Weighting life domains with *Data Envelopment Analysis*

Jorge Guardiola (University of Granada, Spain; jguardiola@ugr.es)
Andrés J. Picazo-Tadeo (University of Valencia, Spain; andres.j.picazo@uv.es)

Abstract. The specialised literature has frequently addressed the relationship between life domains and people's satisfaction with life. Some researchers have posed questions regarding the importance of domains, therefore interpreting them as weights and creating domain satisfaction indices. This paper employs *Data Envelopment Analysis* (DEA) and *multi-criteria-decision-making* techniques to obtain a series of computer-based weightings for life domains from a sample of 178 people living in a rural community in Yucatan (Mexico). The main feature of these weightings is that they might differ from one individual or domain to another. Consequently, several weighting schemes are used to compute different DEA-based life satisfaction indices and also a constant *equally-weighted* index. Based on the *goodness-of-fit* criteria commonly employed in this literature, our main result is that computer DEA-based indicators do not improve the relationship with self-reported life satisfaction in comparison to the *equally-weighted* index of life satisfaction.

Keywords. *Data Envelopment Analysis*; domains of life satisfaction; life satisfaction indicators; *Multi-Criteria-Decision-Making*; weightings.

1. Introduction

The literature on the domains of life states that life satisfaction can be related to a general construct involving the satisfaction of specific domains of life. Examples of these domains are people's satisfaction with their marriage, leisure, health, job or financial status. However, the field of domain analysis still has issues that are open for debate. One of these issues is causality, as domain satisfaction is assumed to influence life satisfaction in two possible ways. Firstly, the *bottom-up model* interprets domains of life as causes of life satisfaction, that is, people evaluate their satisfaction in several domains, giving rise to general satisfaction with life. On the other hand, the *top-down interpretation* assumes that satisfaction with life might be determined by personality traits rather than circumstances and, therefore, life satisfaction would determine domain satisfaction (Diener, 1984). Some research has tested both models (Lance et al., 1989; Headey et al., 1991) finding both kinds of effects for several domains. As a result, the debate over which model is the best remains an ongoing issue.

In addition to causality issues, the nature of the domains that determine life satisfaction is a matter of controversy. While some researchers have centred their attention on several domains (e.g., Cummins, 1996; Møller and Saris, 2001; Rojas, 2006, 2007; van Praag et al., 2003), others have focused on the importance of a particular domain and how it affects life satisfaction. Examples of the latter include Michalos et al. (1999) for health, Clark and Oswald (1994) for job satisfaction, Wills (2007) for spirituality and Guardiola et al. (2013a, 2013b) for water access. The number of domains to study is not clear, as the literature has addressed more than 170 (Cummins, 1996). Moreover, some of the studies focusing on a single domain highlight its importance in a certain context or culture that may not be of any use in another scenario when it comes to explaining life satisfaction.[1]

Subjective well-being studies have also attempted to assign weightings to life domains, an issue that has generated widespread debate. There are at least two ways of identifying the weighting or importance of domains. The first involves computer-based methods, such as factor analysis (e.g., Campbell et al., 1976), econometric regressions (e.g., Rojas, 2006, 2007; van Praag el al., 2003) and structural equation modelling (e.g., Møller and Saris, 2001).[2] In the second, surveys are conducted to ascertain the importance that individual respondents assign to each domain (e.g., Campbell et al., 2006; Hsieh, 2003, 2004, 2012a, 2012b; Wu, 2008; Wu and Yao, 2006, 2007). The first branch of the literature normally applies regression methods such as ordinary least squares or ordered *probit* or *logit* models to explore whether each domain is statistically significant in explaining life satisfaction and, should this be the case, what their marginal effect is. Statistical significance means that the domain is important and in this case, the greater the marginal effect, the more important it is. In order to choose the domains before incorporating them into the regressions, a correlation matrix or factor analysis could disregard those which are overly correlated to others, leading to the conclusion that they explain a similar dimension of life.

The second branch of the literature is rather different due to relying on the opinion of respondents instead of statistical analysis to gauge the importance of individual domains. In addition to enquiring about domain satisfaction, the researcher asks respondents to score each domain in terms of importance, using a *Likert*-type scale.[3] For

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[1] Choosing the domains to describe life satisfaction is not, therefore, an easy task. Rojas (2006) proposed three criteria to choose domains: *parsimony* (the number of domains must be manageable and represent separate information), *meaning* (they should be related to the way people think about their lives) and *usefulness* (they must contribute to the understanding of the subject). Beyond the criteria of the researcher or the limitations of data to choose the domains, techniques such as factor analysis can be used to group domains when they are too numerous.

[2] Computer-based methods using econometric regressions normally employ *bottom-up* approaches, while structural equation modelling can take into account both *bottom-up* and *top-down* approaches.

[3] Other weighting measures beyond importance have also been proposed, such as ranking several domains, ordering them from the most important to the least important for respondents (e.g. Hsieh, 2003) and rating the direct *have–want* discrepancy. For example, Wu (2009) rates the *have–want* discrepancy for several domains using a 5-point *Likert*-type scale ranging from -4 (marked discrepancy from the *want* status) to 0 (the same as the *want* status).

instance, Hsieh (2003) asked people to evaluate eight domains of life satisfaction and the importance of each domain as follows: (1) not at all important, (2) not too important, (3) somewhat important, (4) very important, or (5) extremely important.

The decision on whether or not to assign weightings to domains should depend on separate criteria in order to be able to independently assess whether or not doing so actually yields better results. The criteria for ascertaining whether or not it is better to assign the weightings used in most of the studies mentioned previously is to analyse whether weighting enhances the relationship between domains of life and life satisfaction. This analysis is normally performed using measures of correlation between a weighted domain index and life satisfaction or by using a *goodness-of-fit* indicator in a regression analysis.

On a different note, in view of the empirical research on the topic of whether or not to weight domains, researchers that plan to implement field work should consider whether the benefits of incorporating weightings (in terms of understanding the quality of life) outweigh the costs involved in adding more questions to the survey. If this were not the case, it would be reasonable to drop weighting. The literature offers support for both strategies, the debate being more heated in the empirical literature that questions individuals about weightings than in the branch of the research devoted to calculating domain importance by means of statistical analysis. On the one hand, regarding the evidence that empirically demonstrates that it is better not to assign weightings, Campbell et al. (1976) find that domain importance weighting does not improve the total variance in the life satisfaction measure that is explained by the domains. In a similar vein, Wu (2008) and Wu and Yao (2006, 2007) demonstrate that weighting by importance does not influence global satisfaction, suggesting that domain satisfaction already incorporates domain importance. In addition, Hsieh (2003, 2004) finds that introducing importance as weightings did not improve the correlation with life satisfaction.

On the other hand, research suggests that weighting has theoretical and empirical advantages over not weighting. In light of the evidence against weighting, as Hsieh (2004) states, the issue is not *to weight or not to weight*, but *how to weight*. Using a shifting tendency index as a method to weight domains, Wu (2009) improves correlation with global satisfaction.[4] The literature on computer-based designs also supports more complex non-linear models that use domains to explain life satisfaction, as they help to better explain satisfaction with life (Rojas, 2006, González et al., 2010). Although there

[4] The shifting tendency index was calculated using the correlation of the level of *have–want* discrepancy (high values denote low discrepancy) and importance (high values represent greater importance) for the domains of life.

is some room to believe that alternative weighting schemes could increase correlation with satisfaction with life, the debate remains ongoing, as opposition to this view has arisen. For instance, Wu (2008) uses four different weighting algorithms without achieving any improvement in predicting life satisfaction.

The discussion continues and theoretical arguments support weighting on the basis of methodological criteria (Hsieh, 2012a, 2012b). In view of the propositions referring to the advent of new weighting schemes for domains of life, we contribute to this debate by introducing *Data Envelopment Analysis* (DEA) as an alternative computer-based approach to weighting the domains of life according to importance, as well as constructing domain-based composite indices of life satisfaction.

The main feature of DEA techniques for the purpose of our research is that the weightings assigned to life domains when building life satisfaction indices are generated endogenously without resorting to exogenous information or personal preferences. Moreover, these weightings might differ across domains and individuals. As commented in detail in the Section on methodology, the computation of such a scheme of weightings is based on the so-called *benefit of the doubt principle* (Cherchye et al., 2007). The central idea of this principle is to construct a domain-based life satisfaction indicator by assigning each individual the scheme of weightings that would rate him/her in the best position when compared to all other individuals in the group he/she belongs to using the same scheme of weightings. In a second stage, in order improve the discriminatory power of our DEA-based composite indicators of life satisfaction we combine DEA with *Multi-Criteria-Decision-Making* (MCDM) techniques to calculate a composite index of life satisfaction with weightings that vary across domains, but which are common across individuals. This latter approach makes it possible to rank domains according to their relative importance.

These approaches are illustrated using an empirical application to compute life domain weighting schemes and composite indices of life satisfaction for 178 individuals that belong to the Mayan community, in a rural area of Yucatan (Mexico). Our DEA-*Benefit-of-the-doubt* and MCDM-based indices of life satisfaction, as well as a common constant *equally-weighted* index of life satisfaction, are then compared to the self-reported life satisfaction of the individuals in the sample. While similar approaches have been taken to building composite indicators at macro-level (e.g., Reig-Martínez, 2012), several recent applications have also focused on micro-level, including André et al. (2010), Rogge (2011), Reig-Martínez et al. (2011), and Bernini et al. (2012).

Judging by the results obtained in this study, weighting life domains and computing domain-based composite indicators of life satisfaction with DEA seems to have both strong and weak points, which are discussed later in the paper accordingly. The greatest advantage is that the weightings assigned to the life domains are endogenously computed and might differ across life domains and individuals. On the weak side, DEA techniques do not seem to improve the life satisfaction-domain satisfaction relationship based on the *goodness-of-fit* criteria commonly employed in this literature, at least in the case of the Mayan people in our sample research.

The rest of the paper is organised as follows. Section 2 discusses the main features of the methodology. Section 3 presents the data and results, while a final Section discusses the results and suggests some avenues for future research.

2. Weighting life domains with *Data Envelopment Analysis*

Data Envelopment Analysis (DEA) techniques were introduced by Charnes et al. (1978) in a paper that used mathematical programming to pursue Farrell's approach to measuring the efficiency of production units (Farrell, 1957). Instead of just a single-output and single-input measure, DEA deals with multiple outputs and multiple inputs. The essence of this technique is to compare each production unit in a sample to the best observed practices in terms of a performance indicator (further details are available in Cooper et al., 2007).

The theoretical framework underlying the basic DEA model is a production function that represents the process of transforming a set of inputs x_i ($i=1,\ldots,I$) into a set of outputs y_o ($o=1,\ldots,O$). Under certain assumptions regarding the underlying technology (see Shephard, 1970), the relative efficiency of each Decision Making Unit (DMU) k' within a given sample ($k=1,\ldots,K$) is evaluated by the maximum of a ratio between a composite indicator of output and a composite indicator of input. Formally:

$$
\begin{aligned}
& Maximise_{u_{ok'},v_{ik'}} \quad \frac{\sum_{o=1}^{O} u_{ok'} y_{ok'}}{\sum_{i=1}^{I} v_{ik'} x_{ik'}} \\
& Subject\ to: \\
& \qquad \frac{\sum_{o=1}^{O} u_{ok} y_{ok}}{\sum_{i=1}^{I} v_{ik} x_{ik}} \le 1 \qquad k=1,\ldots,K, \\
& \qquad u_{ok} \ge 0 \qquad\qquad\quad o=1,\ldots,O \\
& \qquad v_{ik} \ge 0 \qquad\qquad\quad i=1,\ldots,I
\end{aligned} \tag{1}
$$

where u_o and v_i represent the weightings assigned to particular outputs and inputs in the construction of their respective composite indicators. These weightings are assumed to be non-negative and their optimal values express how highly outputs and inputs are rated (Cooper et al., 2007:25); e.g., the solution to u_o would provide a measure of the relative contribution of y_o to the optimal value of the efficiency ratio in expression (1).

One relevant feature of DEA techniques is that weightings are endogenously generated at DMU level using, as noted in the introduction, the so-called *benefit of the doubt principle* (Cherchey et al., 2007). According to this criterion, each DMU is evaluated using the set of weightings that rates it in the most favourable light when compared to all other DMUs in the sample using the same set of weightings, subject to the constraint that all the efficiency ratios for each DMU in the sample have an upper limit of one as a normalisation criteria. Weightings are thus idiosyncratic and differ across observations and also outputs and inputs.

The basic DEA model can be easily transformed to compute a composite indicator of life satisfaction.[5] After a simple transformation of expression (1) from a fractional to a linear program (see Cooper et al., 2007:23), assuming a single input equal to unity for each observation (Lovell et al., 1995) and replacing outputs with life domains ld_d ($d=1,\ldots D$) and DMUs with individuals, a composite indicator of life satisfaction, which is denoted by ls, for individual k', can be computed as:

$$\begin{aligned}
&Maximise_{\mu_{dk'}}\ ls_{k'} = \sum\nolimits_{d=1}^{D} \mu_{dk'} ld_{dk'} \\
&Subject\ to: \\
&\qquad \sum\nolimits_{d=1}^{D} \mu_{dk} ld_{dk} \le 1 \qquad\qquad k = 1,\ldots,K \\
&\qquad \mu_{dk} \ge 0 \qquad\qquad\qquad\qquad d = 1,\ldots,D
\end{aligned} \tag{2}$$

where $ld_{dk'}$ represents the value of life domain d for individual k' and $\mu_{dk'}$ the weighting assigned to domain d in the assessment of the life satisfaction of individual k'.

Noticeably, instead of measuring the relative efficiency of DMUs in an input-output framework, as expression (1) does, the objective function in expression (2) entails the attainment of the maximum value for a composite indicator of life satisfaction made up of a weighted average of a set of partial indicators corresponding to different domains of life. The idiosyncratic nature of the structure of weightings means in this case that no exogenous information or *a priori* judgments on the relative importance of life domains are required to construct the composite indicator of life satisfaction. Furthermore, according to the *benefit of the doubt principle*, the weightings of life domains are chosen in such a way that they maximise the life satisfaction index of each individual relative to all other individuals in the sample. Accordingly, life domains in which an

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[5] Zhou et al. (2007) highlight the ability of DEA techniques to build composite indicators reflecting a variety of economic, social and environmental factors (see also Zaim et al., 2001). Furthermore, some researchers have used several variants of these techniques to compute quality of life indicators, including Hashimoto and Kodama (1997); Zhu (2001); Murias et al. (2006); Jurado and Perez-Mayo (2011); Domíguez-Serrano and Blancas (2011).

individual manifests a low level of satisfaction will be assigned a lower weighting when constructing his/her index of life satisfaction.

While flexibility in determining the structure of optimal weightings constitutes one of the main strong points of the DEA-*Benefit-of-the-doubt* approach to computing a composite indicator of life satisfaction, this technique might not be so advantageous when it comes to ranking individuals according to their satisfaction with life. There are several reasons for this. In the first place, DEA techniques assess life satisfaction by comparing each individual with a different set of peers and, also, using different sets of weightings for life domains, which makes it difficult to compare individuals on a common basis (Kao and Hung, 2005). Second, optimisation algorithms used to find a solution to program (2) could lead to a set of optimal weightings that assign low or even null importance (i.e., awarding a weighting of zero) to life domains that are considered important by experts in well-being. Moreover, great importance might be given to life domains judged as scarcely relevant. Finally, an individual could be deemed to be fully satisfied with his/her life (i.e., awarded an index of life satisfaction equal to one) due to the lack of discriminatory power of the DEA model. This problem usually arises when there is only a small number of individuals in the sample in regard to the number of life domains included in the life satisfaction indicator.

The literature in this field of research has proposed different solutions to addressing the abovementioned shortcomings of DEA-based models in the assessment of relative efficiency, or life satisfaction as in this research. In the case of unrealistic endogenous idiosyncratic weightings, the opinion of experts, or other *ad hoc* criteria, can be used to impose *a priori* restrictions on program (2) regarding the relative importance of different life domains (i.e., restrictions on the optimal set of weightings)[6]. This approach leads to restricted multiplier models such as the *region-assurance* model or the *cone-ratio* model (Charnes et al., 1990; see also Cooper et al., 2007:178). The so-called *cross-efficiency* approach (Sexton, 1986) also faces this problem due to enlarging the set of weightings used to evaluate each individual life satisfaction considering not only the individual's most favourable set, but also the set of most favourable weightings for all other individuals in the sample. Furthermore, in a recent paper, Zhou et al. (2007) introduced a simple method that, adapted to our case study, would consist of computing a composite indicator of life satisfaction as a linear combination of two indices computed for each individual under the sets of most and least favourable weightings, respectively. However, the relative importance that researchers assign to both sets of weightings entails introducing some degree of arbitrariness in the method.

[6] Allen and Thanassoulis (2004) review the techniques available to incorporate weighting restrictions into the framework of DEA-based models.

Regarding the lack of capacity of DEA-based models to discriminate between individuals according to their life satisfaction, several potential solutions have been proposed, including *principal component analysis*, which eliminates redundant information in life domains, thus reducing the dimensionality of the problem (Adler and Golany, 2002); *super-efficiency-analysis*, which relaxes the upper bound of one for the life satisfaction indicator by excluding the individual evaluated from the reference set (Andersen and Petersen, 1993); or other simpler solutions such as that proposed by Torgersen et al., (1996), which discriminates between efficient units, or satisfied individuals in our case, taking into account the number of times they appear as efficient (satisfied) peers for other individuals.

One stream of literature proposes combining DEA and *Multi-Criteria-Decision-Making* (MCDM) techniques to overcome the shortcomings of lack of discriminating power and unrealistic idiosyncratic weightings in DEA-*Benefit-of-the-doubt* models (see Golany, 1988; Despotis, 2002; Jahanshahloo, 2005). Discriminating power would be improved through the introduction of multiple criteria concerning life satisfaction assessment, while preserving a common set of weightings for life domains across the individuals in the sample. In this sense, a common set of weightings might be preferable as it provides a single measure of the relative importance of each life domain in the composite life satisfaction indicator. Golany (1988) was the first to propose the integration of DEA and *multi-objective-programing*, a particular MCDM technique, to find common weightings. Furthermore, Li and Reeves (1999) proposed a *Multiple-Criteria-Data-Envelopment-Analysis* (MCDEA) model that combines *minimax* and *minsum*-type objective functions with the classical DEA objective function.

In this line of research, Despotis (2002) proposed the so-called *global-efficiency* approach, which combines DEA and MCDM and, in our case, would permit the calculation of a common set of weights across all individuals in the sample to achieve *global-life-satisfaction* scores. The linear form of this model is (Despotis, 2005):

$$
\begin{aligned}
&Minimise_{c_k,\mu_d,z}\ t\frac{1}{K}\sum_{k=1}^{K} c_k + (1-t)z \\
&Subject\ to: \\
&\qquad \sum_{d=1}^{D} \mu_d\, ld_{dk} + c_k = ls_k^* && k = 1,\dots,K \\
&\qquad (c_k - z) \le 0 && k = 1,\dots,K \\
&\qquad c_k \ge 0 && k = 1,\dots,K \\
&\qquad \mu_d \ge \varepsilon && d = 1,\dots,D \\
&\qquad z \ge 0
\end{aligned}
\qquad (3)
$$

ε being a *non-Archimedean* small number that assures all life domains ld_d are considered with positive weightings in the computation of life satisfaction scores. Furthermore, c_k

is a measure of the distance between the unconstrained DEA-*Benefit-of-the-doubt* score of life satisfaction for individual k with idiosyncratic weightings, namely ls_k, and his/her life satisfaction score constrained to common weightings for life domains, namely the DEA-*Benefit-of-the-doubt*-MCDM score.

In program (3), different sets of common weights and global life satisfaction scores might be generated by changing the parameter t between values zero and one, thus providing more or less relative importance to the norms implied by the first and second terms of the objective function. As highlighted by Bernini et al. (2012), different values for t represent different theoretical assessments. Accordingly, a value for this parameter equal to one corresponds to the *city-block* or *Manhattan* concept of distance, the objective function to be minimised, becoming the average deviation across individuals between their DEA-*Benefit-of-the-doubt* scores of satisfaction with life computed with the most self-favourable scheme of weightings, namely ls_k^*, and global life satisfaction scores with common weightings. Following Bernini et al., (2012), we call this solution the *collective optimum*, as the structure of common weights maximises the mean of satisfaction life indicators across individuals.

On the opposite side, when t takes a value of zero, which corresponds to the *Chebychev* concept of distance, the objective function to be minimised, through the non-negative variable z, is the maximal deviation between the DEA-*Benefit-of-the-doubt* score of life satisfaction and the score computed with a common scheme of weightings. Bernini et al. (2012) call this solution the *most penalised individual optimum*, because it maximises the life satisfaction score of the most penalised individual in the unconstrained idiosyncratic weightings DEA-*Benefit-of-the-doubt* solution. Different values of t between zero and one represent different schemes of preferences regarding these two extreme objectives, leading to different structures of common weightings and rankings of individuals according to their life satisfaction.

Finding the common weightings solution for expression (3) requires previously computing a set of DEA-based-scores of life satisfaction allowing for idiosyncratic weightings, namely, DEA-*Benefit-of-the-doubt* scores. Instead of using expression (2) directly, as other papers do (Bernini et al., 2012), here we follow the approach by Reig-Martínez et al., (2011) and Reig-Martínez (2012), which consists of using the additive output-oriented *slacks-based measure* (SBM) introduced by Tone (2001).[7] Contrary to the approaches based on radial or proportional measures, the SBM measure integrates both proportional potential improvements in all life domains, i.e., radial efficiencies in genuine efficiency terminology, and slacks into a single scalar measure of life satisfaction. Formally, life satisfaction for individual k' is computed as:

[7] This model is closely related to Russell's non-radial efficiency model (Russell, 1985).

$$ls^*_{k'} = Min_{\lambda_k, s_d^+} \frac{1}{1+\frac{1}{D}\sum_{d=1}^{D} s_d^+ / ld_{dk'}}$$

$$\begin{aligned}
&\textit{Subject to}: \\
&\qquad x_{k'} \geq \sum_{k=1}^{K} \lambda_k x_k \\
&\qquad ld_{dk'} = \sum_{k=1}^{K} \lambda_k ld_{dk} - s_d^+ && d = 1,\ldots,D \\
&\qquad \lambda_k \geq 0 && k = 1,\ldots,K \\
&\qquad s_d^+ \geq 0 && d = 1,\ldots,D
\end{aligned} \tag{4}$$

where s_d^+ is the slack in the domain of life d and λ_k represents the intensity with which each individual k in the sample enters the reference set to which individual k' is being compared. Moreover, the parameter $ls_{k'}$ is upper-bounded to one, with a unity score indicating best satisfaction. Finally, x is assumed to be a single vector of ones for each individual (once again, see Lovell et al., 1995).

3. Data, variables and results

3.1. Data and variables

The dataset used in this paper comes from original field work carried out in 2008 in a rural area of Yucatan (Mexico). Sampling was random and performed in 39 towns in proportion to the size of their population. In particular, our sample is made of 178 Mayan people who at the time of their interviews declared they were not going hungry. Further information on this database and the region of study can be found in Guardiola et al. (2013a, 2013c). The domains of life used in this study refer to the *health* of the people interviewed, their *work*, the *money* they earn in the household, the quality of the *house* where they live, the *nurture* they experience, their *leisure* time, the *community* where they dwell as a physical space, their access to *water* in the household, the *love* they experience and the *confidence* they have in other people.

In order to value the life satisfaction of the individuals in our sample, they were first asked: *In general terms, how happy do you feel with your life?* Additionally, for each domain of life, they were asked: *How happy do you feel in relation to…?* and then the domain of life was named. Respondents were asked to rate their life satisfaction and satisfaction with domains of life on a *Likert*-scale ranging from 0 to 10, where 0 means *very unhappy* and 10 *very happy*. Table 1 presents some descriptive statistics for overall life satisfaction and also satisfaction with the different domains of life considered. Overall satisfaction averages 8.3, the highest satisfaction scores for the domains considered corresponding to *love*, access to *water*, *confidence* and *nurture*.

PLEASE, INSERT TABLE 1 AROUND HERE

3.2. Results

In this paper, as noted in the introduction, we compute several composite indicators of life satisfaction for the 178 individuals in our sample using different weighting schemes. In the first place, we have calculated an *equally-weighted* indicator by averaging the ten life domains considered into a single composite life satisfaction score using a scheme of constants and equal weightings across individuals, namely 0.1. Secondly, we have computed what we have referred to as the DEA-*Benefit-of-the-doubt* composite indicator of life satisfaction using expression (4), according to which weightings are idiosyncratic across life domains and individuals. In the third place, taking the DEA-*Benefit-of-the-doubt* scores as a basis, we have obtained a series of DEA-*Benefit-of-the-doubt*-MCDM life satisfaction indicators in which weightings are restricted so as to be common among individuals but different across life domains. These indicators are, by construction, all normalised to range from zero to one.

Furthermore, the common weighting DEA-*Benefit-of-the-doubt*-MCDM life satisfaction indicators have been computed in three different scenarios; firstly, a *collective optimum* scenario in which, as explained in the Section on the methodology, the structure of common weightings maximises the mean of life satisfaction indicators across individuals ($t=1$); secondly, a *most penalised individual optimum* scenario in which the life satisfaction of the most penalised individual in the unconstrained idiosyncratic weighting DEA model is maximised ($t=0$); and finally, in order to avoid the subjectivity of choosing an extreme value for the parameter t, or any other intermediate arbitrary value, we have also calculated the definite integral of the composite life satisfaction indicator with t ranging from 0 to 1 (Reig-Martínez et al., 2011).[8] *Table 2* presents some descriptive statistics for all these composite indicators of life satisfaction.

PLEASE, INSERT TABLE 2 AROUND HERE

The life satisfaction indicator in the DEA-*Benefit-of-the-doubt* scenario averages 0.778, with 25 individuals (14% of the sample) tied with scores equal to unity, i.e., fully satisfied. This concentration highlights the potential lack of discriminating power of the DEA-based models mentioned in the Section on methodology.[9] Conversely, all the

[8] In practice, such integration procedures have been carried out by computing a series of 101 composite life satisfaction indicators for each individual allowing the parameter t to vary between 0 and 1 at intervals of 0.01. Then, these estimates of life satisfaction and the corresponding estimates of common weights have been averaged into a single life satisfaction indicator and a single set of common weights, respectively (see Reig-Martínez et al., 2011 for details).

[9] Additionally, we have computed a DEA-*Benefit-of-the-doubt* composite indicator of life satisfaction using proportional or radial measures, as in Bernini et al., (2012), with the result of 138 individuals (77% of the sample) scoring full satisfaction, i.e., with composite indicators equal to

individuals in the sample are unequivocally ranked according to their DEA-*Benefit-of-the-doubt*–MCDM scores of life satisfaction restricted to common weightings in all three scenarios considered; averages are 0.451 and 0.458 when the parameter t takes values of zero and one, respectively, and 0.456 in the integer case.

In order to analyse the relationship between our composite indicators of life satisfaction and the overall life satisfaction reported by the Mayan people in our sample, *Table 3* presents some *Spearman* rank correlation coefficients for all the indicators. In addition, *Figures 1* and *2* display *Kernel density* estimates of the overall self-reported life satisfaction and our five composite indicators of life satisfaction respectively, thus providing an illustration of their respective distributions. In the first place, using standard confidence levels, results from the *Spearman* correlations indicate that the different composite indicators of life satisfaction computed in this paper, including the *equally-weighted* indicator, do not rank individuals differently in statistical terms. Furthermore, pair-wise rankings in the sample from the self-reported overall life satisfaction, on the one hand, and each one of these computed composite indicators, on the other, are not statistically different either. The highest correlation was recorded by the *equally-weighted* composite indicator with a score of 0.42.

PLEASE, INSERT TABLE 3 AROUND HERE

PLEASE, INSERT FIGURES 1 AND 2 AROUND HERE

In the same vein as Rojas (2006) and González et al., (2010), we have also used univariate *Ordinary Least Squares* estimations to assess the relationship between overall self-reported life satisfaction, as the dependent variable, and each of our five life satisfaction composite indicators, as explanatory variables. Results are presented in *Table 4* and can be interpreted similarly to the *Spearman* results. In particular, the model that includes the *equally-weighted* composite indicator as an independent variable yields the highest adjusted R-squared, at 0.239, followed immediately by the DEA-*Benefit-of-the-doubt*-MCDM *collective optimum*, with an adjusted R-squared of 0.212.

PLEASE, INSERT TABLE 4 AROUND HERE

Let us now move on to the analysis of the particular weightings of the ten life domains included in our life satisfaction composite indicator. The weightings obtained in the different scenarios considered in the DEA-*Benefit-of-the-doubt*-MCDM common weightings approach are presented in *Table 5.* While the first and second columns display the scheme of optimal weightings in the *collective optimum* and *most penalised individual*

one. These results are available upon request and strongly justify our choice of a slack-based approach to improve the capacity of our basic DEA model to discriminate among individuals.

optimum solutions, respectively, the last column shows the weightings obtained in the integer solution. One of the first results from these figures is that the ranking of life domains according to their importance in the construction of the composite life satisfaction indicator is quite similar in all three scenarios considered. However, comparing the *collective optimum* solution to the *most penalised individual optimum* does provide for some interesting additional comments. The individual optimum criterion assigns more importance to life domains such as *money*, *confidence* and *work*, suggesting that more dissatisfied individuals give greater importance to these life domains. Conversely, lower relative importance is assigned to *health* and the quality of the *house*.

PLEASE, INSERT TABLE 5 AROUND HERE

Focusing now our comments on the optimal set of weightings obtained in the case of the integer solution, *money* is the main domain affecting life satisfaction, closely followed by *confidence* and *work*, with similar weightings, and *community*. Conversely, the life domains weighted the least important were clearly the quality of the *house*, access to *water* and *nurture*.

4. Discussion and suggestions for further research

In this paper we propose the use of *Data Envelopment Analysis* techniques as an alternative computer-based approach to design weightings for domains of life in the construction of life satisfaction indicators. The main feature of DEA is that the weightings awarded to different life domains are generated endogenously, without resorting to exogenous information or personal preferences. In addition, weightings might differ across life domains and individuals.

From the theoretical approach and our empirical results, we find DEA has both strengths and weaknesses when it comes to analysing life satisfaction using the domains of life. As regards the weak points, we must first mention the ethical issue that it is a *machine* that assesses or ranks the importance of life domains, rather than individuals. In this sense, it might seem more sensible for individuals to have the right to decide for themselves regarding their own subjective satisfaction (Rojas, 2008) and also, should this be the case, to decide the relative importance of the different domains of life in this assessment. This ethical issue appears to acquire greater importance when the domain satisfaction approach involves political issues. Secondly, according to our empirical results, DEA-based composite indicators of life satisfaction do not seem to have a closer relationship with self-reported life satisfaction than other more common and simpler indicators in the literature, such as the *equally-weighted* indicator. This result is in keeping with those in other papers mentioned in the introduction that empirically demonstrate that it is better not to weight, due the minimal capacity of several composite indicators with different weighting schemes to explain life satisfaction.

However, we must also highlight several strong points of DEA in life satisfaction analyses. First, the fact that weightings are calculated endogenously could be considered, as mentioned above, as a weakness but also as strength of these techniques, as it permits ranking domains without having to ask individuals, which might be costly and highly time consuming. Second, DEA-based composite indicators of life satisfaction can be computed in different scenarios, thus providing different schemes of weightings that can model researchers' preferences. In the simplest DEA-*Benefit-of-the-doubt* scenario, each individual is assigned a different set of weightings that maximise their life satisfaction compared to all the other individuals in the sample when they are evaluated using the same weightings. Although this model makes it difficult to assess the relative importance of life domains, DEA can be combined with MCDM techniques to calculate common weightings that only change across domains, but not among individuals. In our case study, as already noted, combined DEA-*Benefit-of-the-doubt*-MCDM analysis lends greater importance to *money*, *confidence* and *work*, while less importance is given to quality of the *house*, access to *water* and *nurture*. Furthermore, combining DEA and MCDM techniques allows several additional schedules of researchers' preferences to be considered in the analysis. In our *most penalised individual optimum* scenario, greater relative importance is assigned to life domains such as *money*, *confidence* and *work*; conversely, the relative importance of these domains is somewhat lower in the *collective optimum* scenario.

Third, according to our DEA-*Benefit-of-the-doubt*-MCDM indicators of life satisfaction, all the individuals in the sample are fully ranked. This situation does not occur either with the self-reported life satisfaction or life satisfaction indicators computed in the simpler DEA-*Benefit-of-the-doubt* scenario and the *equally-weighted* indicator. Fourth and finally, from a methodological point of view our DEA-based approach might well outperform econometric techniques in calculating life domain weightings when the importance of particular domains differs a great deal from one person to another. The reason is that by estimating the significance of the variables and their coefficients, econometric techniques assume universal cause effects for all the individuals in the sample. Accordingly, the impact on life satisfaction of a life domain that is important only for a small subset of individuals might well be underestimated. For instance, in the case of the Mayan people, a computer-based statistical approach to identify importance and weightings, e.g., *Ordinary Least Squares*, could have disregarded the importance of life domains that in our DEA-MCDM-based display low weightings.

Whether or not the strengths of DEA for weighting domains really overcome the weaknesses of this technique depends, however, on researchers' perceptions. In our opinion, the ethical principle of asking individuals how they rate life domains is an important issue that could affect the usefulness of computer-based approaches to designing weightings. More broadly, embedded in the discussion over whether or not to weight, we should disregard DEA on the basis of the lack of capacity of DEA-based indicators to explain life satisfaction. However, this criterion might not be sufficient to disregard weighting, as other theoretical issues could arise. As argued by Rojas (2006), following Gujarati (1995), the theoretical relevance of the method could be more important than a better *goodness-of-fit* when it comes to choosing the best model. In this vein, Hsieh (2012a, 2012b) argues that criteria based on correlations and *goodness-of-fit* regression analysis can produce misleading conclusions when not all the life domains that affect people's satisfaction are included in the analysis. This issue is related to the ongoing debate discussed in the introduction about which life domains should be taken into consideration in life satisfaction analysis.

As regards the ongoing debates mentioned throughout the paper, we consider that the issue of *whether or not to weight* the domains of life when computing life satisfaction indicators and the possible usefulness of DEA-based techniques to do so still require further research. Here we suggest two issues that future empirical research should address in order to evaluate whether or not weighting is appropriate and, in particular, further support the usefulness of DEA to compute domain-based indicators of life satisfaction. Firstly, it would be interesting to compare computer-DEA weightings to those directly reported by individuals, in order to ascertain possible convergence or divergence. Secondly, relating computed-based weightings and life domains to objective features of people's well-being would also, in our opinion, be a potentially fruitful avenue for future research. Comparison of weightings, domain satisfaction and objective well-being and satisfaction with life, as well as comparing reported and estimated weightings, could yield a more robust body of evidence on the usefulness of DEA and other weighting methods in analysing life satisfaction.

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Figures and Tables

Table 1
Descriptive statistics of life domains and overall self-reported life satisfaction

	Mean	SD	Max	Min
Health	8.0	1.7	10	2
Work	8.0	2.0	10	0
Love	8.9	1.5	10	1
Money	7.0	2.0	10	1
Quality of the *house*	7.7	1.8	10	1
Nurture	8.1	1.4	10	3
Access to *water*	8.4	1.8	10	0
Leisure	7.2	2.3	10	0
Community	7.9	1.9	10	0
Confidence	8.3	1.7	10	1
OVERALL SELF-REPORTED LIFE SATISFACTION	8.3	1.5	10	3

Table 2
Composite indicators of life satisfaction

	Mean	SD	Max	Min
Equally-weighted	8.0	1.0	9.7	4.6
DEA-*Benefit-of-the-doubt*	0.778	0.172	1.000	0.256
DEA-*Benefit-of-the-doubt*-MCDM				
Collective optimum (*t*=*1*)	0.451	0.062	0.572	0.205
Most penalised individual optimum (*t*=*0*)	0.458	0.062	0.582	0.214
Integer with $t \in$ *[0,1]*	0.456	0.064	0.582	0.194

Table 3
Spearman rank correlations between composite indicators of life satisfaction and overall life satisfaction[1]

	(A)	(B)	(C)	(D)	(E)	(F)
OVERALL LIFE SATISFACTION (A)	1	-	-	-	-	-
Equally-weighted (B)	0.423	1	-	-	-	-
DEA-*Benefit-of-the-doubt* (C)	0.362	0.942	1	-	-	-
DEA-*Benefit-of-the-doubt*-MCDM						
Collective optimum (*t*=*1*) (D)	0.391	0.945	0.902	1	-	-
Most penalised individual optimum (*t*=*0*) (E)	0.338	0.926	0.901	0.973	1	-
Integer with $t \in$ *[0,1]* (F)	0.341	0.923	0.900	0.969	0.995	1

[1] *Correlations are all statistically significant at a confidence level of 1%.*

Table 4
Univariate *Ordinary Least Squares* estimation with self-reported life satisfaction as dependent variable

	Coefficient [1]	Adjusted R-squared
Equally-weighted	0.748	0.239
DEA-*Benefit-of-the-doubt*	3.557	0.170
DEA-*Benefit-of-the-doubt*-MCDM		
Collective optimum (*t*=1)	10.808	0.212
Most penalised individual optimum (*t*=0)	9.908	0.174
Integer with $t \in [0,1]$	9.689	0.177

[1] *All variables are significant at 1% confidence level.*

Table 5
DEA-*Benefit of the doubt*-MCDM common weightings estimates[1]

	Collective optimum (*t*=1)	*Most penalised individual optimum* (*t*=0)	Integer with $t \in [0,1]$
Money	0.0101	0.0132	0.0118
Confidence	0.0078	0.0107	0.0106
Work	0.0052	0.0080	0.0105
Community	0.0100	0.0093	0.0095
Leisure	0.0055	0.0065	0.0079
Love	0.0061	0.0058	0.0055
Health	0.0096	0.0026	0.0021
Quality of the *house*	0.0037	0.0001	0.0002
Access to *water*	0.0001	0.0013	0.0002
Nurture	0.0001	0.0001	0.0001

[1] *Domains of life are in decreasing order according to their estimated weightings under the DEA-Benefit-of-the-doubt-MCDM integer criteria.*

Figure 1
Kernel density estimates of the overall self-reported life satisfaction

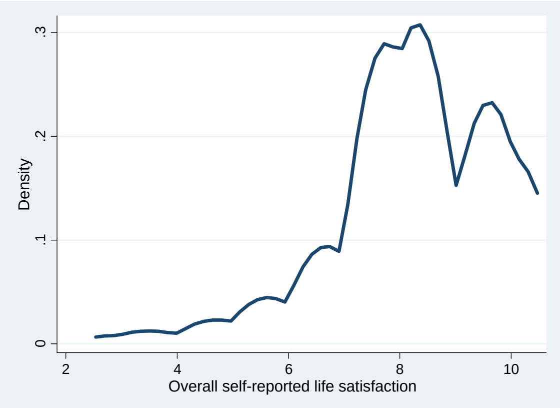

Figure 2
Kernel density estimates of the composite indicators of life satisfaction