Evaluating well-being in the Colombian regions. Disparities and spatial patterns

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Abstract

This paper provides two composite well-being indicators for the 33 Colombian departments for year 2016. The indicators are built following as much as possible the the well-known OECD Better Life Index. The first indicator measures global well-being, and includes the dimensions of income, health, education, safety, housing, environment, labour market and civic engagement and governance. The second indicator excludes the economic dimensions, namely income and labour market. The indicators are constructed using Data Envelopment Analysis in combination with Multicriteria Decision Making techniques, which allow to objectively compare well-being across departments and elaborate well-being rankings. The composition of rankings is similar for both indicators, and show great disparities across departments. Beyond the identification of these within-country differences, our research yields three additional take away messages. First, when economic dimensions are excluded from the composite indicator, well-being generally increases. Second, despite average well-being in Colombia is relatively low, the departments with the highest well-being levels are those most populated. Third, spatial spillovers matter, as departments have similar well-being levels than their neighbours. This effect is more intense when considering global well-being.

Keywords: Colombia, composite indicators, data envelopment analysis, well-being

JEL classification: C16, O18, O47, R11

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1. Introduction and motivation

The interest of society in well-being has rocketed in the last few years. A quick search in Scholar Google yields 1,790,000 results only for the last decade. There are several reasons behind this trend. One of the most important is rooted in the limitations of GDP per capita as an appropriate well-being measure (see Stiglitz et al. 2009; Ven, 2015; Rojas and García-Vega, 2017). In response, some projects have tried to provide more comprehensive well-being measures, considering information on other well-being domains beyond income. A pioneering initiative was the well-known Human Development Index, although including only income, education and life expectancy is still rather limited.

Much more recent is the OECD Better Life Index (BLI), which provides comparable information for up to ten well-being domains and has become one of the most used frameworks in the related literature (see, for instance, Mizobuchi, 2014, 2017a; Lorenz et al., 2016; and Peiró-Palomino and Picazo-Tadeo, 2018; Peiró-Palomino, 2019). The dataset, however, has two important limitations. First, it does not provide a global or composite measure of well-being. This limitation can be overcome using a wide variety of techniques. In fact, the aggregation problem has been the focus of most of the above-mentioned references using this dataset. Second, the BLI provides information only for the 35 OECD economies, plus Russia, South Africa and Brazil. This means that analyses are confined to relatively advanced economies, whereas little evidence is available for developing countries.

This is precisely the case of Colombia, the focus of this paper. If country-level analyses for developing countries are scarce, let alone analyses at the regional level. Most of the times, the main barrier is the lack of information. In that regard, Colombian official statistics have improved notably in recent times in terms of both availability and reliability, which offers an excellent opportunity for empirical research. As many other developing countries, Colombia faces important economic and social disparities, consequence of differences, among others, in human capital, low-quality institutions and incidence of civil conflicts (García and Benítez, 1998; Galvis and Meisel, 2010; Galvis-Aponte et al., 2017). The literature that has dealt with income convergence is relatively abundant, although the most recent papers were written a while ago and are mostly in Spanish. In that regard, Bonet and Meisel (2008) and Branisa and Cardozo (2009a) found that sizeable disparities persist since the 1990s. The absence of economic convergence manifests the limited effect of public policies in providing favourable conditions to push the lagged economies towards a sustainable growth pattern.

However, for well-being dimensions others than income, the only precedent is Royuela and García (2015), who extended the income analysis to other well-being indicators such as life expectancy, infant mortality, educational enrolment and crime for the period 1975–2005 and for 24 out of the 33 Colombian departments. The authors report convergence for some social indicators (education, health, crime), while income per capita showed a divergent trend. After 2005, the literature is completely silent.

Despite for data availability reasons our paper cannot examine convergence (most of the data used have been made available very recently), it provides fresh evidence on some aspects which have been overlooked by the literature so far. As a first contribution, it elaborates two composite well-being indicators for the Colombian departments in 2016 (the latest available year for most variables). One indicator measures global well-being, while the other focuses on non-economic dimensions only. The dimensions considered are those included in the OECD BLI framework and the indicators were constructed using Data Envelopment Analysis (DEA) in combination with Multicriteria Decision Making (MCDM). These are state-of-the-art techniques in the composite indicators literature (see Peiró-Palomino and Picazo-Tadeo, 2018) that allow for an objective comparison of departments, being possible the elaboration of well-being rankings. These composite indicators and the rankings are, to the best of our knowledge, completely novel for the case of Colombia. As a second contribution, the paper considers the 33 Colombian departments. Previous papers are usually based on the former 24 departments before the last administrative reform that took place in 1991. Finally, the distribution of well-being is studied via kernel densities. In doing so, we take into account the different population sizes of the departments, which offer a much more realistic picture of how people are in terms of well-being. Also, departments are not isolated units, and we incorporate to the analysis spatial spillovers, able to explain in large amount regional well-being in Colombia.

The rest of the paper is structured as follows. Section 2 provides the data description and some descriptive statistics. Section 3 introduces the methodology whereas Section 4 provides the results. Finally, conclusions and some prospects for future research can be found in Section 5.

2. Data and descriptive statistics

In this section we explain the sample, variables and their sources. Our well-being benchmark is that defined by the OECD Better Life Index. Unfortunately, not all the dimensions are available for the Colombian departments. Each dimension is proxied by one or several indicators. Again, our indicators are as close as possible to those suggested by the OECD, although there are some differences due to data constraints. Taking into account these limitations, our composite well-being indicator is based on the following eight dimensions, which are represented by the indicators listed below. Table 1 reports a full description, unit of measure, sources and temporal availability.

- Income: GDP per capita
- Housing: i) Aqueduct coverage; ii) sanitation coverage; iii) housing quantitative deficit; iv) housing qualitative deficit
- Health: i) Vaccination coverage; ii) child mortality rate
- Education: i) Primary education; ii) secondary education; iii) results from Saber 11 tests, critical reading; iv) results from Saber 11 tests, maths
- Civic engagement and governance: i) Transparency index for government offices; ii) transparency index for public accounting offices, iii) electoral participation, national elections; iv) electoral participation, local elections
- Environment: i) CO2 emissions; ii) water quality
- Safety: i) Homicide rate; ii) domestic violence rate
- Labour market: Unemployment rate

Given that each indicator is measured in a different unit, data should be first standardised before being aggregated. In doing so, we followed the OECD methodology in the BLI. Accordingly, for indicators associated to positive outcomes (e.g. income or education) we assign the value of 0 for values below the 4th percentile and the value 10 to those above the 96th percentile. The rest of values of the distribution are scored using the min-max:

$$\hat{x_c} = \Big(\frac{x_c - max(x)}{max(x) - min(x)}\Big) \cdot 10 \tag{1}$$

Those indicators associated to negative outcomes (for instance, mortality rates or CO2 emissions), are inversely coded. Values above the 96th percentile are assigned a value of 0 and values below the 4th percentile are assigned a value of 10. The intermediate values are scored as follows:

$$\check{x_c} = \Big(\frac{max(x) - x_c}{max(x) - min(x)}\Big) \cdot 10 \tag{2}$$

where x_c represents the original value of the indicator and $\hat{x_c}$ and $\check{x_c}$ are the standardised scores. Once the data have been standardised we obtain the aggregate score for each dimension by computing the arithmetic mean of all the indicators.

Our sample comprises the 33 Colombian departments. Colombian official statistics have witnessed a remarkable improvement in recent times, being possible to undertake analyses at the department level. The major drawback nowadays is the impossibility to consider a long time span, as most of the data we use in our analysis have been made available recently. In other cases it is not available on a yearly basis. As can be seen in Table 1, most data correspond to the period 2015–2017. In all cases, we compute the average of the available data for that period. However, for the indicators of the housing dimension, data refer to year 2005, as the information was collected from the latest municipal census. In any case, we consider that the indicators representing that dimension are relatively stable as they refer to infrastructure variables that are persistent in the short run. As our objective is the construction of a well-being indicator as comprehensive as possible for a recent period, we consider that the benefits of including the housing dimension largely outweigh the costs. Finally, for the dimensions of education, housing, health and safety, the data for our indicators are provided at the municipal level. We therefore obtained department level data by averaging the values of the municipalities in each department.

Table 2 provides some descriptive statistics of the normalised scores for all the dimensions. These figures are actually the input for the elaboration of the composite indicator. Figures at the department level are available upon request. As can be seen in the table, there are important disparities across dimensions. The worst performance is for material dimensions such a income (only 3.02) and housing (4.81). Both show large departmental disparities, especially income, whose standard deviation is also the largest (2.68). The dimensions of environment, labour market and safety are the ones with the best average scores (above 7 points). Finally, health, education and civic engagement and governance have intermediate scores, in the interval 5–7.

Figure 1 displays the kernel density distributions for all the dimensions. Some of them, such as education, civic engagement and housing are relatively normal. However, other dimensions including income, health and environment are clearly bimodal, showing a marked polarisation between departments above and below the mean.

3. Methodology

3.1. Computing a composite well-being index

Weights selection becomes an essential problem when computing composite indicators. The most immediate solution is the use of equal weights, although it is totally subjective. In order to overcome this limitation, we adopt an objective solution, which is also more aligned to the most recent literature on the matter and to the OECD guidelines (OECD, 2008).

In this paper, we use Data Envelopment Analysis (DEA) techniques and Multi-Criteria-Decision-Making (MCDM), techniques that allow weights to be endogenously determined. Beyond the OECD recommendations, DEA models have been systematically used for the construction of composite indicators in recent times.[1]. In particular, we consider the approach by Guardiola and Picazo-Tadeo (2014). Given our sample of $r = 1, \ldots, 33$ Colombian departments and the $d = 1, \ldots, 8$ well-being domains introduced in the data section, the mathematical program to compute the composite indicator for department $r\prime$ is the following:

$$\begin{aligned} Max_{\omega_{dr\prime}} WB_{r\prime} = \sum_{d=1}^{8} \omega_{dr\prime} S_{dr\prime}, \\ subject \quad to: \\ \sum_{d=1}^{8} \omega_{dr\prime} S_{dr} \leq 1, \quad r = 1 \ldots, 33 \\ \omega_{dr\prime} \geq 0, \quad d = 1 \ldots, 8 \end{aligned} \tag{3}$$

where S_{dr} denotes the value of dimension d in region r, and $\omega_{dr\prime}$ stands for the weight assigned to domain d in the composite indicator of $r\prime$.

This mathematical program is based on the well-known Benefit-of-the-Doubt (DEA-BoD) principle (see Cherchye et al., 2007), and therefore assigns those weights maximising well-being in department $r\prime$, provided that this set of weights is applied to the rest of departments in the sample. In addition, the resulting indicator is normalised between 0 and 1, which represent the lowest and highest well-being, respectively.

One of the major drawbacks of combining DEA with the BoD approach is that cross-regional comparisons are not possible, as the composite indicator of each geographical unit is elaborated using a different scheme of weights (Kao and Hung, 2005). A second limitation lies in the relatively low discrimination capacity when there is a large number of variables in the optimisation program with respect to the number of observations (departments in our case), which can lead to a scenario in which a large proportion of departments can be considered as fully efficient units.

There are several alternatives to deal with these shortcomings (see, for a review, Reig-Martínez et al. (2011; p.564).) We follow Despotis (2002), which combines DEA with multicriteria decision making (MCDM) techniques, i.e. the DEA-BoD-MCDM model. The most interesting feature of this combined program is that apart from an increased discrimination

[1]See, for instance, Bernini et al. (2013), Guardiola and Picazo-Tadeo (2014), Mizobuchi (2014) and Peiró-Palomino and Picazo-Tadeo (2018).

capacity, it uses a common weighting scheme for all the departments, enabling comparisons. As described in Despotis (2005), the program is defined as follows:

$$
\begin{aligned}
Min_{m_r,\omega_d,z} \quad t\frac{1}{33}\sum_{r=1}^{33} m_r + (1-t)z \\
subject \quad to: \\
\sum_{d=1}^{8} \omega_d S_{dr} + m_r = WB_r^*, \quad r = 1,\ldots,33 \\
(m_r - z) \leq 0, \quad r = 1,\ldots,33 \\
m_r \geq 0, \quad r = 1,\ldots,33 \\
\omega_d \geq \varepsilon, \quad r = 1,\ldots,33 \\
z \geq 0, \quad d = 1,\ldots,8
\end{aligned}
\tag{4}
$$

where ω_d denotes the common weight assigned to domain d ;z is a non-negative parameter to be estimated; ε stands for a non-Archimedean small number (0.001 in our case) ensuring that all the domains have positive weight; m_r quantifies the deviation between the DEA-BoD composite well-being indicator for region r, namely WB_r^*, and its DEA-BoD-MCDM score; and t, lying in the 0–1 interval, is a parameter that represents different scenarios by determining the importance given to the terms of the DEA-BoD-MCDM objective function.

In particular, when $t = 1$, the objective function to be minimised is the first term in Expression (2). This corresponds to the mean regional deviation between the DEA-BoD and DEA-BoD-MCMD scores. Conversely, under the $t = 0$ scenario, it is the second term of the objective function that is minimised, which represents the maximal deviation between the DEA-BoD and the DEA-BoD-MCDM well-being indicators. As our purpose is to avoid as much as possible subjectivity in the analysis, our preferred option is what is known as the *integer solution*, proposed by Reig-Martínez et al. (2011) (see also Despotis, 2002). Instead of selecting a particular value for t, this approach considers the value of the definite integral for t in the interval 0–1 for computing the composite well-being indicator.[2]

3.2. Kernel densities and spatial spillovers

After the computation of the well-being scores we perform additional analyses to better understand departmental well-being patterns in Colombia. These analyses consist of kernel density estimation (weighted and unweighted) and the identification of spatial spillovers.

[2]As a robustness test, we also performed the analysis using the scenarios of $t = 0$ and $t = 1$, being the results very similar. These results are provided in Appendix A.

Kernel densities are well-known non-parametric methods (see Henderson and Parmeter, 2015 for a recent in-depth discussion). We compute the following well-being density function:

$$\hat{f}(wb) = \frac{1}{33h} \sum_{d=1}^{33} K\Big(\frac{wb - wb_c}{h}\Big) \tag{5}$$

where wb_c stands for well-being in department d; K is a kernel function, and h is the bandwidth parameter. A common approach is the use of Gaussian kernel functions, given by:

$$K(wb) = \Big(\sqrt{2\pi}\Big)^{-1} exp\Big(-\frac{1}{2}wb^2\Big) \tag{6}$$

More momentous is the choice of the bandwidth (h), as it can entail undersmoothing (when h is too small) or oversmoothing (in case h is too large). In this paper bandwidths are computed following the Sheather and Jones (1991) solve-the-equation plug-in approach, preferable in terms of performance than other competing methods.

The interpretation of the kernel functions is straightforward. When the probability mass for a given domain concentrates around a particular score, it means that departments are similar in terms of that domain. Conversely, multimodal cases imply polarisation, compatible with the existence of well-being clubs. Moreover, given that departments widely differ in population, population-weighted kernels are computed. This might have important implications when interpreting the results, as highly populated departments have more weight in the construction of the kernel and it could help to better understand how most Colombian are in terms of well-being.

Formally:

$$\hat{f}(wb) = \frac{1}{33h} \sum_{d=1}^{33} \lambda_d K\Big(\frac{wb - wb_c}{h}\Big) \tag{7}$$

where λ_d stands for the weighting for department d, corresponding to the share of total Colombian population living in that department.

Finally, we take into account spatial spillovers, which entails the identification of neighbours and the computation of a spatial matrix (W), which summarises all the neighbouring links in the sample. Formally, the matrix can be defined as:

$$W = \begin{cases} w_{ij}(k) = 0 \;\; if \;\; i = j \\ w_{ij}(k) = 0 \;\; if \;\; i \neq j, j \notin nbd(i)_k \\ w_{ij}(k) = \frac{1}{k} \;\; if \;\; i \neq j, j \in nbd(i)_k \end{cases}$$

where w_{ij} terms denote the spatial weights connecting departments i and j, $nbd(i)_k$ denotes the neighbourhood of i given k.

Following common practice in the literature (see LeSage and Pace, 2009), all the rows in the matrix sum one. There are several alternatives for setting which departments can be considered neighbors. Here we have adopted the k-nearest criterion, which considers as neighbours the k nearest departments.[3] Given the nature of the Colombian geography, in which departments typically share borders with three to five departments, we set $k = 4$, that is, each department has as neighbours the four nearest departments; then $w_{ij} = 0.25$ when $i \neq j, j \in nbd(i)_4$.[4] The matrix is then used for the computation of spatial tests and the generation of spatial lags of the variables of interest. Spatially lagged variables are the result of the product of a given variable and the spatial matrix W. Accordingly, each element in the resulting vector is the weighted average of the neighbour departments, as $\mathrm{w}_{ij} = 0$ when $i \neq j, j \notin nbd(i)_4$.

The spatially lagged series can be then compared with the original ones, which allows to analyse the particular effect of the spatial component. In doing so, the series are first relativised to the sample mean in such a way that a value of one for a particular department indicates that that department is exactly on the country average, a value of two means twice the average and so on. Accordingly, if the probability mass in the distribution of the spatially lagged variable is more concentrated than in the original one, it means that departments are much more similar to their neighbours than when compared to the entire country, that is, if space matters we should expect more probability mass around the unity in the spatially lagged distribution than in the original one.

4. Results

4.1. Composite well-being scores and ranking of departments

Results for the composite indicator are available in Table 3. The table reports the scores for the global indicator of well-being and also for the non-economic well-being indicator. Regarding the global well-being, the top three departments are Casanare, Cundinamarca and Bogotá, respectively. At the bottom of the ranking are the regions of Guaviare, Vaupés and Vichada. If we consider non-economic well-being, we find some expected differences, although the correlation between the two rankings is above 90%. In this case, the top three departments are Bogotá, Quindío and Santander, whereas the three departments at the bottom are Vichada, Guaviare and Chocó.

[3]The spatial analysis is performed excluding the department of San Andrés y Providencia, since it is located in an island far away from the coast. We therefore consider that spatial spillovers are nonexistent.

[4]As a robustness test, all the computations were also performed setting $k = 3$ and $k = 5$. The results, available upon request, are virtually analogous.

Figure 2 maps the results, showing important spatial patterns. The panel a) displays global well-being. In general, well-being is higher in the central departments, whereas the peripheral ones have medium-low and low scores. Given the strong correlation between the global and the non-economic well-being indicators, it is not surprising that the map in panel b), considering non-economic well-being, shows a similar picture.

4.2. Well-being kernel distributions and spatial spillovers

Figure 3 shows kernel densities for the composite well-being indicators. Global well-being is represented by the dotted line, whereas non-economic well-being is displayed by the solid line. Both distributions have differentiated modes, indicating a high polarisation. Nonetheless, if economic dimensions are not taken into account, the scenario is slightly better. Despite polarisation is persistent, well-being scores are comparatively greater than those for global well-being.

What really matters when dealing with well-being is people. Panel b) in Figure 3 compares unweighted and population weighted distributions. The solid line represents the density for the well-being score, which is clearly bimodal. It indicates a polarisation situation between a group of departments with relatively high well-being levels and other more numerous group with medium-low and low levels of well-being. In terms of population, however, there is a remarkable improvement. The population weighted density (dotted line) shows that, whereas the bimodality persists, the group of high well-being is much more important than in the unweighted case. This means that departments with relatively high levels of well-being are highly populated, whereas less people are living in the peripheral departments with the lowest levels.

The case of the non-economic well-being is slightly different. If we examine the unweighted distribution (solid line), we observe three different modes, with one mode around the score of 0.7 and other two modes around lower well-being levels. In contrast, the population weighted distribution is bimodal and, interestingly, far more prominent and around higher well-being levels. This means, again, that population concentrates in departments with relatively high levels of non-economic well-being.

Regarding the analysis of the spatial spillovers, the upper panels in Figure 4 display Moran plots for both global and non-economic well-being. In both cases, positive spatial patterns are observed. The dotted lines stand for the mean value of the series. It can be observed that departments above the mean are typically surrounded by departments which are also above the mean and vice versa.

The lower panels in Figure 4 display the three-dimensional counterparts, which can better show the changes between the original and the spatially conditioned distributions. It can be observed that in the latter case the probability mass in much more concentrated around the unity than in the original series, meaning that spatial spillovers matter. This effect is clearer when considering global well-being, which indicates that economic variables are those with more intense spatial concentration.

5. Conclusions and prospects for future research

This paper has constructed two composite well-being indicators for the 33 Colombian departments for year 2016. Taking as a benchmark the Better Life Index developed by the OECD, the first indicator considers eight economic and non-economic well-being dimensions. The second indicator is made only with non-economic dimensions. These indicators are constructed using state-of-the-art techniques in the composite well-being indicators literature. In particular, we use Data Envelopment Analysis, combined with Multicriteria Decision Making. These methods provide a satisfactory solution to the aggregation problem, allowing for an objective selection of weights for each of the dimensions. In addition, they are successful in dealing with well-known shortcomings in the literature, as for instance the limited discrimination capacity or having a common weight scheme making comparisons across units feasible.

Whereas these methods have been recently applied in related papers, the existing evidence is mostly confined to developed economies–generally the OECD context. However, evidence is much more scant for developing countries such as Colombia. The scarcity of analyses is even more evident for the subnational level, the focus of our paper. With respect to previous studies, the paper attempts to contribute in several ways. First, it is, to our knowledge, the first precedent providing composite well-being indicators for the subnational level in Colombia and considering as benchmark the comprehensive and well-accepted Better Life Index, covering a wide array of well-being dimensions. Moreover, it is one of the very few papers considering the current 33 Colombian departments, as most of the previous literature (mostly constrained to the income dimension) has traditionally used samples made of the 24 existing departments before the last territorial reorganisation in 1991. Second, we rank the 33 Colombian departments in terms of global and non-economic well-being, showing remarkable disparities across Colombian departments.

As a first insight, we find that, regardless of the indicator considered (global or non-economic), the composition of the ranking is similar. Our results also suggest that non-economic well-being is generally higher than the global indicator, suggesting that economic dimensions are among those with the poorest performance. Besides the ranking, the paper devotes a great deal of attention to the analysis of well-being distribution. To do so, we elaborate kernel densities. The results from these analyses suggest that there are strong spatial patterns in the distribution of well-being, i.e. departments with similar well-being levels are surrounded by departments with similar levels and vice versa. Finally, as well-being directly affects people's life, we include the demographic element into the analysis by computing population-weighted kernel densities. Interestingly, the densities clearly show that well-being improves when considering the population factor. This indicates that those departments with the highest well-being are also the most populated, whereas departments at the bottom of the ranking are poorly populated. Therefore, incorporating the population dimension becomes essential to better understand how people really are.

Despite the above results are novel for the Colombian case, the paper has also some limitations, which can be considered as opportunities for future research. The first shortcoming is the static nature of the analysis. The data used to represent some of the dimensions are actually really new, and it is not possible to take into account a long-run perspective. Yet this is something that can be easily addressed in the years to come, as official statistics in Colombia are improving. Extending this analysis for a period of several years might be of interest for evaluating well-being tendencies and convergence/divergence patterns. The second limitation is that we are unable to unveil well-being disparities inside departments. For instance, the fact that the departments with the highest well-being levels are those most populated does not mean that well-being is equally distributed among inhabitants. The nature of our data (macro level) makes it impossible to address this relevant issue. In any case, we consider that our results offer a comprehensive perspective of well-being in Colombia at the subnational level and might be useful to understand the Colombian reality and to the design of appropriate policies aimed at reducing the regional gap. We hope our findings encourage future contributions able to deal with the mentioned shortcomings in a successful way.

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Table 1: Dimensions and indicators

Dimension	Indicator	Description	Source (year)
Income	Income per capita	GDP, thousands of pesos of 2005	DANE (2015-16)
Health	MMR vaccine	Rate vaccination coverage %)	DANE (2015-16)
	Pentavalent vaccine	Rate vaccination coverage (%)	DANE (2015-16)
	Child mortality	Mortality rate under 5 years old (cases per 1,000 childs)	DANE (2015-16)
Education	Primary education	People (%)	Ministry of Education (2015-16)
	Secondary education	People (%)	Ministry of Education (2015-16)
	Saber 11 (Reading)	Points (0-100)	Ministry of Education (2015-16)
	Saber 11 (Maths)	Points (0-100)	Ministry of Education (2015-16)
Safety	Homicides	Homicides per 1,000,000 inhabitants	DANE (2015-16)
	Domestic violence	Reported cases per 1,000,000 inhabitants	DANE (2015-16)
Housing	Aqueduct coverage	(%)	Municipal census (2005)
	Sanitation coverage	(%)	Municipal census (2005)
	Housing quantitative deficit	Precarious or unstable material and/or with non-mitigable overcrowding (%)	Municipal census (2005)
	Housing qualitative deficit	Inadequate floors, mitigable overcrowding, inadequate services, absence of an adequate place for cooking (%)	Municipal census (2005)
Environment	Co2 emissions	Tons per capita	PNU and IDEAM (2012)
	Water quality	IRCA index	Health Ministry (2016)
Labour market	Unemployment rate	(%)	Labour Ministry(2016-17)
Civic engagement and governance	Transparency of government offices	ITD Index	ITP (2015-16)
	Transparency of accounting offices	ITD Index	ITP (2015-16)
	Voter turnout (National elections)	House of representatives and congress, participation (%)	NCSR (2018)
	Voter turnout (Local elections)	Mayor, governors, councils and assembly, participation (%)	NCSR (2015)

DANE: National Administrative Statistical Department
PNU: United Nations Program for Development
IDEAM: Institute of Hydrology, Meteorology and Environmental Studies
ITD: Public Entities Transparency Index
NCSR: National Registry for Civil State
MMR vaccine protects against measles, mumps and rubella; Pentavalent vaccine protects against diphtheria, tetanus, pertussis (whooping cough), hepatitis B and Haemophilus influenzae type b.

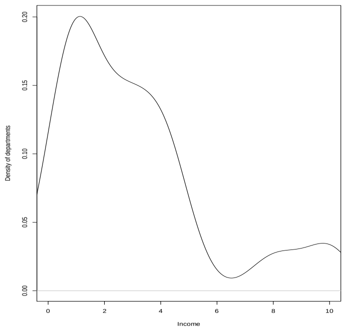
Table 2: Descriptive statistics for the well-being dimensions

Dimension	Mean	S.d.	Min.	Q25	Q75	Max.
Income	3.029	2.689	0.000	1.066	4.057	10.000
Health	6.801	1.637	2.109	6.405	8.015	9.252
Education	5.655	1.685	1.442	5.062	6.924	7.895
Safety	7.023	1.700	2.119	6.387	8.374	9.207
Housing	4.816	1.921	2.046	3.664	5.865	9.461
Environment	7.460	1.651	3.547	6.811	8.572	9.864
Labour market	7.284	2.374	0.000	6.313	8.789	10.000
Civic and Governance	5.098	1.634	2.342	3.925	6.221	7.969

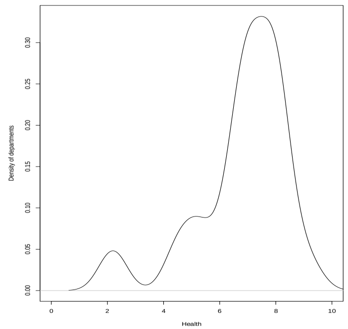
Table 3: Ranking of Colombian departments, global and non-economic well-being

Position	Department	Population share	Global well-being	Position	Department	Population share	Non-economic well-being
1	Santander	0.0426	1.0000	1	Bogotá	0.1636	0.8831
2	Casanare	0.0074	0.9624	2	Quindío	0.0117	0.8436
3	Bogotá	0.1636	0.8863	3	Santander	0.0426	0.7658
4	Meta	0.0200	0.8556	4	Cundinamarca	0.0557	0.7605
5	Boyacá	0.0263	0.6657	5	Valle del Cauca	0.0957	0.7561
6	Antioquía	0.1340	0.6143	6	Cesar	0.0214	0.7557
7	Valle del Cauca	0.0957	0.6031	7	Atlántico	0.0511	0.7555
8	Cundinamarca	0.0557	0.5930	8	Risaralda	0.0197	0.7520
9	San Andrés y Providencia	0.0016	0.5618	9	Boyacá	0.0263	0.7452
10	Atlántico	0.0511	0.5537	10	Caldas	0.0204	0.7429
11	Cesar	0.0214	0.5497	11	Antioquía	0.1340	0.7377
12	Risaralda	0.0197	0.5201	12	Huila	0.0240	0.7223
13	Caldas	0.0204	0.5169	13	Casanare	0.0074	0.7164
14	Bolívar	0.0435	0.5158	14	Tolima	0.0291	0.7089
15	Arauca	0.0054	0.5107	15	Sucre	0.0177	0.7047
16	Huila	0.0240	0.5070	16	Meta	0.0200	0.6991
17	Tolima	0.0291	0.4961	17	Norte de Santander	0.0281	0.6959
18	Quindío	0.0117	0.4919	18	Córdoba	0.0355	0.6460
19	Norte de Santander	0.0281	0.4171	19	Nariño	0.0362	0.6400
20	Cauca	0.0286	0.4007	20	Arauca	0.0054	0.6351
21	La Guajira	0.0200	0.3823	21	Putumayo	0.0072	0.6341
22	Sucre	0.0177	0.3804	22	Magdalena	0.0261	0.6288
23	Magdalena	0.0261	0.3784	23	San Andrés y Providencia	0.0016	0.6280
24	Putumayo	0.0072	0.3721	24	La Guajira	0.0200	0.6167
25	Córdoba	0.0355	0.3720	25	Cauca	0.0286	0.5990
26	Nariño	0.0362	0.3639	26	Guainía	0.0009	0.5566
27	Caquetá	0.0099	0.3145	27	Bolívar	0.0435	0.5422
28	Amazonas	0.0016	0.2912	28	Amazonas	0.0016	0.5027
29	Guainía	0.0009	0.2684	29	Vaupés	0.0009	0.4778
30	Chocó	0.0104	0.2443	30	Caquetá	0.0099	0.4600
31	Guaviare	0.0023	0.2394	31	Vichada	0.0015	0.4427
32	Vaupés	0.0009	0.2392	32	Guaviare	0.0023	0.4151
33	Vichada	0.0015	0.1915	33	Chocó	0.0104	0.3972
	Average	0.4927				0.6536	
	Weighted average	0.6056				0.7307	

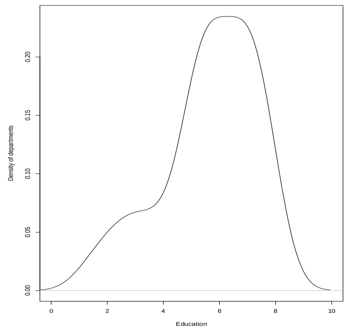
Figure 1: Well-being dimensions



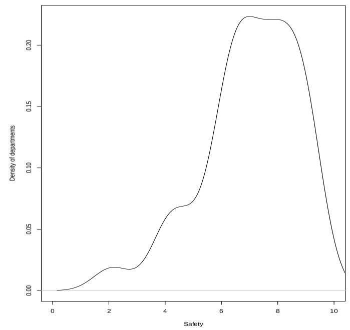
(a) Income



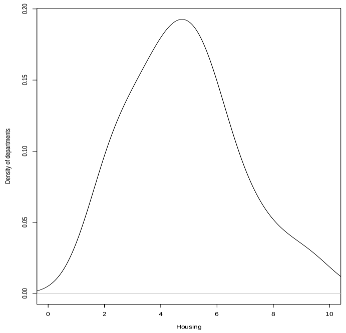
(b) Health



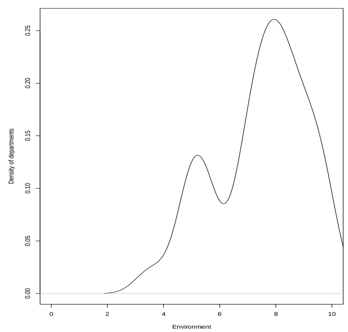
(c) Education



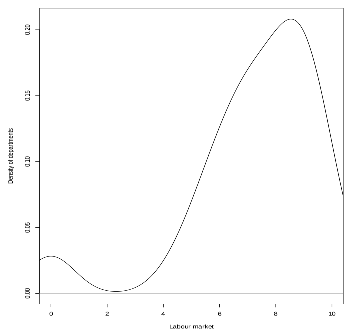
(d) Safety



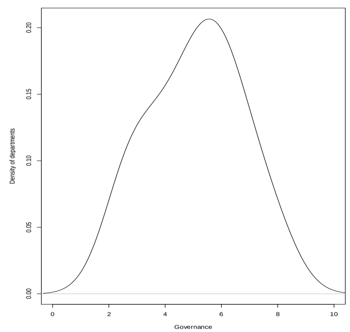
(e) Housing



(f) Environment

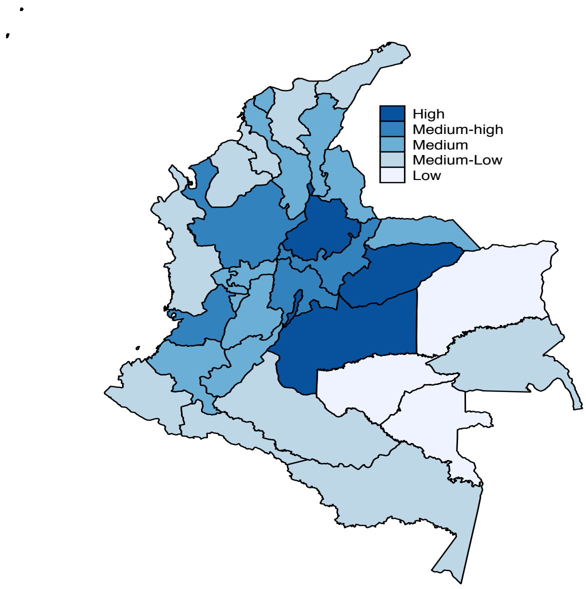


(g) Labour market

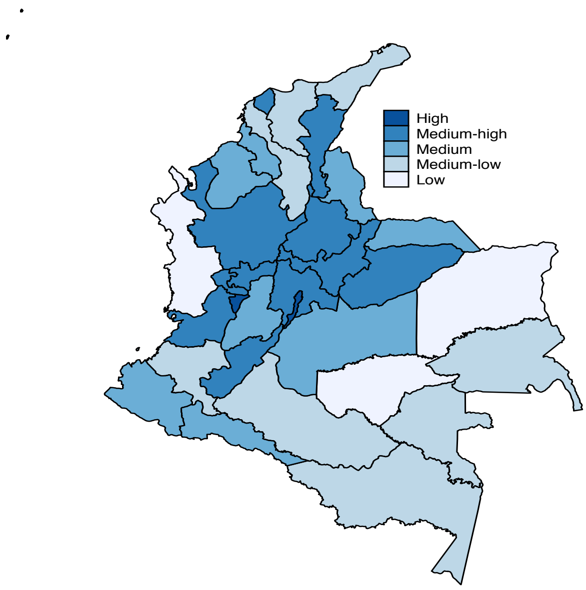


(h) Civic engagement and governance

Figure 2: Well-being, geographic distribution

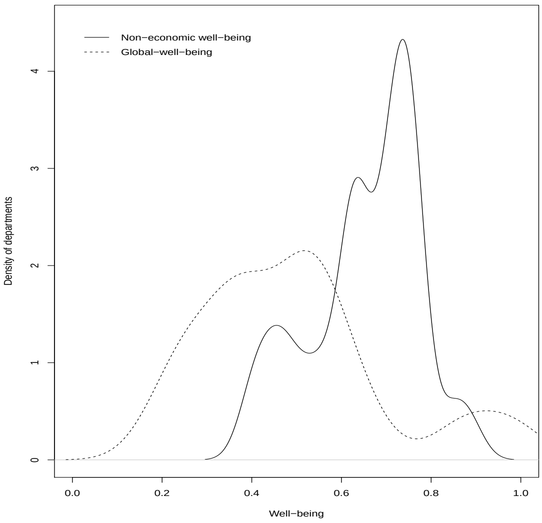


(a) Global well-being

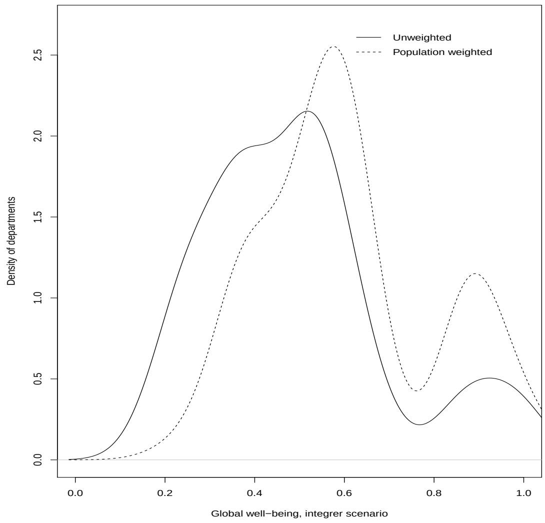


(b) Non-economic well-being

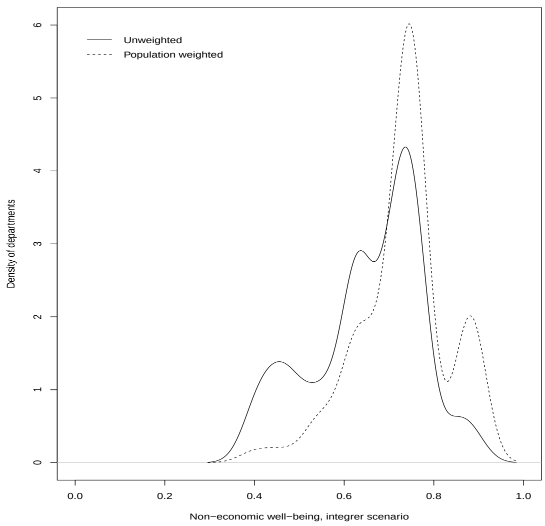
Figure 3: Global and non-economic well-being



(a) Global and non-economic well-being

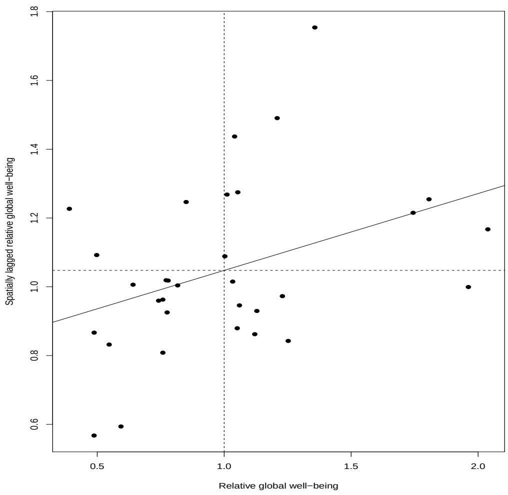


(b) Global well-being

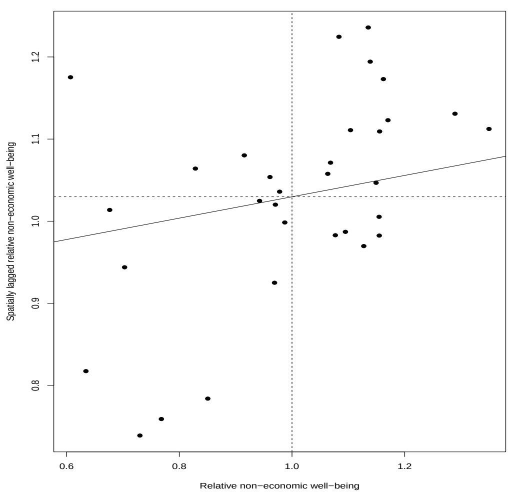


(c) Non-economic well-being

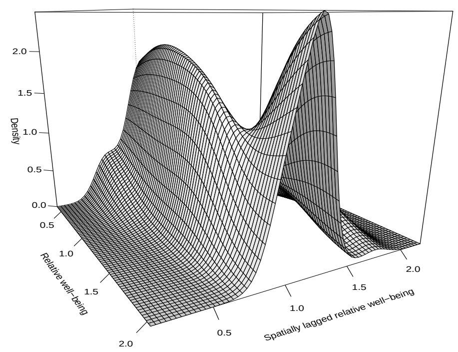
Figure 4: Well-being, spatial effects



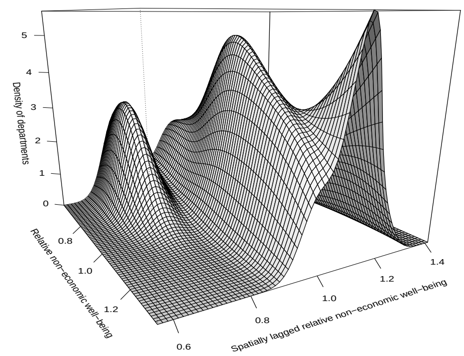
(a) Moran plot, global well-being



(b) Moran plot, non-economic well-being

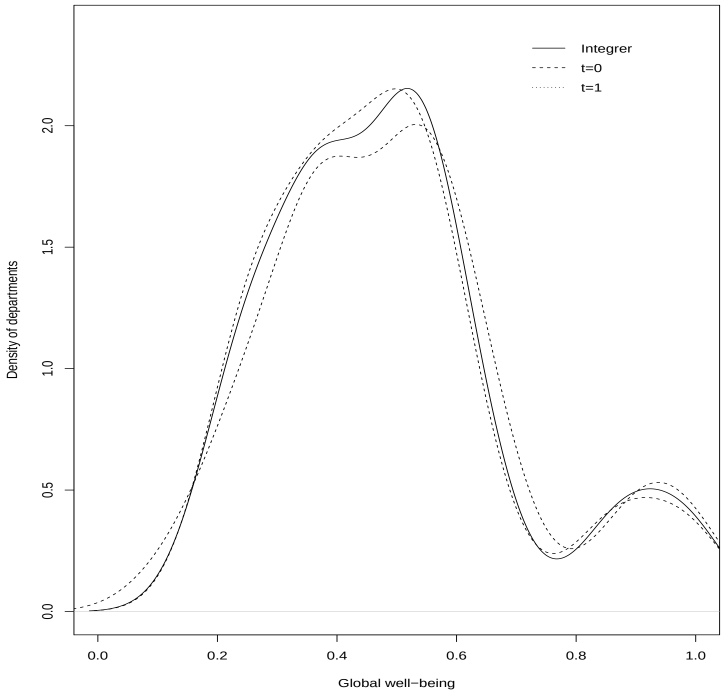


(c) Kernel densities, global well-being

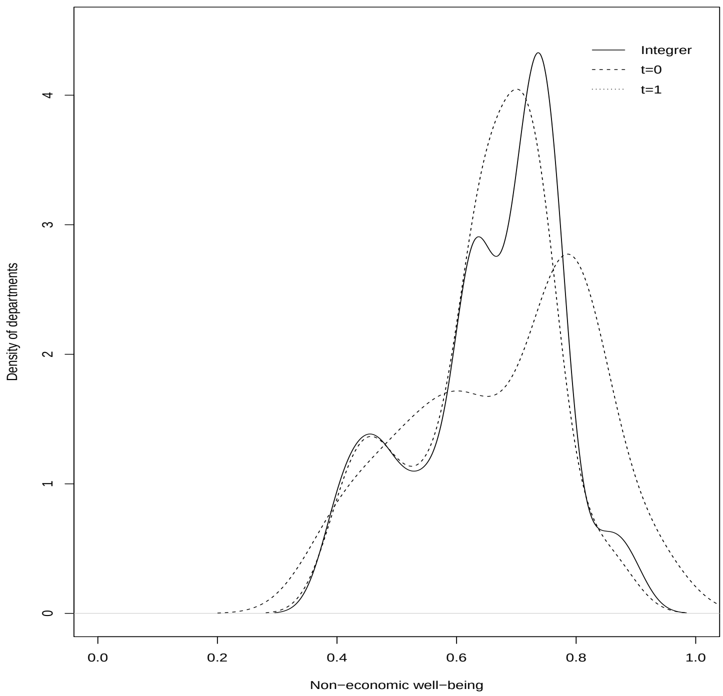


(d) Kernel densities, non-economic well-being

Appendix A. Robustness test, well-being distributions in different scenarios



(a) Global well-being



(b) Non-economic well-being