PAPER

Title: Assessing well-being in European regions. Does government quality matter?

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Abstract: This paper presents a composite indicator of well-being for 168 European regions built with data from 10 well-being domains provided by the OECD *Regional Well-being Dataset*. Regions are then ranked according to their respective levels of well-being. Furthermore, the role of the quality of regional governments in explaining regional well-being disparities is assessed using data from the *Quality of Government EU Regional Dataset*. Results reveal notable well-being differences across European regions, especially between core and periphery ones, with the former enjoying higher levels of well-being. Besides, government quality is found to boost regional well-being

Keywords: Composite well-being indicators; European regions; government quality

JEL codes: C14; C61; I31; H41; R50

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1. Introduction

Why do some regions perform better than others in terms of well-being? This question is attracting growing interest among academics, policymakers and society as a whole. Providing an answer is a complex task, since along with the difficulties of analysing the determinants of well-being, there is the added challenge of measuring well-being itself. In this regard, there exist subjective measures of well-being as self-reported levels of life satisfaction or happiness, in addition to a vast literature measuring well-being with objective dimensions, traditionally GDP per capita. However, well-being is a complex and multidimensional concept that goes far beyond income and involves many additional dimensions, including jobs, education, health, safety and the environment, to mention just some of the most relevant (Rojas, 2011; Ven, 2015; Fleurbaey, 2015; Rojas and García-Vega, 2017).

Within the branch of literature focused on developing objective measures of well-being, the creation in the 1990s of the *Human Development Index* (HDI), incorporating specific measures of income, education and life expectancy, represented a first attempt at building a comprehensive measure of well-being. Later on, the founding in 2009 of the *Commission on the Measurement of Economic Performance and Social Progress*, headed up by the Nobel laureate Joseph Stiglitz with the aim of proposing alternatives to GDP as measures of well-being and social progress (Stiglitz et al., 2009), constituted a further step in this direction.[1] In parallel to this social and academic debate, some international institutions such as the OECD have made available comparable data for several well-being dimensions and different territorial units –e.g., the *Better Life Index* recently provided by the OECD (see Durand, 2015)–, which has prompted insightful contributions, especially at the country level.

Accordingly, authors such as Mizobuchi (2014; 2017), Lorenz et al. (2017) or Peiró-Palomino and Picazo-Tadeo (2018) have contributed several composite indicators of well-being for dif-

[1] The need for more inclusive measures of well-being has recently been underlined by other voices in academia (see Ven, 2015; Fleurbaey, 2015).

ferent groups of countries, which have enabled the construction of well-being rankings. Although interesting, these classifications are unable to reveal within-country disparities, which are likely to be sizeable in many countries. To date, the literature has been silent on this matter, and regional well-being rankings have yet to be produced.

In addition, in spite of the remarkable efforts devoted to addressing the issue of the construction of composite well-being indicators –at least at the country level–, the analysis of its determinants has received less attention. In this regard, some authors have focused on the individual level using subjective measures, analysing the determinants of citizens' happiness (Bohnke, 2008; Stanca, 2009; Abbott and Wallace, 2014). The strand of the literature based on objective well-being indicators, however, fails to address this issue, especially at the regional level.

One potential candidate for explaining territorial well-being disparities is the quality of government (QoG henceforth). As with well-being, QoG is a complex concept encompassing a variety of elements such as corruption, impartiality and quality of public services (Charron et al., 2015). In the European context, there are notable differences in QoG at the regional level, and given the importance of regions in the European Union (EU) policy agenda, a proper understanding of the role of QoG in explaining regional well-being might be of particular interest for policy design. As acknowledged by Charron et al. (2015), some previous attempts, including Golden and Picci (2005) and León et al. (2013), considered QoG regional analyses but restricted their focus to particular countries. Moreover, these analyses were not linked to well-being issues. The main reason for this is that comparable transnational data at the regional level have been made available only recently with the database created by Charron et al. (2014; 2016) –the *Regional Quality of Government Database*– providing homogenous data on QoG for a wide sample of European regions.

Against this background, our contribution in this paper is twofold. Firstly, building on the literature on objective indicators, we construct a composite indicator of well-being at the regional level using data from 168 European regions and 10 different dimensions provided by the OECD *Regional Well-being Dataset*; regions are then ranked according to their respective

levels of well-being. Secondly, we evaluate the role of QoG in explaining well-being by means of regression analysis.

Results reveal notable regional well-being disparities in Europe, with those between core and periphery regions being especially important. The ranking shows that the well-being levels in the majority of regions in the Eastern ex-communist member states that joined the European Union from the 2000s onward, and in some Mediterranean regions in Greece and Italy (all peripheral regions), are a long way off those in regions from Central and Northern European countries belonging to the former EU-15 (mostly core regions). This highlights the need for appropriate policies to reduce the gap. To that end, QoG should be an important instrument, as our regression analysis predicts a positive and significant effect of this variable on well-being. We also find that different dimensions of QoG have uneven impacts in core and periphery regions.

The rest of the paper is structured as follows. Section 2 summarises the theoretical and empirical links between QoG and well-being. Section 3 describes the sample, the data and their sources. Section 4 explains the methodology and the empirical strategy. The results are detailed in Section 5 and, finally, Section 6 provides some conclusions, policy issues and directions for future research.

2. Quality of government and well-being: Theoretical and empirical linkages

There are several definitions and measures of QoG (Bjørnskov et al., 2010); indeed, this is one of the major drawbacks when dealing with this concept. In a broad sense, QoG can be understood as the extent to which governments and public administrations perform their duties appropriately. Most of these duties are specifically aimed at the creation and sustainability of a welfare system able to guarantee citizens' quality of life. In this regard, Holmberg et al. (2009), Kaufmann et al. (2009) and Rothstein and Teorell (2008) have found that QoG improves the performance of several aspects related to welfare. Conversely, low levels of QoG lead to a wide array of economic and social troubles.

The literature is extensive on subjective well-being measures such as happiness or life satisfaction. Frey et al. (2000), Ott (2010a,b, 2011), Helliwell and Huang (2008) and Orviska et al. (2014) found that higher levels of QoG and democratic satisfaction correlate significantly with citizens' happiness. Frey and Stutzer (2005) and Ott (2010b) found that people are more satisfied with life in good government contexts. More recently, Helliwell et al. (2018) argue that apart from the direct effects of QoG on life satisfaction, there are also important indirect mechanisms. These include a variety of aspects related to the welfare system –e.g., income, education or the environment–, which may be positively influenced by QoG and translate into higher well-being. However, disentangling the mechanisms is a challenge due to the difficulty in accounting for all the potential factors that might affect well-being (Helliwell et al., 2018), as well as all the possible interdependencies.

This strand of the literature evaluating transmission channels directly connects with the studies considering objective well-being measures, i.e., variables somehow related to the welfare state. The first attempts are found in Easterlin (1974), who links happiness and income, showing that as countries become richer, happiness does not evolve in step, giving rise to the so-called *Easterlin Paradox.* Support for the paradox, however, critically depends on the period of analysis and the sample composition. Subsequent studies at the country level in this line include Knack and Keefer (1995), Mauro (1995), Mo (2001) or Easterlin and Sawangfa (2010), reporting mixed results. Other studies such as Dasgupta et al. (1998) linked QoG with inequality and poverty; Morse (2006) and Welsch (2004) linked it with environmental sustainability; and Mauro (1998) with education and health outcomes, to name just some of the most relevant contributions. The roots of these positive associations might be found in seminal contributions from the nineties. North (1990) concluded that both formal and informal institutions are needed for territories to react and adapt to changes efficiently, maximising their capacity to adopt innovation and knowledge, which ultimately generate positive externalities for welfare. Similarly, Morgan (1997) argued that regions' learning capacity is heavily influenced by their institutions.

Most of the empirical support for the positive linkage between QoG and well-being is found at the country level, generally using QoG information for several domains from the *World Bank Governance Indicators*.[2] At the regional level, the literature is, to the best of our knowledge, completely silent on this matter. In that regard, data limitations heavily constrain the possibilities of analysis, although there have been notable advances in that sense in recent years. Two examples are the databases used in this paper, which are introduced in the next section.

3. Sample and data

The sample used in this research comprises 168 European regions at different aggregation levels (NUTS 1 and NUTS 2) from 20 European countries. This selection –in terms of both the number of regions and the aggregation level– has been entirely determined by the availability of data on the two main variables of interest, namely well-being and QoG.[3]

3.1. Well-being

The data on well-being are taken from the OECD *Regional Well-being Database*[4], which provides information at the regional level for OECD members on several indicators from 10 different well-being domains. These domains and their corresponding indicators are listed in Table 1, which also includes means and standard deviations on a normalised scale of 0 to 10 for the domains, where higher values indicate better performance. This scale, provided by the OECD to allow direct comparisons, is constructed using the *min-max* criterion.[5] The database

[2] These domains are government effectiveness, regulatory quality, rule of law, control of corruption, voice and accountability, political stability and absence of violence.

[3] In any case, combining NUTS 1 and NUTS 2 levels is a common strategy in empirical analyses for the European regional context.

[4] Accessible at https://www.oecdregionalwellbeing.org/

[5] All the details on the rescaling procedure are available in the database users' guide, accessible at https://www.oecdregionalwellbeing.org/assets/downloads/Regional-Well-Being-User-Guide.pdf. Furthermore, note that for those domains defined by more than one indicator, the reported value is the arithmetic mean of their normalised scores.

also includes as an 11th well-being domain *self-reported life satisfaction*, although we excluded it from the construction of the composite indicator since, as pointed out by Rojas (2007), life satisfaction can actually be considered a measure of subjective perceived well-being rather than an individual objective domain.[6]

At the time of writing this paper, the latest version of the OECD *Regional Well-being Database*, which was released in June 2016, provided data for the years 2000 and 2014, although we use only the final update for reasons of compatibility with the rest of the variables. Moreover, it is worth mentioning that the reported figures for 2014 actually refer to years 2010 to 2014, depending on the indicator and the region. As noted in the Introduction, since the database fails to provide a composite well-being indicator –or measure of *global objective well-being*– we have constructed one. To do so, we use *Data Envelopment Analysis* (DEA) and *Multi-Criteria-Decision-Making* (MCDM) techniques, as explained in detail in Section 4.1.

3.2. Quality of government (QoG)

The data for QoG at the regional level are taken from the *Quality of Government EU Regional Dataset*, produced by the Quality of Government Institute of the University of Gothenburg (see Charron et al., 2014, 2016). In this case, the database directly provides a composite measure of QoG –the so-called EQI index–, so the figures were taken with no additional treatment. This synthetic measure is based on 16 survey questions covering the dimensions of corruption, impartiality and quality. The database aggregates individual responses to the questions at the regional level, following the guidelines issued by the OECD (see Nardo et al., 2008). In this paper, we use both the composite EQI index and individual information on its three dimensions. For each dimension, we consider the average of the score recorded for the questions associated with that pillar. In all cases, higher values correspond to better performance. Information on the specific questions regarding each domain and all the computation details of the composite EQI index are in the seminal papers by Charron et al. (2014; 2015;

[6] It is important to note that in some geographical contexts, especially in Latin America, the correlation between objective and subjective measures of well-being is quite low. This may explain why these two types of approaches are rarely combined in empirical analyses.

2016). Two surveys, for years 2010 and 2013, were available at the time of carrying this research out, covering most of the European regions.

An additional concern in our research context is reverse causality (see, for instance, Guven, 2011, De Neve et al., 2013). As well-being data refers to years 2010 to 2014, we have considered QoG data only from the EQI for 2010 to prevent, as far as possible, reverse causality issues in the analysis of the determinants of well-being.

Figure 1 maps the QoG scores for our 168 European regions. The highest scores are concentrated in the Nordic countries, the Netherlands, and some UK and Austrian regions. Most of the German and Irish regions display relatively high scores, whereas the Spanish and French regions show medium values. The lowest levels are found for Italian, Polish and Greek regions. Although within-country disparities are non-negligible, the map reveals a marked country-level pattern, as well as a clear difference between regions in the core and at the periphery of Europe, with the former showing noticeably better performance.

3.3. Control variables

Finally, as a control variable, we include population density in 2013 (measured in thousands of inhabitants per km^2), taken from Eurostat[7], as a measure to capture agglomeration. The expected relationship between this variable and well-being is, however, ambiguous, since an improvement in some well-being domains can occur in densely populated regions due to increased economic dynamism and more available services (e.g., accessibility to services may improve in this case), while other domains can be negatively affected by the same factors (e.g., environment). Moreover, we include a dummy variable for core regions, as disparities between core and periphery regions in Europe can be important. As there is no formal definition for core and periphery regions, we considered as peripheral those regions defined as 'less developed' in the framework of the *EU Cohesion Policy 2014-2020*, corresponding to regions

[7] Accessed through http://ec.europa.eu/eurostat/data/database.

with GDP per capita below 75 per cent of the European Union average.[8] Generally speaking, periphery regions correspond to Eastern Europe countries and Southern regions in Mediterranean countries such as Spain, Italy and Greece.

In addition, in the most comprehensive model estimated to explain well-being, we also include country-level dummies, capturing country-specific conditions equally affecting regions in the same country. This strategy may also help to alleviate omitted variable bias or model specification problems. Unfortunately, more controls would not be advisable because the calculation of the well-being composite indicator used as dependent variable already involves a large set of variables, and endogeneity problems may easily arise.

4. Empirical strategy and methodology

4.1. Constructing a composite well-being indicator

One of the main concerns in computing composite indicators is the selection of weights. While the use of subjective weights, such as an equally weighted indicator, could be a solution, in this paper we compute a composite indicator with endogenously determined weights. To do so, we use *Data Envelopment Analysis* (DEA) techniques and *Multi-Criteria-Decision-Making* (MCDM). DEA was initially proposed by Charnes et al. (1978) as a way of assessing the technical performance of production units (Farrell, 1957). Later on, Lovell et al. (1995) pioneered the adaptation of this technique to the computation of composite indicators involving a range of economic, social and/or environmental factors (also see Zaim et al., 2001; Zhou et al., 2007). Furthermore, several papers have used DEA, alone or in combination with other techniques, to build composite indicators of well-being, or the closely-related concept of life

[8] The *EU Cohesion Policy* addresses NUTS 2 regions and our sample is a combination of NUTS 1 and NUTS 2 regions. NUTS 1 were classified according to the predominant category in the NUTS 2 contained in each case. In addition, the use of the income criterion to define different sample groups is common in well-being studies (see Bjørnskov et al., 2010).

satisfaction.[9] Besides, the OECD (2008) has acknowledged the usefulness of DEA to avoid subjectivity in the choice of weights when calculating composite well-being indicators.[10]

In order to calculate our well-being indicator, we follow Guardiola and Picazo-Tadeo (2014), which explains in detail the relationships between the formulation of the conventional DEA model and the mathematical programs required to build composite indicators of well-being (see also Bernini et al., 2013). Taking into account our sample of r = 1,…,168 European regions and the d = 1,…,10 domains described in Section 2, the program that enables an assessment of the well-being of region r' is:

$$\begin{aligned}&\text{Maximise}_{\omega_{dr'}}\ \text{well}-\text{being}_{r'} = \textstyle\sum_{d=1}^{10} \omega_{dr'}\,\text{domain}_{dr'}\\&\text{Subject to:}\\&\qquad \textstyle\sum_{d=1}^{10} \omega_{dr'}\,\text{domain}_{dr} \leq 1 \qquad\qquad r = 1,\ldots,168\\&\qquad \omega_{dr'} \geq 0 \qquad\qquad\qquad\qquad\quad\ d = 1,\ldots,10\end{aligned} \tag{1}$$

where $domain_{dr'}$ stands for the observed score for domain or dimension d in region r', and $\omega_{dr'}$ is the weight assigned to domain d in the computation of the weighted well-being composite indicator of region r'.

Grounded in the *Benefit-of-the-Doubt* (BoD) principle (see Cherchye et al., 2007), program (1) looks for the set of weights that maximises the composite well-being indicator of region r' when compared to all other regions in the sample using the same weighting scheme. That is, domains in which a given region performs poorly would be assigned lower weights when building its composite indicator, while domains in which it performs well would be assigned higher weights. Furthermore, a normalisation constraint is added by imposing an upper bound of 1 on the composite indicator. This value represents the highest well-being, and well-being declines as the indicator moves away from 1 and approaches 0, a score that would represent

[9] Some examples are Hashimoto and Kodama (1997), Murias et al. (2006), Bernini et al. (2013), Guardiola and Picazo-Tadeo (2014), Mizobuchi (2014) and Peiró-Palomino and Picazo-Tadeo (2018).

[10] Scientific literature has also acknowledged that, in spite of its shortcomings, weighting is a useful practice that merits consideration in empirical analyses of well-being, e.g., Hsieh (2004).

the lowest well-being; accordingly, a score of, let us say, 0.8 for a given region would imply that it achieves only 80% of the well-being attained by its peers.

Whereas combining DEA and the BoD principle provides a successful approach to the issue of selecting weightings in constructing composite well-being indicators, it might be less effective when it comes to ranking regions. In the first place, some authors have pointed out that comparisons across regions might be meaningless as their well-being composite indicators are computed using different sets of weightings (Sinuany-Stern and Friedman, 1998; Kao and Hung, 2005; Bernini et al., 2013; Guardiola and Picazo-Tadeo, 2014). Secondly, the DEA-BoD approach could assign a score of 1 –meaning highest well-being– to some regions simply due to a lack of discriminating power of the model, i.e., these regions are self-evaluated (see technical details in Dyson et al., 2001). The latter limitation, which can be particularly relevant when there is a relatively small number of observations in the sample with respect to the dimension of the DEA problem (in our case study, determined by the number of domains in the composite well-being indicator), would prevent European regions in our sample from being fully ranked against each other.

Researchers in the field have proposed several ways to overcome the abovementioned limitations of the DEA-BoD approach, including principal-component analysis (Adler and Golany, 2002), cross-efficiency analyses (Sexton et al., 1986; Doyle and Green, 1994) or super-efficiency analysis (Andersen and Petersen, 1993). In this paper, again following Guardiola and Picazo-Tadeo (2014), we employ the approach suggested by Despotis (2002) that, based on previous work by Li and Reeves (1999), combines DEA with MCDM. This enables an increase in the discriminating power of our DEA-BoD model while keeping a common set of weightings for well-being domains across regions; i.e., the DEA-BoD-MCDM model. Following Despotis (2005), the linear program needed to compute these common weights is:

$$\text{Minimise}_{m_r\, \omega_d\, z}\ t\,\frac{1}{168}\sum_{r=1}^{168} m_r + (1-t)z$$

Subject to:

$$\begin{aligned} &\sum_{d=1}^{10} \omega_d\, \text{domain}_{d_r} + m_r = \text{well-being}_r^{*} && r = 1, \dots, 168 \\ &(m_r - z) \leq 0 && r = 1, \dots, 168 \end{aligned} \qquad (2)$$

$$\mathrm{m_r} \geq 0 \qquad\qquad\qquad\qquad \mathrm{r} = 1, \dots, 168$$
$$\omega_\mathrm{d} \geq \mathcal{E} \qquad\qquad\qquad\qquad \mathrm{d} = 1, \dots, 10$$
$$\mathrm{z} \geq 0$$

where ω_d is the common weight –across regions– assigned to domain d in the DEA-BoD-MCDM model; z stands for a non-negative parameter to be estimated; $\mathcal{E}$ is a non-Archimedean small number which ensures that all 10 domains enter the construction of the composite well-being indicator with positive weightings –in our case study it has been set at 0.001–; m_r stands for the deviation between the DEA-BoD composite well-being indicator for region r, namely $\textit{well-being}_r^*$, and its DEA-BoD-MCDM score; finally, *t* is a parameter ranging from 0 to 1 that represents different theoretical assessments by setting the relative importance given to the first and second terms in the objective function of the DEA-BoD-MCDM model.

When $t = 1$, which corresponds to the *Manhattan* or city-block distance concept, the objective function to be minimised is the first term in expression (2), representing the average deviation across regions between the well-being scores computed with the DEA-BoD and DEA-BoD-MCMD approaches (see Bernini et al., 2013). On the contrary, when $t = 0$, the function to be minimised –through the non-negative parameter z– is the second term of the objective function in (2), which represents the maximal deviation between the DEA-BoD and the DEA-BoD-MCDM scores of well-being. Accordingly, in this case –which corresponds to the *Chebyshev* or chessboard concept of distance– the well-being score of the most penalised region in the DEA-BoD model is maximised.

In order to avoid a source of subjectivity in choosing the value for the parameter *t*, here we follow the proposal by Reig-Martínez et al. (2011) (see also Despotis, 2002), which consists of taking for each region the value of the definite integral of the composite indicator for *t*

ranging from 0 to 1 as the sole composite well-being indicator, known as the *integer solution*.[11]

4.2. Measuring the impact of government quality on well-being

In order to assess the impact of QoG on regional well-being, different models including a variety of control variables are estimated. Formally, the most general one takes the following form:

$$\mathrm{WB_r} = \beta'\mathrm{X_r} + \varepsilon_\mathrm{r} \tag{3}$$

where $\mathrm{WB_r}$ is the composite well-being score for region r obtained from expression (2), $\mathrm{X_r}$ is a vector of independent variables intended to explain well-being, including a constant, the variable of interest (QoG) and the control variables (population density and geographical dummies), ε_r stands for the error term and, finally, β is a vector of parameters to be estimated. As is common in DEA literature, this second stage is carried out using truncated regression and bootstrapping, as proposed by Simar and Wilson (2007).

Specifically, it requires simulating a sensible data-generating process, generating artificial bootstrap samples from this process, and building standard errors and confidence intervals for the parameters of interest through bootstrapping. According to the first algorithm proposed by Simar and Wilson (2007; pp.41-42), in our case study it would entail the following steps:

1. Compute a set of well-being measures for the 168 European regions using the DEA-BoD-MCDM approach.
2. Use maximum likelihood techniques to estimate the parameters β and σ_ε in the truncated regression of the well-being scores obtained in step 1 on a set of covariates X, using the subset of regions with scores below one ($\widehat{\mathrm{WB}}_\mathrm{r} < 1$). Formally:

[11] In practice, this can be easily done by obtaining a series of well-being scores with enough values for the parameter *t* –for example, at intervals of 0.001 as we do in this paper– and then calculating the average as the single well-being composite indicator.

$$\widehat{WB}_r = \beta' X_r + \epsilon_r, \text{ with } \epsilon_r \equiv \varepsilon_r + \zeta_r \text{ and } \zeta_r \equiv \widehat{WB}_r - WB_r \quad (4)$$

3. Loop over the following three steps L times to obtain a set of bootstrapped estimates of the parameters β and σ_ε; namely, $B = \left[\left(\hat{\beta}'^b, \hat{\sigma}_\varepsilon^b\right)\right]_{b=1}^{L}$.

   3.1. For each region with score of well-being below one, draw ε_r^b from the following normal distribution: $N(0, \hat{\sigma}_\varepsilon)$ right − truncated at point $\left(1 - \hat{\beta}' X_r\right)$.

   3.2. Compute $WB_r^b = \hat{\beta}' X_r + \varepsilon_r^b$, again for regions with well-being below one.

   3.3. Estimate $\hat{\beta}^b$ and $\hat{\sigma}_\varepsilon$ by truncated regression and maximum likelihood using the simulated efficient scores computed in step 3.2 as the dependent variable.

4. Finally, use values in B and the original estimates to build a confidence interval for the parameters β and σ_ε.

5. Results and discussion

5.1. Ranking European regions according to their well-being

Let us start by commenting on the results obtained for our composite indicator of well-being, computed, as explained in Section 4.1, by combining DEA with the BoD principle and MCDM.[12] Table 2 shows the 168 European regions included in our study, ranked according to their computed well-being score.[13] The rankings are mostly headed up by regions from Finland, Sweden, Austria, Germany, France, as well as some Northern Spanish regions such as Navarre and the Basque Country. In contrast, regions from Central and Eastern European

[12] In order to keep our assessment as neutral as possible, well-being scores have been computed, as already mentioned, by means of the *integer solution*. However, all the analyses have also been carried out in the *most penalised region optimum* and the *collective optimum* scenarios. The results obtained do not differ significantly from those presented in the paper, and are available to readers on request.

[13] In this respect, the DEA-BoD model with idiosyncratic weightings results in 92 out of 168 regions, i.e., more than half, reporting a well-being score of one, which points to a worrying lack of discrimination capacity of this approach. Conversely, with the DEA-BoD-MCDM approach only two regions –Western Finland, and the Basque Country in Spain– achieve a well-being score of one. In our opinion, this strongly supports our decision to combine DEA, the BoD principle and the MCDM approach to assess well-being.

countries that joined the European Union from the 2000s onward, along with numerous regions from Southern countries such as Italy, Greece and Portugal, occupy the lowest positions in the ranking. This initial picture of well-being in Europe highlights remarkable regional disparities, especially between core and periphery regions. To the best of our knowledge, there are no other composite well-being indicators built using such a broad range of dimensions and for such a wide set of European regions, meaning that a direct comparison of our results is unfeasible. However, we believe that our ranking of regions fits quite well with both our general knowledge of well-being in Europe, as well as with existing literature on well-being at the country level assessed using similar methods (see Peiró-Palomino and Picazo-Tadeo, 2018).

As with QoG, a country-level pattern is also observable for well-being, although within-country disparities are notable in some countries. In this respect, Table 3 reports mean values and regional standard deviation –as a measure of disparities– of well-being and QoG at the country level. Regional disparities in well-being are evident in countries such as Spain and Italy, where a North-South divide is apparent (see Figure 2). Furthermore, we found relatively large within-country disparities in Belgium and Finland; in the latter, the region of Åland, which lies far below the country average, is mainly responsible for the difference. However, in other countries such as Denmark, Sweden, Portugal and the Slovak Republic, differences are negligible.

Finally, Figure 3 shows the kernel density distribution of well-being scores for all 168 regions in our study, as well as separate density distributions for core and periphery regions. The distribution of well-being for all regions exhibits a main mode between the scores of 0.9 and 1, and a long left tail representing a large number of regions with lower well-being scores. Moreover, average well-being is 0.868, with a standard deviation of 0.108. However, splitting the sample by differentiating between core and periphery regions results in quite different average well-being scores of 0.905 and 0.756, respectively. Also, within-group differences are high in both groups, and similar in magnitude (the standard deviation is 0.085 and 0.093 for core and periphery regions, respectively). Finally, we have tested the equality of core and pe-

riphery distributions by means of the Simar-Zelenyuk-Li test[14] (Simar and Zelenyuk, 2006), and the null hypothesis of equality is clearly rejected at standard confidence levels (the *p-value* is virtually zero).

5.2. Assessing the effect of quality of government on regional well-being

Moving now to the analysis of the role of QoG in explaining well-being differences in Europe, let us first focus on Figure 4, which provides a scatterplot for QoG and well-being, showing a positive and statistically significant association between the two variables (the Spearman-*rho* reaches 0.77, while the *p-value* is negligible). Furthermore, the regression results reported in Table 4 confirm the positive and statistically significant relationship between QoG and well-being, which holds when control variables are accounted for. As discussed above, the dependent variable in the regression analysis is our composite indicator of well-being, which, as explained in Section 4.1, is censored between zero and one. Accordingly, as already noted, all models are estimated *via* Simar and Wilson (2007).[15]

Model 1 is a simple model that includes only QoG as an explanatory variable. The estimated coefficient is positive and statistically significant, in line with previous arguments in the related literature. Model 2 incorporates as controls population density and a dummy variable for core regions. The estimated parameter is non-significant for the former, but positive and statistically significant for the latter, indicating that regions in the core of Europe enjoy, on average, higher well-being than those located in the periphery. Again, these results are as expected, as already indicated by both the ranking in Table 2 and the map in Figure 2.

Furthermore, Model 3 incorporates individual country dummies capturing unobserved country-level characteristics that might affect well-being. As a more comprehensive model, its overall significance is comparatively larger than that for Models 1 and 2, and as such it is

[14] The algorithm of this non-parametric test –which is particularly well suited for testing differences in the distributions of scores from DEA-based analyses– is based on calculating and bootstrapping the Li statistic (Li, 1996) using DEA estimates, where values equal to unity are first smoothed by adding a small noise.

[15] Estimations have been carried out with Stata 15 software, and the Stata module developed by Tauchmann (2016).

preferable in terms of explanatory power. After controlling for unobserved country effects, the estimated coefficient for government quality is slightly smaller, but maintains its statistical significance. The country dummies included in this last model, which are not reported for reasons of space but are available to readers on request, are also mostly significant.

Data limitations at the regional level prevent us from using alternative measures of QoG from different sources and of a different nature. However, similarly to Bjørnskov et al. (2010), who use data from the *World Bank Governance Indicators*, we can still make use of the separate domains of the EQI index, namely corruption, impartiality and quality.[16] Models 4-7 in Table 4 report these results, showing that the three components are significant individually. The control variable population density is non-significant across models, while the dummy variable core region is significant in all models except in Model 5. Despite the fact that correlations between domains are high,[17] Model 7 accounts for the three components and only corruption and quality –which registers only a slight change in its coefficient– remain significant. This is in line with Ott's (2010a) findings, showing the remarkable importance of the quality component.[18]

As we found marked differences between core and periphery regions in terms of both well-being and QoG, we analyse whether the impact of QoG and its components differ between groups. Despite not being directly comparable due to the different nature of both the dependent and independent variables, Bjørnskov et al. (2010) found that in low-income countries happiness is more sensitive to improvements in the quality of economic–judicial institutions, whereas in middle and high-income countries it is the quality of political institutions that really matters. The results, available in Tables 5 and 6 for core and periphery regions, respective-

[16] As explained in Section 3, these three dimensions are directly derived from the 16 questions used to construct the EQI index. This information is missing for some regions, which constrains our sample to 159 observations. For additional details see Charron et al. (2016).

[17] Spearman correlations are 0.763, 0.766 and 0.391 for corruption vs. impartiality, corruption vs. quality and quality vs. impartiality, respectively. They are all significant at the 1% level.

[18] In Ott (2010a), results are provided at the country level, showing that technical government quality is important for both rich and poor countries. However, democratic quality only matters for rich countries. Unfortunately, data limitations at the regional level prevent us from performing this interesting analysis.

ly, reveal some interesting patterns. For the case of core regions, QoG and all its components are positively related to well-being (Models 8 to 11). However, when the three components are jointly considered in Model 12, only corruption and quality remain significant, and at the 10% confidence level in the case of the latter. In contrast, the same exercise for periphery regions yields non-significant coefficients, with the exception of the quality component (Models 13 to 17).

Therefore, in the more developed regions of the core of Europe, despite their high quality and impartial government services, differences in corruption are still important and results corroborate its damaging impact on well-being. In the less developed peripheral regions, what matters is having quality in government services; interestingly, this is the case regardless of their impartiality or corruption levels.

5. Conclusions, policy issues and prospects for further research

In this paper we propose a composite indicator to rank 168 European regions according to their well-being. This indicator is built using information on 10 well-being domains provided by the OECD *Regional Well-being Database*. The resulting ranking shows that spatial disparities are important, especially between regions from the core and from the periphery of Europe, with the former enjoying higher levels of well-being. Furthermore, we find that the quality of regional governments substantially improves well-being.

These results might be useful for the design of future regional policies in the European context. In this respect, well-being should be understood as a collection of dimensions that, alone or in combination with each other, directly affect citizens' life satisfaction. Indeed, the ultimate responsibility of governments is to achieve and guarantee higher living standards for their citizens and, in that sense, government quality is found to be an important condition for well-being. Therefore, policies should follow different paths: on the one hand, they should be aimed at improving particular well-being domains; while on the other hand, they should also pursue the improvement of the quality of government, which might have an indirect effect on the application and effectiveness of other policies.

The paper has also some limitations directly related to the nature of the sample and the scarcity of data at the regional level. For example, it provides evidence using only one measure of institutional quality, in contrast with cross-country studies that rely on a wider set of institutional measures. In this respect, we tried to overcome this shortcoming by reporting separate results for each of the individual dimensions of the EQI index, which also revealed interesting subtleties. Whereas for the more developed core regions of Europe what basically matters is corruption, for peripheral regions the greatest effects are found for the quality of public services. This may help in the design of region-specific policies and encourage policymakers to abandon one-size-fits-all strategies, which would be in line with the current guidelines for the European Union's policies in a variety of spheres. Another shortcoming is that the analysis is based on a cross-section of regions, while more precise conclusions can be drawn from panel data analyses, as shown in the recent paper by Helliwell et al. (2018).

At any rate, it is our belief that the paper still provides an interesting contribution to this branch of literature and we hope it will encourage further contributions from scholars, especially at the regional level, on these and other issues. For instance, upcoming updates of the two novel datasets used in this paper will allow researchers to exploit the temporal dimension of the data with the construction of panel data models, which might shed additional light on well-being and its determinants. Moreover, the specific mechanisms through which the quality of government translates into higher well-being still remain widely unexplored. In this regard, the multidimensionality of the concepts represents an additional handicap. As such, future updates of the *Quality of Government EU Regional Dataset* should consider other measures of democratic quality apart from institutional quality, as these different types of measures are found to have varying effects on well-being at the country level. Finally, the analysis of nonlinearities and parameter heterogeneity can be another potential extension of our research, especially after having found different effects for core and peripheral regions.

References

Abbott, P., Wallace, C., 2014., Rising economic prosperity and social quality the case of new member states of the European Union. Social Indicators Research 115, 419–439.

Adler, N., Golany, B., 2002. Including principal components weights to improve discrimination in data envelopment analysis. Journal of the Operational Research Society 53, 985–991.

Andersen, P., Petersen, N., 1993. A procedure for ranking efficient units in data envelopment analysis. Management Science 39, 1261–1264.

Bernini, C., Guizzardi, A., Angelini, G., 2013. DEA-like model and common weights approach for the construction of a subjective community well-being indicator. Social Indicators Research 114(2), 405–424.

Bjørnskov, C., Dreher, A., Fischer, J., 2010. Formal institutions and subjective well-being: revisiting the cross-country evidence. European Journal of Political Economy 26(4), 418–430.

Bohnke, P., 2008. Does society matter? Life satisfaction in an enlarged Europe. Social Indicators Research 87, 189–210.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2(6), 429–444.

Cherchye, L., Moesen, W., Rogge, N., Van Puyenbroeck, T., 2007. An introduction to 'benefit of the doubt' composite indicators. Social Indicators Research 82(1), 111–145.

Charron, N., Dahlberg, S., Holmberg, S., Rothstein, B., Khomenko A., Svensson, R., 2016. The Quality of Government EU Regional Dataset, version September 2016. University of Gothenburg: The Quality of Government Institute. Accessed at http://www.qog.pol.gu.se

Charron, N., Dijkstra, L., Lapuente, V., 2015. Mapping the regional divide in Europe: A measure for assessing quality of government in 206 European regions. Social Indicators Research 122, 315–346.

Charron, N., Lapuente, V., Rothstein, B., 2014. Regional governance matters: Quality of government within European Union member States. Regional Studies 48(1), 68–90.

De Neve, J., Diener, E., Tay, L., Xuereb, C., 2013. The Objective Benefits of Subjective Well-Being. In: Helliwell, J., Layard, R., Sachs, J. (Eds.), UN Sustainable Development Solution Network, New York, pp. 54–79, World Happiness Report 2013.

Despotis, D.K., 2002. Improving the discriminating power of DEA: Focus on globally efficient units. Journal of the Operational Research Society 53, 314–323.

Despotis, D.K., 2005. A reassessment of the human development index via data envelopment analysis. Journal of the Operational Research Society 56(8), 969–980.

Durand, M., 2015. The OECD better life initiative: How's life? and the measurement of well-being. Review of Income and Wealth 61(1), 4–17.

Dyson, R., Allen, R, Camanho, A., Podinovski, V., Sarrico, C., Shale, E., 2001. Pitfalls and protocols in DEA. European Journal of Operational Research 132, 245–259.

Easterlin, R., 1974. Does economic growth improve the human lot? Some empirical evidence. In: David, P.A., Reder, M.W. (Eds.), Nations and Households in Economic Growth: Essays in Honor of Moses Abramovitz. Academic Press, New York, pp. 89–125.

Easterlin, R., Sawangfa, O., 2010. Happiness and economic growth: does the cross-section predict time trends? Evidence from developing countries. In: Diener, E., Helliwell, J.F., Kahneman, D. (Eds.), International Differences in Well-Being. Oxford University Press, Oxford, pp. 166–216.

Farrell, M., 1957. The measurement of productive efficiency. The Journal of Royal Statistical Society Series A 120, 253–281.

Fleurbaey, M., 2015. Beyond income and wealth. Review of Income and Wealth 61(2), 199–219.

Frey, B., Rey, B., Stutzer, A., 2000. Happiness, economy and institutions. Economic Journal 110, 918–938.

Frey, B.S., Stutzer, A., (2005). Beyond outcomes: measuring procedural utility. Oxford Economic Papers, 57 (1), 90–111.

Golden, M.A., Picci, L., 2005. Proposal for a new measure of corruption, illustrated with Italian data. Economics and Politics 17(1), 37–75.

Guardiola, J., Picazo-Tadeo, A.J., 2014. Building weighted-domain composite indices of life satisfaction with Data Envelopment Analysis. Social Indicators Research 117, 257–274.

Guven, C., 2011. Are happier citizens better citizens? Kyklos 64 (2), 178–192.

Dasgupta, S., Davoodi, H., Alonso-Terme, R., 1998. Corruption affect income inequality and poverty? Working Paper, Number 98/76. International Monetary Fund (IMF), Washington, DC.

Doyle, J.R., Green, R.H., 1994. Efficiency and cross-efficiency in DEA: derivations, meanings and uses. Journal of the Operational Research Society 45 (5), 567–578.

Hashimoto, A., Kodama, M. 1997. Has livability of Japan gotten better for 1956–1990? A DEA approach. Social Indicators Research 40, 359–373.

Helliwell, J.F., Huang, H., 2008. How’s your government? International evidence linking good government and well-being. British Journal of Political Science 38, 595–619.

Helliwell, J.F., Huang, H., Grover, S., Wang, S., 2018. Empirical linkages between good governance and national wellbeing. Journal of Comparative Economics, in press.

Holmberg, S., Rothstein, B., Nasiritousi, N., 2009. Quality of government: What you get. Annual Review of Political Science 12, 135-161.

Hsieh, C., 2004. To weight or not to weight: The role of domain importance in quality of life measurement. Social Indicators Research 68, 163–174.

Kao, C., Hung, H.T., 2005. Data envelopment analysis with common weights: The compromise solution approach. Journal of the Operational Research Society 56, 1196–1203.

Kaufmann, D., Kraay, A., Mastruzzi, M., 2009. The worldwide governance indicators: Methodology and analytical issues. World Bank Policy Research, Working Paper, No. 5430.

Knack, S., Keefer, P., 1995. Institutions and economic performance: Cross-country tests using alternative institutional measures. Economics & Politics 7(3), 207-227.

León, C.J., Araña, J.E., de León, J., 2013. Correcting for scale perception bias in measuring corruption: an application to Chile and Spain. Social Indicators Research 114, 977–995.

Li, Q., 1996. Nonparametric testing of closeness between two unknown distribution functions. Econometric Reviews 15, 261–274.

Li, X., Reeves, G.R., 1999. A multiple criteria approach to data envelopment analysis. European Journal of Operational Research 115, 507–517.

Lorenz, J., Brauer, C., Lorenz, D., 2017. Rank-optimal weighting or 'How to be best in the OECD Better Life Index?' Social Indicators Research,134, 75–92.

Lovell, C.A.K., Pastor, J.T., Turner, J.A., 1995. Measuring macroeconomic performance in the OECD: A comparison of European and non-European countries. European Journal of Operations Research 87, 507–518.

Mauro, P., 1995. Corruption and growth. Quarterly Journal of Economics 110, 681–712.

Mauro, P., 1998. Corruption and composition of government expenditure. Journal of Public Economics 69, 263–279.

Mizobuchi, H., 2014. Measuring world better life frontier: a composite indicator for OECD better life index. Social Indicators Research 118, 987–1007.

Mizobuchi, H., 2017. Incorporating sustainability concerns in the Better Life Index: Application of corrected convex non-parametric least squares method. Social Indicators Research 131(3), 947–971.

Mo P.H., 2001. Corruption and economic growth. Journal of Public Economics 29, 66–79.

Morgan, K., 1997. The learning region: Institutions, innovation and regional renewal. Regional Studies 31(5), 491–503.

Morse, S., 2006. Is corruption bad for environmental sustainability? A cross-national analysis. Ecology and Society 11(1), 1–22.

Murias, P., Martínez, F., de Miguel, C., 2006. An economic wellbeing index for the Spanish provinces: A data envelopment analysis approach. Social Indicators Research 77, 395–417.

Nardo M., Saisana, M., Saltelli, A. Tarantola, S., 2008. Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD, European Commission, Joint Research Centre. OECD Publications. Paris.

North, D., 1990. Institutions, Institutional Change and Economic Performance. Cambridge, MA: Cambridge University Press.

OECD, Organization for Economic Cooperation and Development, 2008. Handbook on Constructing Composite Indicators: Methodology and User Guide. Paris: OECD Publishing.

Orviska, M., Caplanova A., Hudson, J., 2014. The impact of democracy on well-being. Social Indicators Research 115, 493–508.

Ott, J.C., 2010a. Good governance and happiness in nations: Technical quality precedes democracy and quality beats size. Journal of Happiness Studies 11, 353–368.

Ott, J.C., 2010b. Greater happiness for a greater number: Some non-controversial options for governments. Journal of Happiness Studies 11 (5), 631–647.

Ott, J.C. 2011. Government and happiness in 130 nations: good governance fosters higher level and more equality of happiness. Social Indicators Research 102 (1), 3–22.

Peiró-Palomino J., Picazo-Tadeo, A.J., 2018. OECD, one or many? Ranking countries with a composite well-being indicator. Social Indicators Research, in press.

Reig-Martínez, E., Gómez-Limón, J.A., Picazo-Tadeo, A.J., 2011. Ranking farms with a composite indicator of sustainability. Agricultural Economics 42, 561–575.

Rojas, M. (2007). The complexity of well-being: A life-satisfaction conception and a domains-of-life approach. In: I. Gough, A. McGregor (Eds.), Researching Wellbeing in Developing Countries: From Theory to Research. Cambridge: Cambridge University Press, 259–280.

Rojas, M., 2011. The measurement of economic performance and social progress report and quality of life: Moving forward. Social Indicators Research 102, 169–180.

Rojas, M., García-Vega, J.J., 2017. Well-being in Latin America. In: R.J. Estes, M.J. Sirgy (Eds.), The Pursuit of Human Well-being. The Untold global History. International Handbooks of Quality-of-Life, Springer International Publishing, 217–255.

Rothstein, B., Teorell, J. (2008). What is quality of government? A theory of impartial government institutions. Governance, 21(2), 165–190.

Sexton, T.R., Silkman, R.H., Hogan, A.J., 1986. Data envelopment analysis: critique and extensions. In: Silkman, R.H. (Ed.), Measuring Efficiency: An Assessment of data Envelopment Analysis. Jossey-Bass, San Francisco, pp. 73–105.

Simar, L., Wilson, PW., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics 136(1), 31–64.

Simar, L., Zelenyuk, V., 2006. On testing equality of distributions of technical efficiency scores. Econometric Reviews 25, 497–522.

Sinuany-Stern, Z., Friedman, L., 1998. DEA and the discriminant analysis of ratios for ranking units. European Journal of Operational Research 111, 470–478.

Stanca, L., 2010. The geography of economics and happiness: Spatial patterns in the effects of economic conditions on well-being. Social Indicators Research 95, 115–133.

Stiglitz, J.E., Sen, A., Fitoussi, J.P., 2009. Technical report. Commission on the Measurement of Economic Performance and Social Progress.

Tauchmann, H., 2016. Simarwilson: Stata module to perform Simar & Wilson efficiency analysis. Statistical Software Components.

Ven, P., 2015. Introduction to the symposium on new measures of well-being: Perspectives from statistical offices. Review of Income and Wealth 61(1), 1–3.

Welsch, H., 2004. Corruption, growth, and the environment: a cross-country analysis. Environmental Development Economics 9, 663–693.

Zaim, O., Färe, R., Grosskopf, S., 2001. An economic approach to achievement and improvement indexes. Social Indicators Research 56, 91–118.

Zhou, P., Ang, B.W., Poh, K.L., 2007. A mathematical programming approach to constructing composite indicators. Ecological Economics 62, 291–297.

TABLES AND FIGURES

Table 1. Descriptive statistics for well-being domains: scale from 0 (worst) to 10 (best)

Domain	Indicator(s) (original measurement unit)	Mean	SD
Income	Household disposable income per capita (real USD PPP)	4.10	1.27
Jobs	Employment rate (%); unemployment rate (%)	5.87	2.38
Education	Share of labour force with at least secondary education (%)	7.47	1.97
Safety	Homicide rate (per 100,000 people)	8.79	1.52
Health	Life expectancy (years); age-adjusted mortality rate (per 1,000 people)	6.68	2.60
Environment	Estimated average exposure to air pollution (µg/m^3)	4.67	2.13
Civic engagement	Voter turnout (%)	5.46	2.65
Accessibility to services	Share of households with broadband access (%)	7.62	1.32
Community	People who have friends or relatives to rely on in case of need (%)	7.82	1.73
Housing	Number of rooms per person (ratio)	4.90	2.08

All scores range between 0 and 10, with a higher value representing a better performance in the corresponding domain. Two different indicators measure the dimensions jobs and health. The reported score corresponds to the average value.

Table 2. Ranking of European regions according to their well-being

Region (1ST QUARTILE)	Well-being score	Region (2ND QUARTILE)	Well-being score
Western Finland (FI)	1.000	Groningen (NL)	0.951
Basque Country (ES)	1.000	Cantabria (ES)	0.950
Midi-Pyrénées (FR)	0.999	North Rhine-Westphalia (DE)	0.949
Saxony (DE)	0.998	*Wales (UK)*	0.949
Bavaria (DE)	0.998	Lower Normandy (FR)	0.949
South East England (UK)	0.994	Central Jutland (DK)	0.948
Baden-Württemberg (DE)	0.992	Alsace (FR)	0.948
Salzburg (DE)	0.991	Northern Jutland (DK)	0.947
Styria (AT)	0.991	Hesse (DE)	0.946
Tyrol (AT)	0.989	Poitou-Charentes (FR)	0.946
South West England (UK)	0.988	Lower Saxony (DE)	0.944
Rhône-Alpes (FR)	0.988	Berlin (DE)	0.941
Aquitaine (FR)	0.987	Île-de-France (FR)	0.941
Thuringia (DE)	0.985	Molise (IT)	0.941
South (FI)	0.982	Luxembourg (LU)	0.941
Pays de la Loire (FR)	0.979	Abruzzo (IT)	0.940
Franche-Comté (FR)	0.978	South Holland (NL)	0.939
Mecklenburg-Vorpommern (DE)	0.975	Southern and Eastern (IR)	0.939
Auvergne (FR)	0.975	North Holland (NL)	0.939
Svealand (SE)	0.974	Lower Austria (AT)	0.937
Greater London (UK)	0.973	Vlaams Gewest (BE)	0.934
Brittany (FR)	0.973	Languedoc-Roussillon (FR)	0.932
Madrid (ES)	0.972	Yorkshire and The Humber (UK)	0.932
Norrland (SE)	0.972	Scotland (UK)	0.931
Navarra (ES)	0.971	West Midlands (UK)	0.931
Hamburg (DE)	0.971	North Brabant (NL)	0.928
Rhineland-Palatinate (DE)	0.970	Southern Denmark (DK)	0.928
Upper Austria (AT)	0.969	Burgundy (FR)	0.925
East of England (UK)	0.969	Centre (FR)	0.924
Drenthe (DE)	0.969	Province of Bolzano-Bozen (IT)	0.921
East (FI)	0.968	Friesland (NL)	0.921
North (FI)	0.968	Overijssel (NL)	0.920
Götaland (SE)	0.966	North West England (UK)	0.920
Schleswig-Holstein (DE)	0.965	Asturias (ES)	0.918
Vorarlberg (AT)	0.964	Brandenburg (DE)	0.915
Carinthia (AT)	0.964	Flevoland (NL)	0.913
Limousin (FR)	0.962	Liguria (IT)	0.910
Saxony-Anhalt (DE)	0.960	Lorraine (FR)	0.909
Utrecht (NL)	0.960	*Northern Ireland (UK)*	0.904
Burgenland (AT)	0.957	Zealand (NL)	0.900
East Midlands (UK)	0.955	North East England (UK)	0.899
Capital (DK)	0.953	Upper Normandy (FR)	0.897

Notes: Country abbreviations are in parentheses. Periphery regions are in italics.

Table 2. Ranking of European regions according to their well-being (*continued*)

Region (3RD QUARTILE)	Well-being score	Region (4TH QUARTILE)	Well-being score
Saarland (DE)	0.896	*Pomorskie (PL)*	0.795
Bremen (DE)	0.892	Bratislava Region (SK)	0.793
Gelderland (NL)	0.891	*Opolskie (PL)*	0.790
Vienna (AT)	0.889	*Kujawsko-Pomorskie (PL)*	0.788
Apulia (IT)	0.889	Région wallonne (BE)	0.788
Limburg (NL)	0.889	Andalusia (ES)	0.784
Aragon (ES)	0.886	*Lubelskie (PL)*	0.783
Castile and León (ES)	0.885	*East Slovakia (SK)*	0.776
Podkarpackie (PL)	0.885	*Central Slovakia (SK)*	0.774
Border, Midland and Western (IR)	0.884	Åland (FI)	0.772
Province of Trento (IT)	0.880	Veneto (IT)	0.768
Zeeland (NL)	0.880	*Warminsko-Mazurskie (PL)*	0.765
Sardinia (IT)	0.877	*Zachodniopomorskie (PL)*	0.763
Calabria (IT)	0.875	Lisbon (PT)	0.761
Catalonia (ES)	0.870	*West Slovakia (SK)*	0.761
Basilicata (IT)	0.869	Aosta Valley (IT)	0.754
Piedmont (IT)	0.866	Közép (HU)	0.753
Campania (IT)	0.865	Brussels-Capital Region (BE)	0.752
Provence-Alpes-Côte d'Azur (FR)	0.864	*Moravskoslezsko (CZ)*	0.752
Castile-La Mancha (ES)	0.858	*Slaskie (PL)*	0.748
Galicia (ES)	0.858	Emilia–Romagna (IT)	0.746
Nord-Pas-de-Calais (FR)	0.858	*Severozápad (CZ)*	0.739
Tuscany (IT)	0.856	*Dolnoslaskie (PL)*	0.736
Lombardy (IT)	0.854	*Swietokrzyskie (PL)*	0.735
Praha (CZ)	0.851	*Strední Cechy (CZ)*	0.709
Valencia (ES)	0.849	*Dunántúl (HU)*	0.706
Murcia (ES)	0.841	*Lódzkie (PL)*	0.705
Champagne-Ardenne (FR)	0.839	Friuli-Venezia Giulia (IT)	0.702
Severovýchod (CZ)	0.838	Corsica (FR)	0.693
Picardy (FR)	0.835	*Alföld és Észak (HU)*	0.690
Malopolskie (PL)	0.835	Umbria (IT)	0.684
Jihozápad (CZ)	0.833	*Lubuskie (PL)*	0.677
Podlaskie (PL)	0.829	*Estonia (EE)*	0.668
Wielkopolskie (PL)	0.825	*North (PT)*	0.665
Balearic Islands (ES)	0.819	Attiki (GR)	0.647
Sicily (IT)	0.813	*Central Portugal (PT)*	0.625
Jihovýchod (CZ)	0.812	*Nisia Aigaiou, Kriti (GR)*	0.604
Lazio (IT)	0.812	*Voreia Ellada (GR)*	0.593
Mazowieckie (PL)	0.811	*Alentejo (PT)*	0.580
La Rioja (ES)	0.806	*Kentriki Ellada (GR)*	0.565
Extremadura (ES)	0.803	*Algarve (PT)*	0.562
Strední Morava (CZ)	0.798	Marche (IT)	0.480

Notes: Country abbreviations are in parentheses. Periphery regions are in italics.

Table 3. Well-being and quality of government at the country level

Country	Number of regions	Well-being Mean	Well-being SD	Quality of government Mean	Quality of government SD *
Austria	9	0.961	0.032	1.200	0.150
Belgium	3	0.825	0.096	0.181	0.713
Czech Republic	8	0.792	0.052	-0.363	0.354
Denmark	5	0.935	0.022	1.639	0.161
Estonia	1	0.668	-	0.092	-
Finland	5	0.938	0.094	1.493	0.000
France	22	0.923	0.071	0.647	0.251
Germany	16	0.956	0.033	0.981	0.197
Greece	4	0.602	0.034	-0.678	0.500
Hungary	3	0.716	0.033	-0.458	0.394
Ireland	2	0.912	0.039	0.948	0.000
Italy	21	0.824	0.108	-0.575	0.934
Luxembourg	1	0.941	-	1.143	-
Netherlands	12	0.925	0.028	1.265	0.216
Poland	16	0.779	0.053	-0.677	0.142
Portugal	5	0.639	0.004	0.226	0.409
Slovak Republic	4	0.776	0.013	-0.520	0.129
Spain	16	0.880	0.066	0.259	0.309
Sweden	3	0.971	0.013	1.361	0.103
United Kingdom	12	0.946	0.031	0.888	0.250

* *The Regional QoG Database reports the same figures in 2010 for all Finnish regions, and also for all regions in Ireland. Accordingly, standard deviations in these two countries are zero.*

Table 4. Determinants of well-being: the role of quality of government

Dependent variable: well-being	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	0.871^{***} (0.015)	0.797^{***} (0.015)	0.903^{***} (0.050)	0.942^{***} (0.049)	0.973^{***} (0.057)	0.950^{***} (0.047)	0.939^{***} (0.045)
Quality of government	0.137^{***} (0.015)	0.103^{***} (0.013)	0.076^{***} (0.014)	-	-	-	-
Corruption	-	-	-	0.100^{***} (0.019)	-	-	0.058^{**} (0.029)
Impartiality	-	-	-	-	0.067^{***} (0.018)	-	-0.032 (0.025)
Quality	-	-	-	-	-	0.097^{***} (0.016)	0.081^{***} (0.023)
Population density	-	-0.003 (0.011)	-0.000 (0.075)	-0.002 (0.007)	-0.001 (0.008)	-0.001 (0.007)	-0.002 (0.007)
Core region	-	0.108^{***} (0.022)	0.041^{**} (0.020)	0.047^{**} (0.021)	0.027 (0.021)	0.039^{**} (0.020)	0.049^{**} (0.019)
Number of observations	168	168	168	159	159	159	159
Country effects	No	No	Yes	Yes	Yes	Yes	Yes
Sigma	0.101^{***} (0.009)	0.092^{***} (0.007)	0.062^{***} (0.004)	0.062^{***} (0.004)	0.066^{***} (0.004)	0.060^{***} (0.004)	0.059^{***} (0.004)
Wald Chi^2	75.965^{***}	94.397^{***}	312.581^{***}	269.651^{***}	231.486^{***}	296.863^{***}	317.109^{***}

*Number of bootstrap replications = 5,000; standard errors in brackets; ** and *** mean statistical significance at 5% and 1% confidence levels, respectively.*

Table 5. Determinants of well-being: the role of quality of government in core regions

	Core regions				
Dependent variable: well-being	Model 8	Model 9	Model 10	Model 11	Model 12
Constant	0.957*** (0.056)	0.993*** (0.049)	1.024*** (0.065)	1.014*** (0.050)	1.003*** (0.048)
Quality of government	0.091*** (0.018)	-	-	-	-
Corruption	-	0.129*** (0.024)	-	-	0.103** (0.042)
Impartiality	-	-	0.091*** (0.026)	-	-0.037 (0.032)
Quality	-	-	-	0.110*** (0.021)	0.059* (0.034)
Population density	-0.002 (0.008)	-0.006 (0.008)	-0.003 (0.010)	-0.004 (0.008)	-0.006 (0.008)
Number of observations	126	118	118	118	118
Country effects	Yes	Yes	Yes	Yes	Yes
Sigma	0.071*** (0.006)	0.067*** (0.006)	0.078*** (0.007)	0.069*** (0.006)	0.065*** (0.006)
Wald Chi^2	102.536***	104.519***	70.320***	100.429***	120.425***

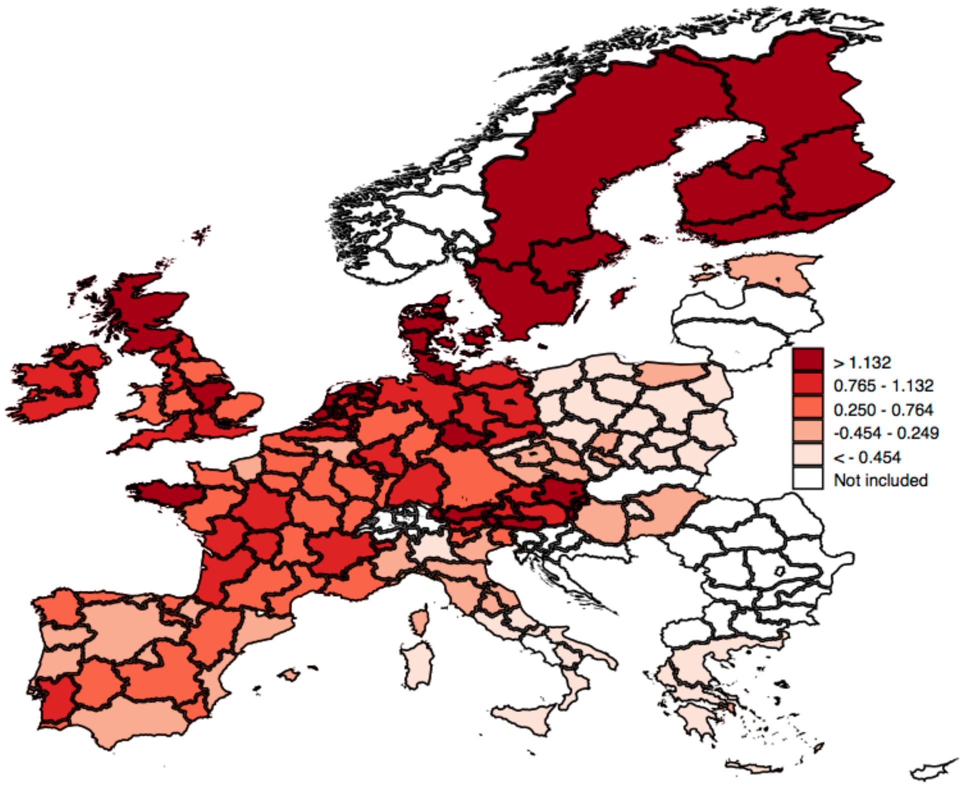
*Number of bootstrap replications = 5,000; standard errors in brackets; *, ** and *** mean statistical significance at 10%, 5% and 1% confidence levels, respectively.*

Table 6. Determinants of well-being: the role of quality of government in periphery regions

	Periphery regions				
Dependent variable: well-being	Model 13	Model 14	Model 15	Model 16	Model 17
Constant	0.784*** (0.019)	0.783*** (0.019)	0.799*** (0.023)	0.835*** (0.032)	0.873*** (0.038)
Quality of government	0.003 (0.029)	-	-	-	-
Corruption	-	-0.038 (0.033)	-	-	-0.010 (0.040)
Impartiality	-	-	-0.040 (0.033)	-	-0.059 (0.042)
Quality	-	-	-	0.054** (0.027)	0.070*** (0.027)
Population density	-0.006 (0.096)	-0.046 (0.094)	-0.050 (0.098)	0.003 (0.090)	-0.062 (0.090)
Number of observations	42	41	41	41	41
Country effects	Yes	Yes	Yes	Yes	Yes
Sigma	0.039*** (0.004)	0.039*** (0.004)	0.039*** (0.004)	0.038*** (0.004)	0.036*** (0.004)
Wald Chi^2	164.349***	157.425***	158.537***	171.858***	200.910***

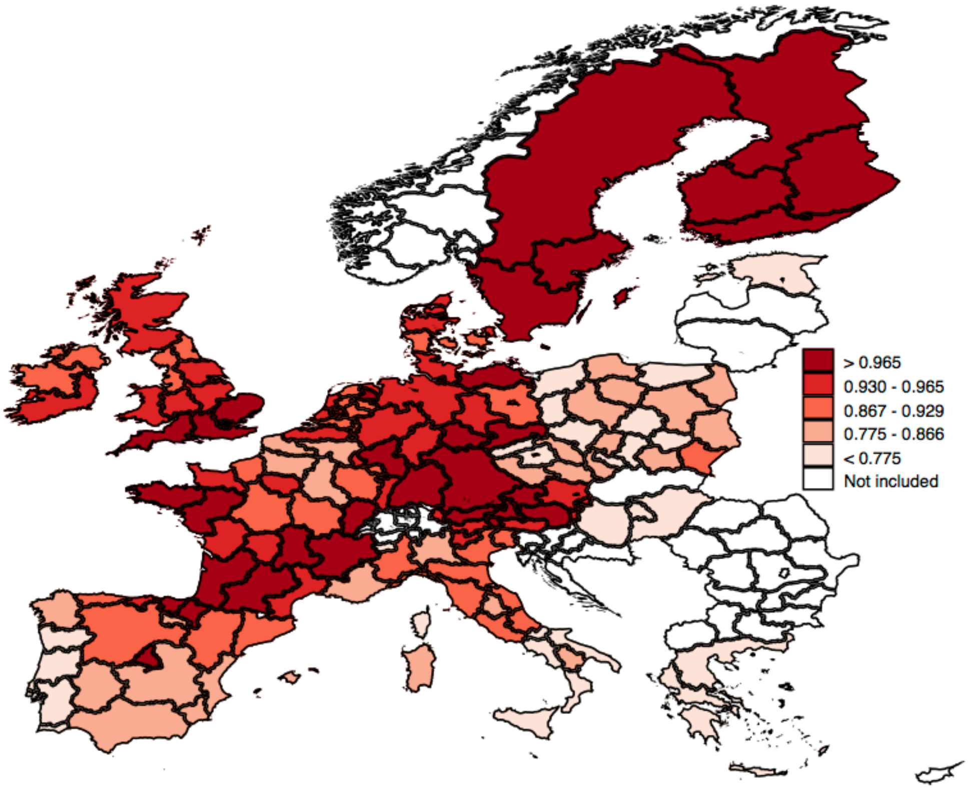
*Number of bootstrap replications = 5,000; standard errors in brackets; ** and *** mean statistical significance at 5% and 1% confidence levels, respectively.*

Figure 1. Quality of government in European regions*



* *Categories correspond to quintiles (low and high are 1st and 5th quintiles, respectively) of the quality of government (QoG) indicator.*

Figure 2. Well-being in the European regions*



* *Categories correspond to quintiles (low and high are 1st and 5th quintiles, respectively) of the composite well-being indicator.*

Figure 3. Distribution of well-being (*kernel densities*)

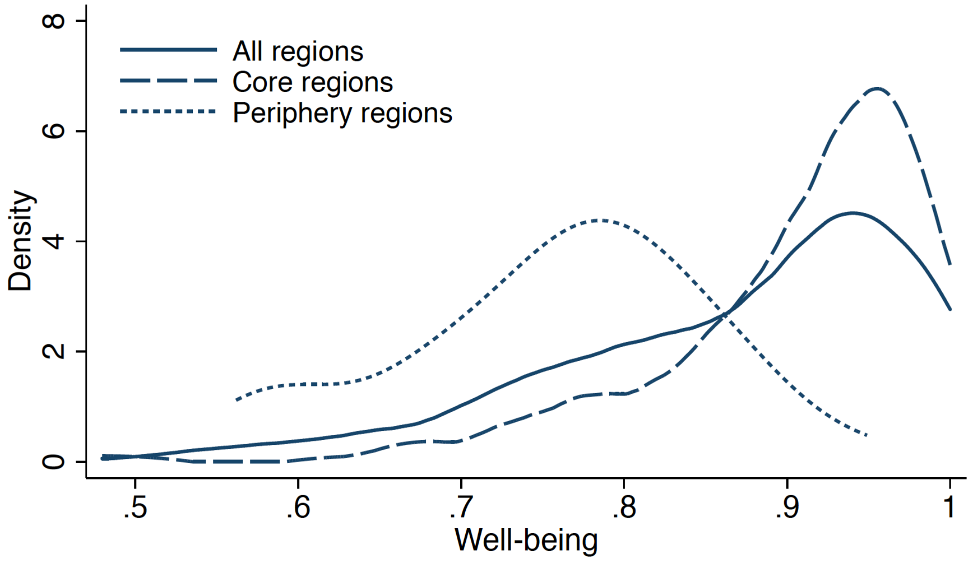


Figure 4. Quality of government and well-being