related to subjective wellbeing refers to age, marital status, religion or being unemployed. In the case of the age, the relationship seems to be U-shaped, with higher levels of well-being at the younger and older age points and the lowest life satisfaction being found in middle age (Blanchflower and Oswald, 2004b, Easterlin, 2006). There is also evidence supporting that married people, or people living with a partner, are more satisfied with their lives (Diener *et al.*, 2000, Stutzer and Frey, 2006) as so do those who are engaged in religious activities (Helliwell, 2003). On the contrary, most empirical evidence finds a significant negative impact of being unemployed on individual wellbeing, this being so even when the effects through income are controlled for (Clark and Oswald, 1994, Di Tella *et al.*, 2001, Winkelmann, 2009). In contrast, other variables such as gender or having children show more ambiguous effects on wellbeing. Hence, as regards gender differences in terms of happiness, some studies suggest that women enjoy higher levels of life satisfaction (Gerdham and Johannesson,

[3] This result, was early pointed by Easterlin (1974) and is known as the 'Easterlin paradox'. Several explanations have been proposed to solve this paradox, most of them pointing to the role of relative income, rising income aspirations or income adaptation. For an extensive review on different explanations to the 'Easterlin paradox', see Easterlin (1995) and Clark *et al.* (2008). A complete study on the relationship between income and subjective wellbeing can also be found in Stevenson and Wolfers (2008).

2001; Salinas-Jiménez *et al.*, 2013) while others do not find significant gender differences (Louis and Zhao, 2002). The evidence is also mixed regarding the effects of having children, with some studies pointing to a positive relationship with life satisfaction (Haller and Hadler, 2006), although this relationship might become negative if the family is poor (Alesina *et al.*, 2004).

Finally, life satisfaction has also proved to differ across countries in ways that can be explained by differences in freedoms, social capital and trust (Heliwell and Putnam, 2004, Halpern, 2010). Thus, in addition to the effects of the individual variables, the empirical evidence suggests that social capital at the aggregate level positively correlates with individual wellbeing, thus pointing to an external or environmental effect of social capital (Portela *et al.*, 2013). Likewise, it is generally acknowledged that the quality of formal national institutions (e.g. justice system, government effectiveness or political stability) can affect people's happiness (Bjornskov *et al.*, 2010), although the existing evidence is still inconclusive.

3. Efficiency measurement based on happiness

Previous evidence about the factors affecting SWB will be very useful for selecting the variables considered in our empirical research. However, our aim is not limited to explore the potential existence of a significant relationship between SWB and its determinants, but also to estimate a measure of the efficiency on how individuals use those determinants to search for the higher levels of wellbeing or happiness that they can achieve given that set of resources.

As mentioned before, we borrow this approach from Binder and Brockel (2012), who consider that it is desirable not only to increase the absolute levels of wellbeing, but also to foster increases in relative levels. This argument is based on the fact that, in some cases, individuals may not increase their level of happiness if they have already reached a certain level, but they might increase the efficiency with which they achieve that level of happiness by freeing resources that could be employed otherwise. Alternatively, fostering happiness efficiency would allow inefficient individuals to increase their levels of happiness given their set of resources, thus avoiding the costs of increasing their resources in order to increase their absolute levels of wellbeing.

Actually, this is the basis of the production theory literature, in which the efficiency of the evaluated units is assessed using an efficiency frontier on which the most efficient units are placed and relative measures of inefficiency are estimated using the distance to that frontier (Farrell, 1957). In the context of our study, this frontier would comprise individuals who have been able to reach the maximum level of wellbeing (output) given a certain level of resources (inputs). These individuals constitute the best performers in the efficient use of those resources to attain happiness. Given that the transformation technology used by individuals to convert inputs into happiness is unknown and extremely difficult to define, we will use a flexible nonparametric approach to estimate the efficiency frontier.

Assuming that it is possible to determine an efficiency measure of happiness, the use of this relative measure of individual efficiency will allow one to distinguish between individuals who are able to reach certain levels of wellbeing and others having difficulties to achieve those levels given a certain set of resources. When using this approach it is also possible to incorporate into the analysis some variables available at the individual level that can have influence on how individuals convert resources into happiness or wellbeing. These variables cannot be considered as inputs or outputs in the process, but they can explain efficiency differentials as well as improve the managerial performance of individuals. A key decision that needs to be undertaken is hence the selection of those resources or input variables and that of the background variables which can influence the conversion of those resources into happiness. Moreover, individuals might face difficulties to convert their resource into happiness derived from some institutional or environmental factors which cannot be included in the analysis. Therefore, it would be useful to explore those inefficiencies and search for common patterns among individuals facing those obstacles to attain a certain level of happiness. The consideration of an international perspective in our study allows us to account for heterogeneity across countries regarding the influence of the aforementioned missing institutional variables.

As it is well-known in the literature on efficiency measurement, the interaction effect between environmental factors and efficiency measures is not only difficult to interpret but also to be correctly disentangled. In fact, the study of this relationship has received an increasing attention in frontier analysis studies (See Badin *et al.*, 2012 for a recent state-of-the-art review of the literature on this topic). The most traditional approach in the literature consists of using a two-stage procedure, where efficiency scores are estimated in a first stage, considering only the input-output space, and then they are regressed on the environmental variables (see Simar and Wilson, 2007 and 2011 for a detailed review of this method). This is the method employed in the empirical analysis carried out by Binder and Broeckel (2012) to estimate efficiency measures in the context of happiness. However, the validity of the results obtained with this method depends on the existence of a restrictive separability condition between the input–output space and the space of environmental factors, assuming that these factors have no influence on the attainable set but affect only the probability of being more or less efficient, an assumption which is often unrealistic. In this paper we use a more general and appealing approach represented by the conditional nonparametric approach proposed by Cazals *et al.* (2002) and extended by Daraio and Simar (2005, 2007a, 207b), which allows us to avoid this problem.

4. Methodology

4.1. The production process and its probabilistic formulation

The definition of the production technology that an individual uses to convert inputs into outputs is a difficult task. In the context of our study, the only thing that we know is that people transform a set of resources $x (x \in \Re_+^p)$ into wellbeing, which will be the output y ($y \in \Re_+^q$). This can be defined as:

$$\psi = \left\{ (x, y) \in \Re_+^{p+q} \;\middle|\; x \text{ can produce } y \right\} \tag{2}$$

Given that the production set ψ cannot be observed, it has to be estimated from a random sample of production units denoted by $X = \left\{ (x_i, y_i) \middle| i = 1,...,n \right\}$. 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:

$$\psi(xi, yi) = \left\{(x, y) \in \Re_{+}^{p+q} \middle| x \geq x_i ; y \leq y_i \right\} \tag{3}$$

According to this definition, the efficient individuals will be part of the frontier, while the output oriented measure of inefficiency for those who do not belong to the frontier can be defined as:

$$\theta(x, y) = \sup\left\{\lambda \middle| (x, \lambda y) \in \psi \right\} \tag{4}$$

A procedure to measure the relative inefficiency scores θ and λ is offered by nonparametric techniques, and mainly by Data Envelopment Analysis –DEA– (Charnes *et al.* 1978). This approach is based on mathematical programming and does not require to impose any determined form on the production function. Following the notation provided by Daraio and Simar (2007a), this estimator $\hat{\psi}_{DEA}$ can be defined as[4]:

$$\hat{\psi}_{DEA} = \left\{ (x, y) \in \Re_{+}^{p+q} \middle| y \leq \sum_{i=1}^{n} \gamma_i y_i ; x \geq \sum_{i=1}^{n} \gamma_i x_i, \text{for} (\gamma_1, \ldots, \gamma_n) \right.$$
$$\left. \text{s.t.} \sum_{i=1}^{n} \gamma_i = 1; y_i \geq 0, i = 1, \ldots, n \right\} \tag{5}$$

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

$$\hat{\lambda}_{DEA}(x_0, y_0) = \sup\left\{\lambda \middle| (x_{0,} \lambda y_0) \in \hat{\psi}_{DEA} \right\} \tag{6}$$

where $\hat{\lambda}_{DEA} = 1$ denotes an efficient unit, while $\hat{\lambda}_{DEA} > 1$ implies that the unit is inefficient. However, this approach presents some significant drawbacks: (i) statistical inference is not possible due to its deterministic nature; (ii) it is very sensitive to the

[4] 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.

presence of outliers and measurement errors in data; (iii) 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 bases on evaluating the efficiency of observations relatively 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 as:

$$\lambda_m = E\left[\min_{i=1,\dots,m}\left\{\max_{j=1,\dots,p}\left(\frac{x_i^j}{x^j}\right)\right\} \middle| y_i \geq y\right] \tag{7}$$

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 ($\hat{\lambda}_m$) tends to the DEA efficiency score ($\hat{\lambda}_{DEA}$)[5]. For acceptable *m* values, the efficiency scores will usually present values higher than unity, which indicates that units are inefficient since the output can be increased without modifying the level of inputs. When $\hat{\theta} < 1$, the evaluated observation can be labelled as super-efficient, since the order-*m* frontier exhibits lower levels of output than the unit under analysis. This is not possible in the traditional nonparametric framework where by construction $\hat{\lambda} \geq 1$.

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), 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):

$$H_{XY}(x, y) = \Pr(X \leq x, Y \geq y) \tag{8}$$

[5] See Daraio and Simar (2007a) for details.

This probability function can be further decomposed as follows:

$$H_{XY}(x,y) = \Pr(Y \geq y \mid X \leq x)\Pr(X \leq x) =$$
$$S_{Y|X}(Y \geq y \mid X \leq x) F_X(X \leq x) = S_{Y|X}(y \mid x) F_X(x) \tag{9}$$

where $S_{Y|X}(y|x)$ represents the conditional function of Y and $F_X(x)$ the cumulative distribution function of X. Therefore, the output oriented technical efficiency measure can 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:

$$\hat{\lambda}(x,y) = \sup\{\lambda \mid S_Y(\lambda y|x) > 0\} = \sup\{\lambda \mid H_{XY}(x,\lambda y) > 0\} \tag{10}$$

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

$$\hat{H}_{XY,n}(x,y) = \frac{1}{n}\sum_{i=1}^{n} I(x_i \leq x, y_i \geq y) \tag{11}$$

$$\hat{S}_{Y,n}(y|x) = \frac{\hat{H}_{XY,n}(x,y)}{\hat{F}_{X,n}(x)} = \frac{\hat{H}_{XY,n}(x,y)}{\hat{H}_{XY,n}(x,0)} \tag{12}$$

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 as: $\hat{\lambda}_{DEA}(x,y) = \sup\{\lambda \mid \hat{S}_{Y,n}(\lambda x|y) \in \hat{\psi}_{DEA}\}$. 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: $\lambda_m(x,y) = \int_0^\infty \left[1-(1-S_{Y|X}(uy|x))^m\right]du$. Similarly to DEA, it is also possible to obtain the order-*m* efficiency by plugging the conditional estimator:

$$\hat{\lambda}_{m,n}(x,y) = \int_0^\infty \left[1-(1-\hat{S}_{Y|X}(uy|x))^m\right]du \tag{13}$$

4.2. Conditional efficiency scores

In order to analyze the effect of environmental variables on the efficiency scores, we use the fully nonparametric conditional approach developed by Daraio and Simar (2005, 2007b). These authors 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 is defined as:

$$H_{XY|Z}(x, y|z) = \Pr(X \leq x, Y \geq y|Z = z) \tag{14}$$

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:

$$\begin{aligned} H_{XY|Z}(x, y|z) &= \Pr(Y \geq y|x \leq x, Z = z) \Pr(X \leq x, Z = z) \\ &= S_{Y|X,Z}(Y \geq y|X \leq x, Z = z) F_X(X \leq x; Z = z) \\ &= S_Y(y|x, z) F_X(x|z) \end{aligned} \tag{15}$$

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

$$\lambda(x, y|z) = \sup\{\lambda > 0 | S_{Y|XZ}(\lambda y|X \leq x, Z = z) > 0\} \tag{16}$$

The conditional order-*m* efficiency measure can be defined using the expression:

$$\lambda_m(x, y|z) = \int_0^\infty \left[1 - (1 - \hat{S}_{Y|X,Z}(uy|x, z))^m\right] du \tag{17}$$

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

$$\hat{S}_{Y,n}(y|x,z) = \frac{\sum_{i=1}^{n} I(x_i \leq x, y_i \geq y) K_{\hat{h}}(z, z_i)}{\sum_{i=1}^{n} I(x_i \leq x) K_{\hat{h}}(z, z_i)} \tag{18}$$

This approach relies therefore on the estimation of a nonparametric kernel function to select the appropriate reference partners and a bandwidth parameter *h* using some bandwidth choice method[6]. This would be straightforward if all the Z variables are continuous, but it becomes more complex if we have mixed data (continuous and discrete variables) as it is the case in our empirical study. De Witte and Kortelainen (2013) proposed a standard multivariate product kernel for continuous, ordered discrete and unordered discrete variables, in order to smooth these mixed variables and obtain a generalized product kernel function ($K_{\hat{\hat{h}}}$) and substitute it for $K_{\hat{h}}$ in equation 16. 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[7]. Subsequently, the conditional estimators $\hat{\lambda}(x, y|z)$ and $\hat{\lambda}_m(x, y|z)$ can be obtained by plugging in the new $\hat{S}_{Y,n}(y|x,z)$ in equations 14 and 15 respectively.

4.3. Determining the effect of environmental variables on efficiency measures

The 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 ($Q^z = \hat{\lambda}_m(x, y|z) / \hat{\lambda}_m(x, y)$) 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 smaller than $\lambda_m(x, y)$ for

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

[7] In the case of discrete variables, we assure that the performance of each unit is compared only to those in the same category (i.e., the same value of the discrete variable) by forcing the bandwidth to be zero for the variable in question.

smaller 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, so $\lambda_m(x, y|z)$ will be smaller than $\lambda_m(x, y)$ for larger values of Z (Daraio and Simar, 2005).

In addition, it is also possible to investigate the statistical significance of Z in explaining the variations of Q. For that purpose, we use local linear least squares for regression estimation as recommended by Badin *et al.* (2010) and Jeong *et al.* (2010). We then 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 (De Witte and Kortelainen, 2013).This model does not suffer from similar inference problems as those previously mentioned for two-stage models.

5. Data and variables

Data used in this study comes from the last wave of the World Values Survey (2005-06 WVS). This dataset provides information on individual socio-economic variables and attitudes and values regarding multiple aspects of life. Data comes from the responses given to a standardized questionnaire. The WVS uses the sample survey for data collection, a systematic and standardized approach to collect information through interviewing representative national samples of individuals. Samples are drawn from the entire population of 18 years and older without imposing upper age limit. In order to obtain representative national samples, some form of stratified random sampling procedure is made based on the given society statistical regions, districts, census units, election sections, electoral registers or voting stations and central population registers.

Although the entire dataset includes data about 57 countries, we focus on the 26 OECD countries participating in the survey. Once some observations have been removed due to the presence of missing data, our final dataset consists of 31,854 observations. The distribution of those individuals across countries is shown in Table 1.

Table 1. Dataset composition: Observations by country

Country	Observations	Country	Observations
Australia	1,282	New Zealand	806
Brazil	1,474	Norway	940
Canada	1,796	Poland	922
Chile	937	Russian Federation	1,660
China	1,553	Slovenia	981
Finland	925	South Africa	2,780
France	881	South Korea	1,195
Germany	1,823	Spain	1,085
Great Britain	808	Sweden	944
Indonesia	1,716	Switzerland	1,086
Italy	661	Turkey	1,303
Japan	968	United States	1,151
Mexico	1,386	**TOTAL**	**31,854**
Netherlands	791		

One of the main advantages of the WVS survey is that it offers a large international sample with consistent data across countries. Moreover, it provides information on most of the variables usually studied in the economic analyses on wellbeing, such as income, employment, health, or education, as well as on other multiple demographic and social variables such us age, gender, civil status or religion. However, the dataset does not provide information on other variables that have proved to be consistent predictors of subjective wellbeing, such as personality or life events[8].

Within the context of our study, we have considered three types of variables: output, inputs and background variables. As the output variable reflecting the level of SWB, we take a life satisfaction indicator derived from individuals' responses to the following question: ''*All things considered, how satisfied are you with your life as a whole these days*''. Responses are based on a scale from 1, which means 'completely dissatisfied', to 10, meaning 'completely satisfied'. The dataset also provides information about the level of happiness, but this indicator can be more influenced by emotions or feelings while life satisfaction involves a more cognitive construct (Nettle, 2005).

As input variables we have selected three variables that represent the main individual resources that contribute to wellbeing and which additionally fulfill the requirement of isotonicity (i.e., *ceteris paribus,* more input implies equal or higher level of output). The

[8]Studies analyzing the effect of variables such as personality, culture or life events can be found, for example, in Headey and Wearing (1989), Schimmack *et al*. (2002) or Diener *et al*. (2003).

first one is the level of income, represented by the relative position of the individuals in the income distribution of their country (in deciles)[9]. The second is the level of education, which is also grouped into ten different categories according to total years of completed education. Third, we have an indicator of the health status perceived by the individuals in a four-level scale (poor, fair, good or very good).

Finally, we also take account of some other well-known individual background variables that the literature identifies as common factors associated with the levels of SWB. In particular, we consider two continuous variables representing the age of the individual and its squared value[10], so we can test the possibility of having a U-shaped curve. In addition, four unordered categorical dummies have been considered in order to take into account the gender of the individuals, and whether they are religious, unemployed or married. These variables have a value equal to 1 for those conditions (female in the case of gender) and equal to 2 otherwise, so that there are no zero values in data. An ordered categorical variable representing the number of children is also included in the analysis. Again, in order to avoid zero values in data, we have re-scaled the original values in the variable, thus the value 1 corresponds to having no child, the value 2 means that the individual has one child, and so on. Table 2 reports the descriptive statistics for all these variables.

Table 2. Descriptive statistics

Variable	**Type**	**Mean**	**Std. Dev.**	**Min**	**Max**
SWB	Output	7.2747	2.0376	1	10
Health	Input	2.9147	0.8494	1	4
Education	Input	4.7725	2.2537	1	8
Income	Input	4.8401	2.4490	1	10
Age	Background	45.6860	16.7858	16	104
Age_sq	Background	2369.1310	1651.2510	256	10816
Gender	Background	1.5200	0.4996	1	2
Religious	Background	1.4017	0.4903	1	2
Unemployed	Background	1.9217	0.2686	1	2
Married	Background	1.3675	0.4821	1	2
Children	Background	2.6719	1.5783	1	9

[9]Considering relative income is usual in the happiness literature and it is generally found that relative income shows at least as much influence on individual satisfaction as absolute income. For a discussion of the effects of absolute vs. relative income in perceived wellbeing, see Clark *et al.* (2008).
[10]More precisely, and to avoid multicollinearity problems, we considered the squared difference between age and mean-age instead of age^2.

On average, individuals in the sample seem to be quite satisfied with their life, with a mean value of 7.2 out of 10. Most of them report to enjoy a good health, while the mean levels of education and income are slightly above and below the average, respectively. With regard to background variables, we observe that our sample is almost evenly distributed by gender (women representing 52 % of the individuals and men 48 %), the average age is around 46 years, 40% of individuals declare to be religious, 37% are currently married and 8% are unemployed. Finally, the mean number of children is placed between one and two, with a maximum value of eight (these values correspond to the original variable before being re-scaled).

6. Results

The main results of the efficiency estimations for both the unconditional and conditional models are summarized in Table 3. In both cases, we estimate the robust order-*m* model ($\hat{\lambda}_m$) using an output orientation. 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*=100.For statistical inference, we use 200 bootstrap replications.

Table 3. Efficiency estimates

	Average	**Std.Dev**	**Minimum**	**5%**	**1st quartile**	**Median**	**3rd quartile**	**95%**	**Maximum**
Unconditional	1.6465	1.2929	0.9999	1.0000	1.1111	1.2500	1.6667	3.3333	10.0000
Conditional	1.5253	1.0802	0.9920	1.0000	1.1110	1.2500	1.4679	2.5000	10.0000

The values presented in the first row (unconditional model), where we do not account for background variables, show an average inefficiency score of 1.64 and a median value of 1.25. However, there is large variation among individuals, as can be seen from the sizeable standard deviation of 1.293 around the average efficiency. These results indicate that a high proportion of individuals could enjoy better SWB according to their situation in terms of income, education and health. Nevertheless, it is also worth noting that some individuals present a performance score below 1, which means that they are performing better than the average 100 individuals in their reference sample. Once we include information about the seven background variables considered in the analysis (conditional model in the second raw), the average efficiency decreases to 1.525, although the median value remains the same (1.25). This is intuitive since the reference sample includes only individuals with similar characteristics. As a result, the variation among individuals is also more reduced (1.080) in this new model.

Some interesting results can be derived by exploring the distribution of the efficiency scores across countries. Table 4 reports the average estimates for both models (unconditional and conditional) in each of the 26 OECD countries considered in our study. Those values are lower for the conditional model, but the ranking of countries is not too influenced by the inclusion of background characteristics[11]. Using this information, it is possible to construct a classification of countries according to the ability of their individuals to maximize their levels of life satisfaction. In this ranking, Netherlands, Norway, Switzerland, Sweden, Finland and New Zealand would be identified as the best performers, while the poorest results are found in transitional economies like the Russian Federation, China, South Korea or Indonesia.

Table 4. Efficiency score distribution across countries

COUNTRY	**UNCONDITIONAL**			**CONDITIONAL**		
	Rank	**Mean**	**Std. Dev.**	**Rank**	**Mean**	**Std. Dev.**
Australia	13	1.5682	1.0661	13	1.4529	0.8064
Brazil	14	1.5793	1.3188	12	1.4527	1.0942
Canada	6	1.4341	0.8167	9	1.3690	0.7307
Chile	15	1.5945	1.0592	15	1.4837	0.8926
China	25	1.9836	1.8478	23	1.7000	1.3833
Finland	7	1.4572	0.9848	4	1.3429	0.8732
France	19	1.7043	1.1578	17	1.5059	0.7790
Germany	21	1.7144	1.1742	21	1.5405	0.8726
Great Britain	8	1.4617	0.9403	8	1.3640	0.6696
Indonesia	23	1.8019	1.5303	24	1.7348	1.4176
Italy	17	1.6512	1.0761	20	1.5279	0.7308
Japan	16	1.6271	0.9840	16	1.4955	0.7993
Mexico	10	1.4840	1.4264	10	1.3879	1.2078
Netherlands	2	1.3625	0.4794	1	1.2664	0.3646
New Zealand	4	1.4018	0.7959	6	1.3598	0.7184
Norway	1	1.3492	0.7363	2	1.2922	0.6539
Poland	18	1.6977	1.2210	19	1.5250	0.8822
Russian Federation	26	2.3113	2.1292	26	2.1501	1.8863
Slovenia	11	1.5404	0.8727	11	1.4202	0.6155
South Africa	22	1.7575	1.5556	22	1.6197	1.3435

[11] The Spearman correlation coefficient between both indicators is 0.889.

South Korea	24	1.9074	1.4671	25	1.8427	1.4084
Spain	9	1.4637	0.6473	7	1.3615	0.4182
Sweden	5	1.4085	0.7694	5	1.3498	0.6603
Switzerland	3	1.3758	0.7406	3	1.3359	0.6192
Turkey	20	1.7118	1.6063	18	1.5229	1.2660
United States	12	1.5576	0.9656	14	1.4631	0.8220
TOTAL		**1.6465**	**1.2929**		**1.5253**	**1.0802**

These results based on an efficiency approach are in accordance with the international evidence about the levels of satisfaction across countries using regression equations or simple tabulations. A number of the small social-democratic countries in Europe are consistently estimated to be among the world's happiest nations (Fahey and Smyth, 2004, Deaton, 2008), and the results of the efficiency approach followed in this study also point to these countries as having certain institutional characteristics which enhance the efficiency with which the individuals living in these countries maximize their levels of wellbeing given their individual set of resources. The causes behind that evidence are difficult to isolate, although these "happy countries" are characterized by having low levels of inequality (Winkelmann and Winkelmann, 2010), high social capital (Bjornskov *et al.*, 2008), high levels of democratic participation (Helliwell and Huang, 2008) and strong welfare states with high levels of public spending (Pacek and Radcliff 2008).

Moreover, the average efficiency scores achieved by individuals from countries such as United States, Japan and, especially, Germany, allow us to reinforce one of the main conclusions derived from the literature focused on explaining the cross-country pattern of subjective well-being as regards the limited role of GDP as a good measure of welfare (Di Tella and MacCulloch, 2008; Blanchflower and Oswald, 2011), showing that living in richer countries does not necessarily enhance the efficiency with which the individuals convert their individual resources into higher levels of wellbeing.

Finally, in order to examine the influence of the individual background variables on happiness efficiency estimates, we regress the ratio between the conditional and the unconditional efficiency scores on those background variables using the local linear estimator described in Section 3.3. Table 5 presents the p-values of the significance tests proposed by Li and Racine (2004) and Racine and Li (2004) obtained after performing

500 bootstrap samples. Results suggest that all the considered variables have a significant impact on individuals´ performance, with the only exception of being married, which is not found to significantly contribute to the process by which individuals convert their resource into happiness.

Table 5. Nonparametric significance test

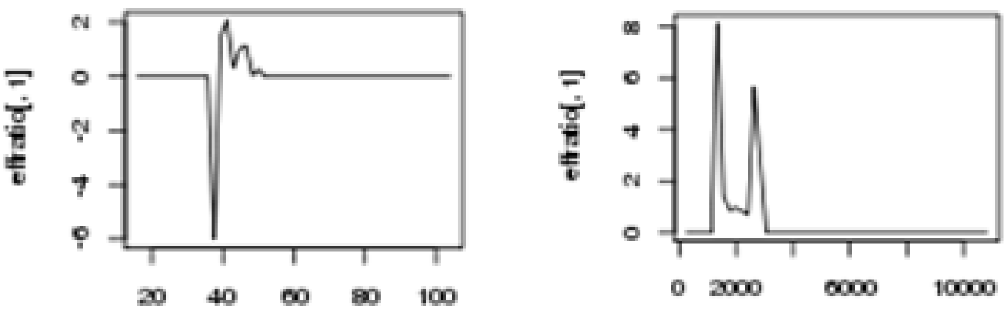
Variable	p-value
Age	0.001***
Age_sq	0.001***
Gender	0.001***
Religious	0.001***
Unemployed	0.001***
Married	0.305
Children	0.001***

*** denotes statistical significance at 1%

As we are interested in identifying the direction of the influence of these background variables on efficiency scores, we analyze these ratios against the contextual variables. Following Daraio and Simar (2005, 2007a), we examine the partial regression scatter plots to visualize and interpret these effects. First, we present the plots for the continuous variables representing the age (Figure 1), which allow us to observe that the average effect has a U-shaped, with the lowest values placed near 40. Likewise, the effect of age squared is favorable, especially for younger people. This result is in line with previous literature about the determinants of life satisfaction (Easterlin, 2006), showing that age does not only contribute to explain absolute levels of wellbeing but also the efficiency with which these levels are reached.

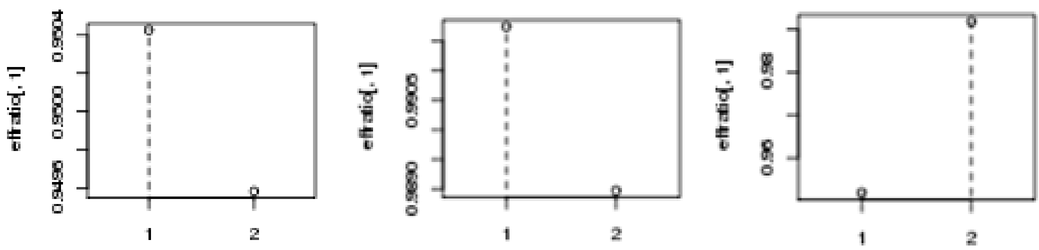
Figure 2 presents the partial regression plots for the categorical variables. In this case, we estimate average efficiency scores for different values of the variables and then we compare these average values. Again, the results are in line with the previous literature on the determinants of subjective wellbeing, although it is worthy to note that, in our case, the dependent variable is the level of efficiency demonstrated by individuals to reach certain levels of life satisfaction given their available resources. In this case, women, religious people and those who are not unemployed seem to be more efficient in the conversion process of resources into happiness. The effect of being married also show the positive sign which is generally found in the literature on the determinants of wellbeing, although, as mentioned before, this effect seems to be non significant to explain happiness efficiency. Finally, as regards the children variable it is found that the number of children has a favorable effect on relative happiness, although this effect is maintained only until the second children and then it becomes unfavorable (remember that the value 3 indeed represents only 2 children).

Figure 1. The effect of age on efficiency scores

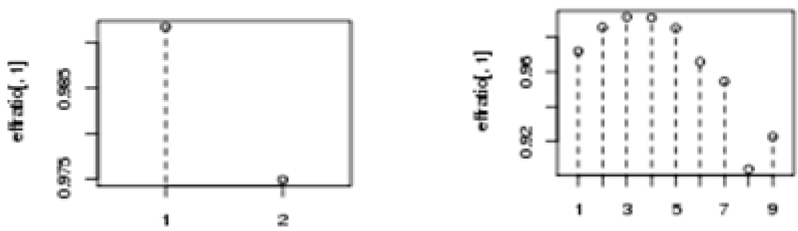


Age Age squared

Figure 2. The effect of discrete variables on inefficiency



Gender Religious Unemployed



Married Children

7. Concluding remarks

This paper aimed to extend the literature on subjective wellbeing by developing an innovative approach to estimate measures of individuals´ performance based on how efficiently they convert their available resources into happiness. Those measures are based on the construction of an efficient frontier using nonparametric techniques employed in production theory. Specifically, we use a robust conditional approach to introduce the effect of various contextual variables (both continuous and discrete) associated to individual wellbeing into the analysis. This method allows us to avoid the restrictive separability assumption between the input-output space and the space of environmental variables required by traditional approaches and thereby provide meaningful results.

This methodology has been applied using international data from 26 OECD countries participating in the World Values Survey (2005-06 WVS). Ranking these countries according to their performance in terms of happiness, the obtained results indicate that individuals with the highest average levels of happiness efficiency are the inhabitants of a group of small social-democratic countries in the Northern and Central Europe composed by Netherlands, Norway, Sweden and Switzerland. In contrast, the worst performers are four transition countries represented by the Russian Federation, China, South Korea and Indonesia. Given that the average efficiency scores before considering individual background variables (unconditional model) does not change too much with the inclusion of those variables (conditional model), we can conclude that the heterogeneity detected across countries cannot be explained by the considered individual factors. Therefore, further research is needed about the potential effect attributable to institutional or environmental factors. For instance, it is possible to find some common patterns among countries with the happiest individuals, such as low levels of inequality or high public expenditures, but it is necessary to explore whether these factors might have an influence on happiness efficiency as well.

The statistical significance of the contextual variables on efficiency scores leads to support previous evidence found in the empirical literature on the determinants of subjective wellbeing, suggesting that the effects of these variables may act through the efficiency with which individuals convert their resources into wellbeing. Thus, women and religious people seem to be more efficient in reaching higher levels of life satisfaction, which can be interpreted that they need less to be happy. Age is also an important factor in determining the happiness efficiency, although our results indicate that its effect is mainly concentrated in early years. Finally, having children is also relevant for explaining efficiency levels in terms of happiness, especially for parents having a low number of children.

This paper represents one of the first attempts to measure efficiency in the context of human subjective wellbeing, in which we advocate for the importance of considering the factors employed by individuals in their search for happiness, since the perception of people about their levels of satisfaction might mask high divergences in terms of available resources.

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