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FULL ARTICLE

Well-being in European regions: Does government quality matter?

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Abstract

This paper constructs a composite indicator of well-being for 168 European regions with data from 10 well-being domains. Regions are then ranked according to their respective levels of well-being. The ranking reveals notable differences across European regions, which follow a marked spatial pattern. As a second contribution, the paper analyses the impact of the quality of government on well-being. Results show a positive association robust to several specifications and scenarios. Moreover, the effects of quality of government on individual well-being dimensions are identified, finding positive links with education, jobs, income, safety civic engagement, access to services, housing and community support.

KEYWORDS

composite well-being indicators, European regions, government quality

JEL CLASSIFICATION

C14; C61; I31; H41; R50

1 | INTRODUCTION

The question of why some regions perform better than others in terms of well-being is attracting growing interest among academics, policy-makers and society as a whole. The answer is complex, 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 are a number of subjective measures of well-being such as self-reported levels of life satisfaction, in addition to a vast literature measuring well-being with objective dimensions, traditionally GDP *per capita*. However, well-being is a complex, multidimensional concept that goes far beyond income and involves many additional dimensions (Rojas & García-Vega, 2017).

Within the branch of objective measures, the Human Development Index (HDI), which accounts for income, education and health, 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 (CMEPSP), constituted a further step in this direction (Stiglitz, Sen, & Fitoussi, 2009). Following the CMEPSP guidelines, the OECD made comparable data available for 10 objective well-being dimensions and different territorial units. At the country level, this information is provided by the Better Life Index (BLI). Unfortunately, the database fails to provide a composite indicator of global well-being, which makes a comparison of territorial units in terms of their global well-being unfeasible. To overcome this issue, recent papers by Mizobuchi (2014), Mizobuchi (2017), Lorenz, Brauer, and Lorenz (2017) and Peiró-Palomino and Picazo-Tadeo (2018) have constructed well-being rankings of countries using a variety of composite indicators.

However, there are fewer contributions at the regional level, despite the well-being information provided by the Regional Well-being Dataset (RWB), the regional counterpart to the BLI. As with the BLI, the aggregation of the 10 well-being dimensions into a global measure of well-being is left to the interested user. In this regard, Peiró-Palomino (2019) used a simple arithmetic mean to examine well-being convergence across OECD regions, showing a polarization over the period 2000–2014. For the specific context of the European regions, Döpke, Knabe, Lang, and Maschke (2017) proposed several composite indicators using a variety of aggregation methods; they then assessed how the different methods would affect regions' eligibility to receive aid from the European Union Structural Funds. Nevertheless, the authors do not explore the determinants of regional well-being. Given the large disparities in well-being and European authorities' interest in achieving socio-economic cohesion, a better understanding of the drivers of well-being could be particularly helpful for policy design. Among several potential well-being determinants, we pay particular attention to quality of government (QoG henceforth), as good government practices are related to better performance in several well-being spheres (Holmberg, Rothstein, & Nasiritousi, 2009).

Against this background, this paper attempts to make a twofold contribution. First, building on the literature on objective well-being indicators and, more particularly, on the recent contribution by Döpke et al. (2017), we rank 168 European regions according to their global well-being, which is assessed with a composite indicator that considers the 10 dimensions provided by the RWB. In doing so, data envelopment analysis (DEA) and multi-criteria-decision-making (MCDM) techniques are employed. In contrast to the methods used by Döpke et al. (2017), the leading advantage of DEA is that the weights needed to aggregate the particular dimensions of well-being into a single composite indicator are endogenously obtained, so that there is no need to resort to exogenous *ad hoc* methods. Second, we evaluate the role of QoG in explaining regional well-being disparities. To this end, we use the Quality of Government EU Regional Dataset (Charron, Lapuente, & Rothstein, 2014; Charron, Dahlberg, Holmberg, Rothstein, Khomenko, & Svensson, 2016; Charron, Lapuente, & Annoni, 2019), which provides data on QoG for a wide sample of European regions estimated by means of the EQI index, a composite indicator based on the pillars of corruption, impartiality and quality of public services. Apart from the results for the composite well-being indicator, we also present results for the 10 individual domains, which can be more informative for policy–makers. In doing so, we address recurring issues in the literature, such as the potential endogeneity of QoG and the non-negligible influence of spatial spillovers, (see, for instance, Bologna, Young, & Lacombe, 2016; Seldadyo, Elhorst, & De Haan, 2010).

As a first result, the ranking reveals notable regional well-being disparities in Europe, which exhibit a marked spatial pattern. In terms of population, we find that only a small proportion of Europeans live in the top well-being regions. Regarding results concerning the second objective of the paper, QoG appears as a valuable instrument to help reduce the gap, as our regression analysis shows a positive effect of this variable on global well-being and most of its dimensions. These findings are robust to a wide variety of scenarios.

The rest of the paper is structured as follows. After this Introduction, Section 2 reviews the literature on the links between QoG and well-being. Section 3 describes the data, Section 4 explains the methodology and Section 5 discusses the results. Finally, Section 6 provides some conclusions, policy issues and directions for future research.

2 | LINKS BETWEEN QUALITY OF GOVERNMENT AND WELL-BEING

Taking North (1990) seminal ideas as a starting point, solid institutions are needed for economies to be able to react and adapt to changes efficiently, maximizing their capacity to adopt innovation and assimilate knowledge, which ultimately generate positive externalities in several spheres of well-being. More recently, Acemoglu, Johnson, and Robinson (2005) defined institutions as a set of rules and policies that provide a framework of guarantees for economic actors, ensuring that economic incentives encourage people to participate in the economy by investing, innovating, saving and solving problems of collective action. Moreover, institutions should ensure an efficient provision of public goods, provided by the government and aimed at the creation and sustainability of a welfare system that can guarantee citizens' quality of life. Rodrick et al. (2004) argued that once QoG is accounted for, other determinants of development are only weakly significant, which implies that their effects are captured via more reliable and solid formal institutional systems. In this line, Ketterer and Rodríguez-Pose (2018) concluded that whereas geographical factors actually affect regional growth, their impact is dwarfed by the overriding influence of institutions. Holmberg et al. (2009) and Rothstein and Teorell (2008) found that QoG improves the performance of several aspects related to welfare, which broadly correspond with different well-being dimensions.

Given the multidimensionality of well-being, the channels through which QoG might exert a positive influence on it are manifold. In this respect, most of the related literature has focused on corruption, an important dimension of QoG. As a general rule, corruption leads to a less efficient provision of government resources and services and to inefficient regulations, which increase transaction costs. Gupta, Davoodi, and Alonso-Terme (2002) argued that corruption might lead to bias in the tax system and in the targeting of social programmes, generating greater uncertainty in factor accumulation and social inequality. Aghion, Akcigit, Cag, and Kerr (2016) concluded that corruption affects the efficiency with which tax revenues are translated into infrastructure. Kyriacou, Muinelo-Gallo, and Roca-Sagales (2015) found that government quality moderates the effect of fiscal decentralization on reducing regional disparities. In this vein, only in contexts where government quality is high, fiscal decentralization is actually a powerful strategy to reduce disparities. This may happen because bad government practices can favour particular elites, generating important social and economic inequalities.

These general mechanisms are indeed reflected in poorer performance in the three basic pillars of the HDI, namely income, education and health. The seminal papers by Knack and Keefer (1995) and Mo (2001) found a negative effect of corruption on income growth, suggesting that the most important transmission channels are political instability, and a decline in human capital and private investment. More recently, Dzhumaskev (2014) added some nuances, showing that the sign and the intensity of the corruption effect depend on the level of development and the size of government.

Regarding education, Mauro (1998) found that corruption has a notable effect on the composition of government expenditure, with education being one of the most strongly affected areas. Suryadarma (2012) focused on the Indonesian regions and concluded that only in the less corrupt regions does public spending on education translate into higher school enrolment rates. Dridi (2014) comprehensively reviews the corruption-education link, providing further empirical evidence of a negative effect. Some of his arguments are based on Gupta et al. (2002), who claimed that corruption leads to education inequalities. This may occur when rich population groups influence governors to devote public resources towards the provision of particular educational services that favour their interests. Therefore, corruption might lead to the misappropriation of public funds, limiting the resources available to improve the educational system. Similarly, lower tax revenues where corruption is high could dramatically diminish the available resources for education.

Considering the health dimension, Gupta, Davoodi, and Tiongson (2001) found corruption to be positively associated with child mortality and the percentage of low-birth-weight babies. Rajkumar and Swaroop (2008) detailed some of the mechanisms for this effect, showing that a reduction in corruption reinforces the positive effect of health spending on infant and child mortality rates. Similarly, Azfar and Gurgur (2008) provide an in-depth analysis for the Philippines, reporting a negative effect of corruption on health, which is manifested in lower immunization rates, delays in child vaccination and longer waiting times at health clinics. Apart from their impact on the three basic pillars of the HDI, bad governance practices have undesirable effects in many other well-being spheres, which are accounted for in the more comprehensive OECD framework that we consider in this paper. For example, high QoG is likely to have a positive impact on economic dynamism, implying greater absorptive capacity and more innovation (Rodríguez-Pose & Di Cataldo, 2014). In a similar vein, the development of the private sector needs a reliable institutional framework that can guarantee private investments, attract foreign inflows (Hakimi & Hamdi, 2017), reduce barriers to entry and ensure an even playing field for all companies (OECD, 2010). Consequently, a more dynamic regional economy would be accompanied by lower levels of unemployment, higher income and a wider array of available services for citizens. Likewise, negative shocks to the labour market can be more easily overcome with a strong institutional system, as the available resources can be better allocated to mitigate negative dynamics (Ezcurra & Rios, 2019).

Regarding the social spheres, corruption exacerbates inequality and poverty, which have negative consequences for social capital (Rothstein & Uslaner, 2005). The erosion of several forms of social capital in highly corrupt regions could drive up crime (Akomak & Ter Weel, 2012; Kang, 2016). In contrast, community involvement reinforces social bonds, which raises the costs of crime (higher social penalties) and could reduce both conflicts and their resolution costs. In that vein, Berggren and Jordhal (2006) showed that a solid legal system perceived as fair and effective fosters the generation of social capital elements such as generalized trust, which may be linked to other community dimensions such as cohesion and civic norms. This leads to more participation of actors in the economy, which in turn may lead to more engaged citizens, who participate actively in the economy and in political processes. In that regard, Stockemer, LaMontagne, and Scruggs (2013) found for a large sample of democratic states that corruption reduces voter turnout, as citizens no longer consider elections to be democratic instruments. Chong, Karlan, De La, and Wantchekon (2015) reinforced that argument, showing that corruption leads to a decrease in the electoral turnout, as voters are not able to identify utility differences between candidates, with abstention thus becoming a rational option.

Taking into account the environmental dimension of well-being, evidence on the influence of QoG is more mixed. Morse (2006) and Welsch (2004) reported a positive link. Bad governance practices may result in inappropriate policy decisions regarding the environmental sphere and a less efficient management of resources, which can eventually translate into a negative impact on environmental performance. Conversely, a negative relationship has also been found for QoG and carbon emissions. According to Holmberg et al. (2009), the more global a particular problem of pollution is and the more externalities it has, the less likely it is that governments are able to deal with the problem. In addition, they call for a careful interpretation of the QoG-environment linkage, since despite the fact that some positive associations have been found, more robust findings are needed due to the broadness of the concept of the environmental dimension.

Going beyond the mentioned specific linkages, the wider importance of institutional quality for regional economic and social progress has been highlighted by Rodríguez-Pose (2013). In practical terms, however, researchers face important obstacles such as the multidimensionality of QoG, the difficulties involved in its measurement and the endogeneity between institutions and development (Rodríguez-Pose, 2013). Most of the theoretical and empirical links presented in this literature review relate to corruption, although other dimensions could have different implications. The empirical evidence is, however, still inconclusive. For example, Versteeg and Ginsburg (2017) have recently shown that despite the disparate conceptualizations and the diversity of strategies for measuring the strength of institutions, the correlation among the common indicators is remarkably high, suggesting that the measures are actually capturing a more general and all-encompassing construct.

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

Notes: All scores range between 0 and 10, with a higher value representing a better performance in the corresponding domain. Since two different indicators measure the dimensions jobs and health, the reported score is the average value.

3 | MEASURING WELL-BEING AND QUALITY OF GOVERNMENT

Our sample comprises 168 European regions at different aggregation levels (NUTS 1 and NUTS 2)[1] from 20 European countries for the year 2014. 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.

3.1 | Well-being

The data on well-being are taken from the OECD Regional Well-being Dataset (RWD), which provides information on several indicators from 10 different well-being domains.[2] These domains are education, jobs, income, safety, health, environment, accessibility to services, housing, community support and civic engagement. The indicators used by the OECD to measure each domain are listed in Table 1, which also includes means and standard deviations on a normalized scale of 0 to 10 for the domains, where higher values indicate better performance. This scale is constructed using the min-max criterion and it is directly provided by the OECD to allow direct comparisons across domains, as the raw indicators have different units of measure. The database also includes self-reported life satisfaction as an 11th domain, which has been excluded from our analysis since it can be considered as a measure of subjective perceived well-being rather than an objective domain of well-being (Rojas & García-Vega, 2017).

The RWD offers detailed information about individual domains of objective well-being, although, as noted in the Introduction, it fails to provide a composite indicator or measure of global well-being. The issue of aggregation is one of the main concerns when computing composite indicators (OECD, 2008); that is, the selection of weights representing the relative importance of domains. While an extended practice in this respect is the computation of equally weighted indicators where all domains are given the same importance (see ; Peiró-Palomino, 2019), current literature offers a range of alternative weighting approaches, all with their *pros* and *cons* (OECD, 2008; see also Greco, Ishizaka, Tasiou, & Torrisi, 2019). Some approaches are grounded on statistical methods, including factor analysis and principal components (see Rencher & Christensen, 2012), which are multivariate techniques for data reduction that, in essence, group domains according to their degree of correlation.

[1]Combining NUTS 1 and NUTS 2 levels is a common strategy in empirical analyses for the European regional context (see Akomak & Ter Weel, 2009; Dettori, Marrocu, & Paci, 2012; Charron et al., 2019).

[2]At the time of writing, data were available for the years 2000 and 2014, although we used only the more recent update for 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.

A mathematical approach is data envelopment analysis (DEA) (Charnes, Cooper, & Rhodes, 1978) that allows weightings to be endogenously determined by the data. Conversely, other approaches obtain weightings exogenously on the basis of experts opinions or subjective participatory methods, including the analytic hierarchy process (AHP) (Saaty, 1980), the budg et allocation process (Jesinghaus, 1997), or the conjoint analysis (Green & Rao, 1971). In line with recent tendencies in this literature and also the OECD recommendations, we adopt an objective criterion and calculate a composite indicator of well-being using DEA. This technique has several advantages over other approaches to computing composite indicators. Among them, as acknowledged by the OECD (2008), it avoids subjectivity in the choice of weights, which are data-driven. Moreover, it constitutes a realistic approach since each observation–regions in our case study–is benchmarked against best observed practices (see Despotis, 2005). Finally, DEA yields composite indicators that are easily understandable for a general audience, as they are bounded between 0 and 1. Accordingly, a great deal of literature has used DEA techniques, alone or in combination with other approaches, to build composite indicators of well-being (e.g., Bernini, Guizzardi, & Angelini, 2013; Guardiola & Picazo-Tadeo, 2014; Mizobuchi, 2014; Peiró-Palomino & Picazo-Tadeo ,2018).[3]

Let us explain now the methodology used to compute our composite indicator of well-being with DEA. Following Guardiola and Picazo-Tadeo (2014) and taking into account our sample of $r = 1, \ldots , 168$ European regions and the $d = 1, \ldots , 10$ well-being domains described above, the program that enables an assessment of the well-being (WB) of region r' is:

$$
\begin{aligned}
Max_{\omega_{dr'}} WB_{r'} &= \sum_{d=1}^{10} \omega_{dr'} S_{dr'}, \\
&\textit{subject} \quad \textit{to}: \\
\sum_{d=1}^{10} \omega_{dr'} S_{dr} &\leq 1, \quad r = 1 \ldots , 168 \\
\omega_{dr'} &\geq 0, \quad d = 1 \ldots , 10,
\end{aligned}
\tag{1}
$$

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

Grounded in the benefit-of-the-doubt (BoD) principle (Cherchye, Moesen, Rogge, & Van Puyenbroeck, 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. Also, a normalization constraint is added by imposing an upper bound of 1 on the composite indicator. Values of 1 and 0 represent the highest and lowest well-being, respectively.

Whereas the DEA-BoD model provides a successful approach to the issue of selecting weights in constructing composite well-being indicators, it might be less effective when it comes to ranking regions. First, it may render comparisons meaningless, as their composite well-being indicators are computed using different sets of weightings (Kao & Hung, 2005). Second, if there is a relatively small number of observations in the sample with respect to the variables involved in the DEA problem, the DEA-BoD approach may prevent European regions from being fully ranked against each other (see Dyson et al., 2001).

Researchers in the field have proposed several ways to overcome the abovementioned limitations of the DEA-BoD approach, which are reviewed in Reig-Martínez et al. (2011). In this paper, we employ the approach suggested by (Despotis, 2002; 2005) that combines DEA-BoD with MCDM; namely, the DEA-BoD-MCDM model. This enables an increase in the discriminating power of our DEA-BoD model while keeping a common set of

[3]DEA techniques have been also applied to a wide variety of economic, environmental and/or social issues (Zhou, Ang, & Poh, 2007 review early contributions; some later papers are Cherchye et al., 2008; Hermans et al., 2008; Reig-Martínez, Gómez-Limón, & Picazo-Tadeo, 2011; Gómez-Vega & Picazo-Tadeo, 2019; Castillo-Giménez, Montañés, & Picazo-Tadeo, 2019, to name a few).

weightings for well-being domains across regions. The linear program needed to compute these common weights is:

$$\begin{aligned} &Min_{m_r,\omega_d,z} \quad t\frac{1}{168}\sum_{r=1}^{168} m_r + (1-t)z \\ &\text{subject to}: \\ &\sum_{d=1}^{10}\omega_d S_{dr} + m_r = WB_r^*, \quad r = 1, \dots, 168 \\ &(m_r - z) \le 0, \quad r = 1, \dots, 168 \\ &m_r \ge 0, \quad r = 1, \dots, 168 \\ &\omega_d \ge \varepsilon, \quad d = 1, \dots, 10 \\ &z \ge 0, \end{aligned} \tag{2}$$

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; ε 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 WB_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.

The objective function to be minimized when $t = 1$ 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. On the contrary, when $t = 0$, the function to be minimized is the second term of the objective function in (2), which represents the maximal deviation between the DEA-BoD and the DEA-BoD-MCDM well-being scores (see details in Bernini et al., 2013). In order to avoid a source of subjectivity in choosing the value for the parameter t, 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*.[4]

We calculate the regional well-being index described above for our sample of regions. The ranking, which is shown in Table A1 of the Appendix, is very much in line with those proposed by Döpke et al. (2017) using different aggregation methods. More specifically, it shows that well-being ranges from less than 0.5 for regions at the bottom of the ranking to 1 for the top regions. Figure 1 maps these results. In the map, regions are classified into six categories of well-being, according to the corresponding percentiles, with darker colours representing higher levels of well-being. As well-being affects people, apart from determining regional well-being levels, it is of particular interest to quantify the share of the population that each category represents. Table 2 reports the average well-being score for each category together with the share of the sample population represented by regions in that category. It can be seen that only 4% of the population enjoy the highest well-being levels (top 5%), while people in the bottom 5% represent almost 10% of the sample population. Taking the bottom three categories together (up to the percentile 50), we can see that about 56% of the population have well-being levels below the average, highlighting the need to close the regional well-being gap. To do so, it is crucial to gain an understanding of the drivers of well-being.

As can be observed, the distribution of well-being is far from homogeneous across the EU. Indeed, there are important geographical differences, with well-being exhibiting considerable spatial variation. The spatial distribution of well-being is quite complex, characterized by marked clusters of very low and very high levels of well-being. The countries in the Southern periphery of Europe (i.e. Portugal, Spain, Italy, and Greece) display lower scores. Likewise, the regions of Poland, Hungary and Czech Republic show relatively low levels of well-being. On the other hand,

[4] In practice, the definite integral is approximated by computing a series of composite indicators with enough values for t, for example, at intervals of 0.001, as we do in this research, and then calculating their average.

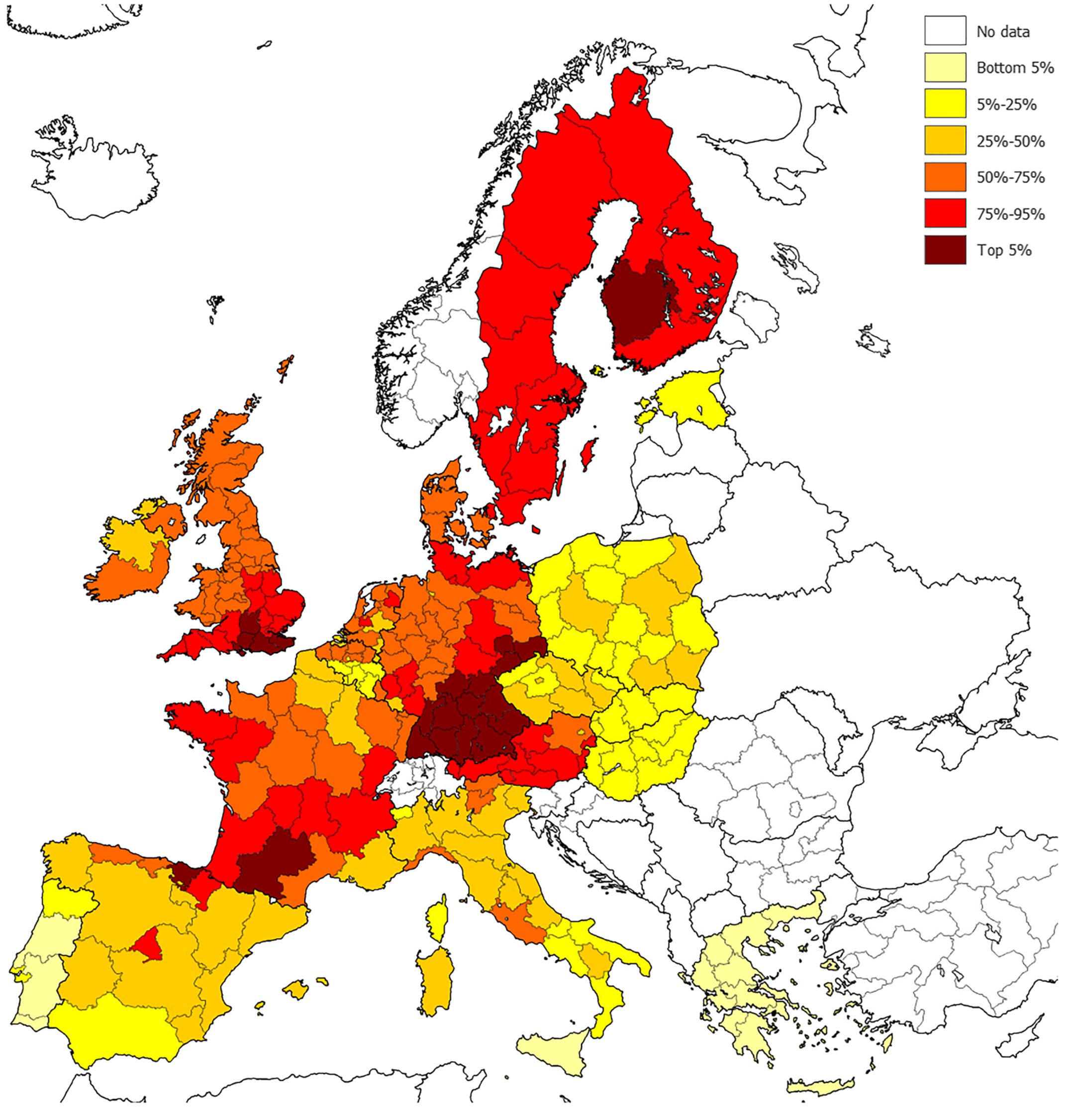


FIGURE 1 Well-being in the European regions. Source: Own elaboration based on OECD data. Notes: The map represents European NUTS 2 regions. In those cases for which our data are available at the NUTS 1 level, that score is applied to all the NUTS 2 regions contained in that area.

we find regions belonging to west-Germany, France, the UK, Finland and Sweden among those with the highest well-being scores. The observed differences between countries, however, do not hide the existence of important within-country disparities. This is particularly evident in countries such as France, Spain or the UK.

3.2 | Quality of government

According to the previous literature, QoG can be postulated as a good candidate to explain such large disparities in well-being. We collected information on QoG in the EU regions, employing the European Quality of Government Index (EQI). This index has been recently constructed with the aim of providing scholars and policy-makers with a comparable and homogeneous measure of governance at the regional level that can be used to make comparisons

TABLE 2 Well-being and population

Category	Population share	Average well-being
Bottom 5%	0.095	0.591
5%-25%	0.189	0.745
25%-50%	0.279	0.854
50%-75%	0.239	0.930
75%-95%	0.153	0.971
Top 5%	0.042	0.996

Notes: Categories correspond to percentiles of the well-being distribution, and are those represented in Figure (1).

within and across countries in Europe (Charron et al., 2014; 2016; 2019). The EQI is based on survey data about European citizens' perceptions and experiences of the quality, impartiality and level of corruption in education, public health and law enforcement. To date, the EQI is available for three years: 2010, 2013 and 2017.[5] As our well-being data refers to years 2010 to 2014, we have considered QoG data from 2010 only. This is to prevent, as far as possible, endogeneity issues due to reverse causality in the analysis of the determinants of well-being.

Figure 2 provides a graphical illustration of the association between QoG and well-being in the EU. The scatter plot suggests the existence of a positive relationship between governance outcomes and regional well-being. This means that regions with better QoG tend to display higher well-being scores.[6] Nevertheless, the information provided by Figure 2 should be treated with caution, as the observed connection between QoG and well-being may simply be a spurious correlation resulting from the omission of other variables affecting both governance and well-being. In the next section we develop a more appropriate statistical analysis of the link between QoG and well-being.

4 | EMPIRICAL STRATEGY AND METHODOLOGY

4.1 | Assessing spatial interdependence

With the aim of providing a first rigorous insight into the spatial pattern of well-being at the regional level, Figure 3a displays the Moran scatter plot. The slope of the regression line is the Moran's I statistic, a measure of spatial correlation, and takes a value of 0.437 (p-value = 0.000). This suggests that regions with high levels of well-being are surrounded by regions with high well-being.[7]

As a further check on the role played by the spatial location of regions in explaining well-being outcomes, we estimate a stochastic kernel following the methodology outlined by Magrini (2009).[8] Stochastic kernel estimation allows the researcher to capture the transitions between the original distribution and the neighbour's relative well-being distribution. To interpret this diagram, note that a value of 1 on the horizontal axis indicates the European average well-being, a value of 2 indicates twice the European average, and so on. On the other hand, contour lines give the probability that any region will experience that specific relative rate of well-being. Estimated stochastic kernel results, shown in Figures 3b and 3c, reveal that the probability mass tends to be located parallel to the axis corresponding to the original distribution. Accordingly, spatial effects appear as a relevant factor in explaining the

[5]The index is available for all EU27 countries at NUTS 2 regional level, with the exception of Belgium, Germany, Greece, Hungary, Sweden and the UK, for which the data are provided at NUTS 1 level.

[6]Indeed, the pairwise correlation of 0.69 between the two variables is statistically significant with p-value = 0.000.

[7]To compute this statistic we employ a $k = 7$ nearest neighbour row-normalized spatial weight matrix W:

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

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

[8]The estimation of the stochastic kernel relies on Gaussian kernel smoothing functions and it uses the L-stage direct plug-in estimator with an adaptive bandwidth that scales pilot estimates of the joint distribution by $\alpha = 0.5$.

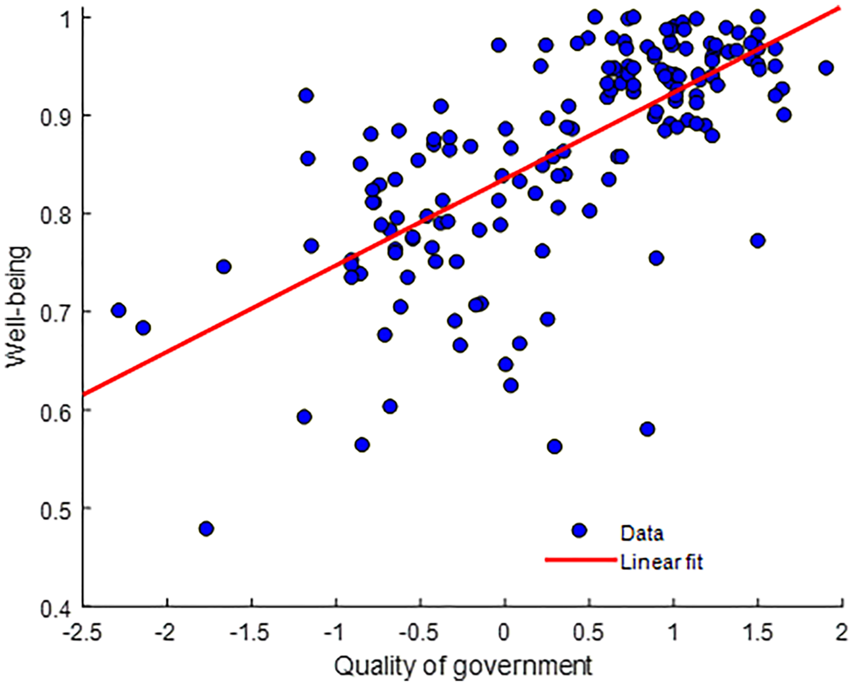


FIGURE 2 Quality of government and well-being

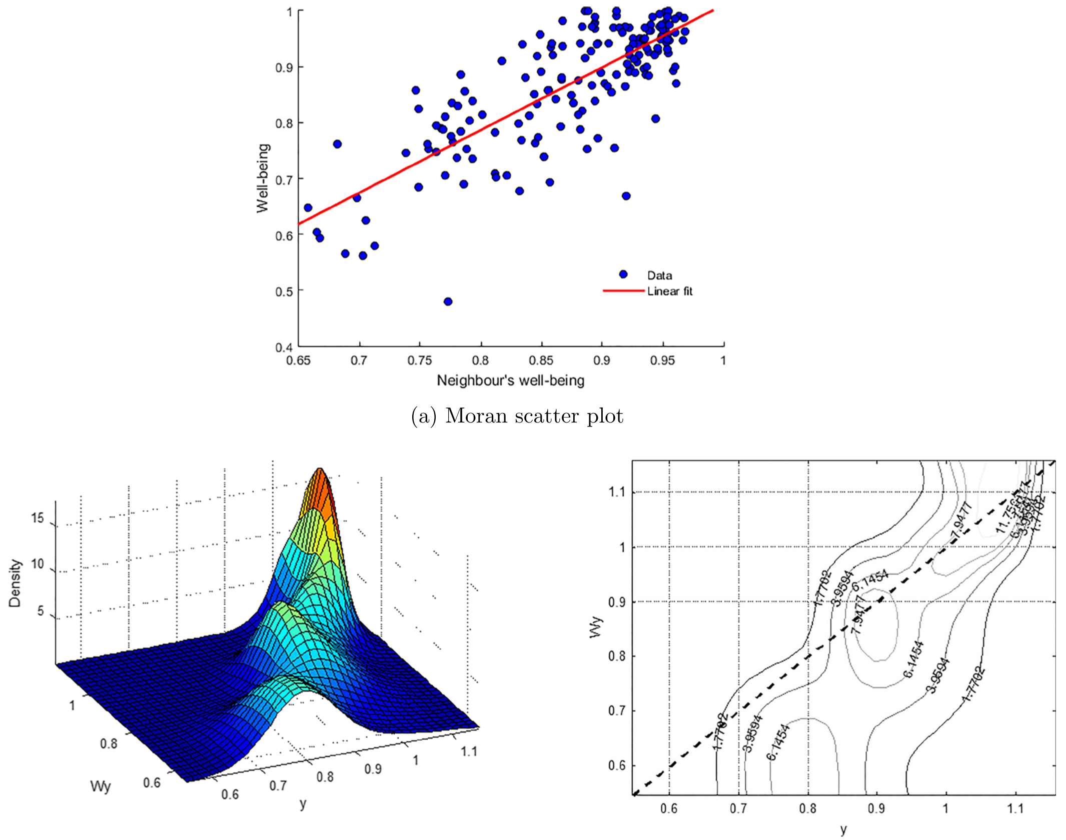
observed variability in regional well-being. These findings regarding the spatial effects suggest that it is necessary to accommodate spatial interdependence in the modelling process and that explicit attention to spatial effects is required by means of spatial econometric models.

4.2 | Econometric model

The recent studies of Döpke et al. (2017) and Peiró-Palomino (2019) analyse well-being at the regional level, but treat the units of analysis as isolated entities, overlooking the spatial characteristics of the data and the potential role of space in modulating well-being. Nevertheless, insofar as the evolution of every region involves the interaction with other regions, as suggested by the preliminary evidence in Figure 3, omitting these interactions is potentially consequential from an econometric perspective, and may result in biased, inconsistent and/or inefficient estimates (Elhorst, 2014; Le Sage & Pace, 2009).

To deal with this issue, we begin by considering the following Bayesian heteroskedastic spatial error model (SEM) specification, which is given by Equation (3):

$$\begin{aligned} y &= \alpha\iota_n + X\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \upsilon \\ \upsilon &\sim N\left[0, \sigma^2 V\right] \\ V &= diag\,(v_1, \, \dots \, , v_2) \\ \pi(\delta) &\sim N\,[c, \Sigma] \\ \pi\,(1/\sigma) &\sim \Gamma\,(v_0, d_0) \\ \pi\left(\frac{r}{v_i}\right) &\sim IID\chi^2(r), \end{aligned} \tag{3}$$



(a) Moran scatter plot

(b) Stochastic kernel

(c) Contour plot

FIGURE 3 Well-being in European regions, spatial spillovers

where y denotes an $N \times 1$ dimensional vector consisting of observations for the well-being index in the year 2014 for region $r = 1, \ldots, N$ and X is an $N \times K$ matrix of exogenous aggregate political, socio-economic and economic covariates with associated response parameters β contained in a $K \times 1$ vector. α reflects the constant term, ι_n is an $N \times 1$ vector of ones while λ is the spatial diffusion coefficient, which captures spatially correlated shocks operating through the error term $W\varepsilon$. W is an $N \times N$ row-standardized matrix of known constants indicating how the regions in the sample are spatially interconnected. Finally, $\upsilon = (\upsilon_1, \ldots, \upsilon_N)'$ is a vector of heteroskedastic disturbances whose elements have zero mean and finite variance. The prior distributions of the parameters are indicated by π. To avoid situations where the conclusions depend heavily on subjective prior information we rely on diffuse or non-informative prior distributions. Diffuse priors are obtained setting parameters c to zero and Σ to a very large number $(1e+12)$ whereas diffuse priors for σ and λ are obtained setting $d = 0$, $v = 0$ and $a_0 = 1.01$. The hyper-parameter r controlling the prior variance scalars $v_1, \ldots, v_n$ is set to $r = 4$, which leads to a skewed distribution that permits large values of v_i that deviate greatly from the prior mean of unity. The role of these large v_i values is to accommodate outliers or observations containing large variances by downweighting these observations LeSage (1997). The estimation of the model parameters relies on a Markov chain Monte Carlo (MCMC) sampling methodology as set out in LeSage and Pace (2009).

Regarding the variables in the model, the set of potential determinants that could be correlated with both regional well-being and QoG includes: (i) *governance factors*; (ii) *socio-demographic factors*; (iii) *knowledge and innovation* *intensity factors*; and (iv) factors related to the *sectoral composition of economic activity and regional specialization*. A detailed description, sources and some descriptive statistics are available in Table A2 in the Appendix.

As regards regional governance, we consider the degree of fiscal and political decentralization as it could be related to regional well-being. In fact, the transfer of resources and powers from central to subnational governments is often justified as a means of improving economic performance, under the rationale that subnational tiers of government are better able than central governments to tailor the provision of public goods and services to citizens' needs thanks to the existence of informational advantages and a better insight into the preferences of the local population (Oates, 1972, Tiebout, 1956). Nevertheless, the literature also warns about the potential risks of decentralization for economic performance, as subnational governments may be more vulnerable to capture by local interests, generating greater corruption, clientelism and nepotism (Rodríguez-Pose & Ezcurra, 2011). This point is relevant in our context, as it suggests the possible existence of a connection between decentralization and QoG (Enikolopov & Zhuravskaya, 2007). To capture differences in regional autonomy, we use an indicator of regional economic *self-rule* proposed by Sorens (2014), which represents the degree of authority exercised by a regional government over citizens. A quadratic specification is also considered to capture non-linearities, given that the existing literature analysing the effect of decentralization on economic development and resilience has reported both positive (Iimi, 2005) and negative relationships (Rodríguez-Pose & Ezcurra, 2011) as well as both U-shaped (Ezcurra & Rios, 2019; Thieben, 2003) and inverted U-shaped relationships (Mauro, Pigliaru, & Carmeci, 2018).

Socio-demographic characteristics might also have effects on well-being. To control for the potential effect of agglomeration, we include in our specification: (i) an indicator of *population density*; and (ii) a dummy variable capturing whether or not the *capital city* of the country is located in the region. Agglomeration economies arise when people and firms locate near to each other in cities and industrial clusters, which generally implies higher population or employment density. Agglomerations ultimately entail transport costs savings, and make it easier to exchange goods, people, and ideas (Ciccone, 2002). However, the impact of agglomeration on regional well-being is not clear *a priori*. On the one hand, highly urbanized and densely populated areas may increase the probability of matching job seekers and firms, which should improve the overall functioning of labor markets. Nevertheless, negative effects on well-being may arise as agglomerations and urbanization are frequently deemed to place an excessive burden on the absorptive capacities of the environment by increasing energy consumption and CO2 emissions, thereby lowering environmental quality (Martínez-Zarzoso & Maruotti, 2011).

The third group of variables includes those capturing the intensity of the innovation system and knowledge diffusion. They are drawn from previous studies of knowledge and development such as those by (Capello & Lenzi, 2013; 2014). This group of factors incorporates: (i) *share of R&D spending over GDP*; (ii) an index of *infrastructure density* based on the kilometres of motorway network; and (iii) the level of *social trust* as a proxy of social capital. Overall, R&D efforts are expected to have positive effects on well-being due to the potential beneficial effect of innovations on the development of new growth paths and the adoption of clean technologies. Infrastructure density may enhance knowledge creation through different mechanisms associated with its influence on the spatial organization of economic activities (Capello & Lenzi, 2013; 2014). However, the effect of higher infrastructure density on well-being is not clear *a priori*. On the one hand, it may increase access to services, reduce barriers to trade and increase regional connectivity thereby boosting GDP and employment, but its effects on environmental quality could be either positive or negative. Transportation systems substantially increase the energy intensity of some activities lead to higher pollutant emissions. Conversely, they could favour the use of mass transport instead of individual motor vehicles, reducing emissions. Finally, social trust is expected to have positive effects on well-being as it may facilitate the diffusion of knowledge and ideas, decrease the level of litigation within firms and reduce the time and resources spent controlling partners, employees, suppliers, etc. (Knack & Keefer, 1997), which might be beneficial for economic development (Forte, Peiró-Palomino, & Tortosa-Ausina, 2015; Peiró-Palomino, 2016). In addition, trust as a form of social capital can enhance civic engagement as citizens may remind one another of the communal benefits of voting and participating in the political process, and accelerate the flow of political information through a community. As a result, community involvement may boost political engagement and help individuals to develop informed opinions regarding upcoming elections (Atkinson & Fowler, 2014). This in turn, might exert indirect effects through the improvement of institutional quality (Cortinovis, Crescenzi, & van Oort, 2018).

Finally, the fourth group of factors relates to the sectoral composition of economic activity and regional specialization. Sectoral diversification in a region may affect unemployment and employment rates (Longhi, Nijkamp, & Traistaru, 2005), thus affecting the well-being pillar of jobs. The more specialized a regional economy is, the less able it is to cope with employment reductions in any given sector. On the other hand, firms located in more specialized regions can gain from agglomeration effects such as knowledge spillovers, and be comparatively more productive, which should increase regional incomes. Therefore, the effect on global well-being is uncertain. Additionally, differences in the industry mix might impact the geographical distribution of unemployment and income levels (López-Bazo, Del Barrio, & Artés, 2005). Accordingly, the model also includes regional employment shares in manufacturing industries and agriculture. Industrial regions specializing in export-oriented manufactures may exhibit lower unemployment rates due to the large employment multipliers associated with manufacturing (Elhorst, 2003). Likewise, the degree of protection and regulation of agricultural markets in the EU implies that regions with relatively large agricultural sectors tend to be less exposed to changes in the business cycle (Fratesi & Rodríguez-Pose, 2016). Nevertheless, a higher share in agriculture is usually related to lower incomes. In addition, the sectoral composition of economic activity may affect the institutional framework (Nunn, 2007).

4.3 | Spatial Bayesian model selection

The model in Equation (3) can be compared against spatial model specifications such as the *spatial lag model* (SLM), the *spatial Durbin model* (SDM) and the *spatial durbin error model* (SDEM). The SDEM reads as:

$$\begin{aligned} y &= \alpha\iota_n + X\beta + WX\theta + \varepsilon, \\ \varepsilon &= \lambda W\varepsilon + \upsilon, \end{aligned} \tag{4}$$

Therefore, the difference with the SEM is that it includes the spatial lag of the rest of the control variables (exogenous effects), WX, whose impact is reflected by the $K \times 1$ vector of coefficients θ. Additionally, we also consider the SLM and the SDM, which are given by Equations (5) and (6), respectively:

$$y = \alpha\iota_n + \rho Wy + X\beta + \upsilon, \tag{5}$$

$$y = \alpha\iota_n + \rho Wy + X\beta + WX\theta + \upsilon \tag{6}$$

The SDEM/SEM do not require a theoretical model for spatial or social interaction processes, as is commonly the case in spatial models including endogenous interactions, such as the SDM/SLM. Indeed, as explained by Gibbons and Overman (2012) and Halleck-Vega and Elhorst (2015), spatial models containing endogenous interactions such as the SDM/SLM are generally difficult to justify from a theoretical basis. In the context of well-being, endogenous interactions would lead to a scenario where changes in one region may set in motion a sequence of adjustments in (potentially) all units in the sample.[9] A feature of the SDEM/SEM type of models is that they highlight the presence of omitted variables with explicit spatial patterns.

Another relevant source of model uncertainty other than the nature of cross-regional interactions in spatial econometrics is the spatial weights matrix. Given that this is a relevant issue in spatial econometric modelling, a broad range of alternative specifications of W are considered. The first alternative consists of several matrices based on the k-nearest neighbours computed from the great circle distance between the centroids of the various regions. Second, exponential distance decay matrices are employed. Furthermore, as is common practice in applied research, all the matrices are row-standardized, so that it is relative rather than absolute distance that matters.

In order to choose between different potential specifications of the spatial weight matrix W, as well as to choose between SDM, SLM, SDEM and SEM specifications, a Bayesian model comparison is performed following Da Silva,

[9]A global spillover implies that a change in region A would lead to a reaction by neighbouring region B, changing their level of well-being. This in turn produces a game-theoretic (feedback) response from region A, and also a response from region C, which is a neighbour to neighbouring region B, and so on.

TABLE 3 Spatial Bayesian model selection

Spatial weight matrix	Posterior model probabilities For Spatial Models $P(SM \mid W, X)$ SLM (1) SLM	SDM (2) SDM	SEM (3) SEM	SDEM (4) SDEM	Posterior model probabilities For W Matrices $P(W \mid SM, X)$ SLM (5) SLM	SDM (6) SDM	SEM (7) SEM	SDEM (8) SDEM
4-nearest neighbours	0.02	0.00	0.98	0.00	0.00	0.00	0.06	0.00
5-nearest neighbours	0.09	0.00	0.91	0.00	0.06	0.01	0.28	0.00
6-nearest neighbours	0.48	0.00	0.52	0.00	0.91	0.09	0.49	0.75
7-nearest neighbours	0.22	0.00	0.78	0.00	0.02	0.01	0.04	0.01
8-nearest neighbours	0.03	0.00	0.97	0.00	0.00	0.00	0.02	0.00
9-nearest neighbours	0.01	0.00	0.99	0.00	0.00	0.01	0.01	0.00
10-nearest neighbours	0.00	0.00	1.00	0.00	0.00	0.45	0.03	0.06
15-nearest neighbours	0.00	0.00	1.00	0.00	0.00	0.23	0.01	0.04
20-nearest neighbours	0.00	0.00	1.00	0.00	0.00	0.17	0.02	0.13
$exp-(\theta d)$, $\theta=0.025$ cut-off at Q1	0.02	0.00	0.98	0.00	0.00	0.00	0.01	0.00
$exp-(\theta d)$, $\theta=0.025$ cut-off at Q2	0.02	0.00	0.98	0.00	0.00	0.00	0.01	0.00
$exp-(\theta d)$, $\theta=0.025$ cut-off at Q3	0.02	0.00	0.98	0.00	0.00	0.00	0.01	0.00
$exp-(\theta d)$, $\theta=0.05$ cut-off at Q1	0.02	0.00	0.98	0.00	0.00	0.00	0.01	0.00
$exp-(\theta d)$, $\theta=0.05$ cut-off at Q2	0.02	0.00	0.98	0.00	0.00	0.00	0.01	0.00
$exp-(\theta d)$, $\theta=0.05$ cut-off at Q3	0.02	0.00	0.98	0.00	0.00	0.00	0.01	0.00

Notes: Q1, Q2 and Q3 refer to the first, second and third quartiles of the distance, respectively. Columns (1) to (4) show the probability of each spatial model SM conditional on W and X ($P(SM \mid W, X)$), while columns (5) to (8) show probability of the W conditional on the spatial model SM and X ($P(W \mid SM, X)$). The Bayesian estimation of the PMPs relies on a Markov Chain Monte Carlo (MCMC) estimation based on 1,100 draws with a burn-in sample of 100 draws. To derive individual PMPs we employ a normal-gamma conjugate prior for $\delta = [\alpha, \beta]$ and σ and a beta prior for λ:

$$\pi(\delta) \sim N[c, \Sigma]$$
$$\pi(1/\sigma) \sim \Gamma(v_0, d_0)$$

To avoid situations where the conclusions depend heavily on subjective prior information we rely on diffuse or non-informative prior distributions. Parameter c is set to zero and Σ to a very large number $(1e+12)$ which results in a diffuse prior for δ. The diffuse priors for σ and λ (in the case of the SLM/SDM ρ), are obtained setting $d = 0$ and $v = 0$ and $a_0 = 1.01$. All the models are estimated assuming heteroskedastic disturbances following LeSage (1997).

Elhorst, and Da Mota Silveira Neto (2017) and Rios (2017). This method of model selection determines the posterior model probabilities (PMP) of the alternative specifications given a particular W, as well as the PMP of different spatial weight matrices given a particular model specification. The results and technical details of the implementation of this procedure are reported in Table 3. We find that SEM appears to be the preferred spatial model specification, as its probability ranges from 52% to 100% depending on the W. Conditional on the SEM specification, the spatial weight matrix displaying the highest probability is the 6-nearest neighbour matrix (49%). Thus, the analysis presented in the next section relies on the SEM specification with a 6-nearest neighbour spatial weight matrix.

5 RESULTS AND DISCUSSION

5.1 Quality of government and well-being

Table 4 presents the results obtained when different versions of the SEM model in Equation (3) are estimated by means of the spatial Bayesian estimator for the case of heteroskedastic innovations of unknown form in the disturbance process. However, before continuing with the discussion of the results, it is worth mentioning the problems that can be solved by the methodology applied here, as well as the unaddressed problems that may affect the quality of the estimates. The strong point of the methodology is that it accounts for spatial dependence in the disturbances, which may affect the efficiency of the parameter estimates while controlling for measurement errors and outliers, since we allow for heteroskedasticity. However, it does not correct for the potential negative effect of endogeneity caused by reverse causality. To deal with the potential negative effect of endogeneity in our baseline regressions, all our control variables are lagged in time. Accordingly, all the independent variables are measured in the period 2000–2007, either as averages or taking the value of a particular year, depending on the variable. The exception is our varibale of interest QoG, measured in 2010.[10]

We now turn our attention to the spatial autocorrelation parameter (λ), which indicates the average intensity of spatial diffusion of a shock in one region to the other regions. It exhibits a positive and significant coefficient at the 1% level in all the models, with an average intensity of estimated effect that ranges between 0.48 and 0.60. This implies that a 1% shock to well-being in one region propagates to all the other regions of the sample with an exponential decay ranging in the 0.48–0.60 interval, as the diffusion of the shocks affects the neighbours and higher-order neighbours of that region, namely, through the spatial transformation $(I_n - \lambda W)^{-1}$. Overall, these findings confirm that the SEM used in this analysis is suitable for the study of regional well-being; moreover, they are in line with the information provided by Figure 3, highlighting the need to take into account spatial effects when modelling regional well-being in the EU.

The main finding is that the coefficient of the QoG measure is in all cases positive and statistically significant at the 1% level, which is consistent with most of the arguments discussed in Section 2 and the preliminary evidence displayed in Figure 2. In fact, this result is not affected by the inclusion in the analysis of the different controls described in Section 4, confirming its robustness and showing that the observed connection between QoG and well-being is not simply a spurious correlation resulting from the omission of these covariates. In fact, the QoG coefficient is relatively stable across specifications, further supporting the idea that the relationship between governance and well-being is not driven by an omitted variable.

Considering the most comprehensive model (see model 5 in Table 4), which includes all the controls and country fixed effects, a one standard deviation increase in QoG is associated with a 0.043 increase in the well-being indicator; this is, for example, the difference between Western Finland (top-ranked position) and Burgenland (Austria, ranked 40th).

With respect to the control variables included in model 5, Table 4 shows the existence of a U-shaped relationship between regional autonomy and well-being. This implies that sub-national governments with a higher degree of economic-self-rule initially exert a negative impact on well-being. However, beyond a certain level, the relationship becomes positive. According to our estimates, the turning point is situated above the level of autonomy in German regions. Furthermore, we find that citizens living in capital cities enjoy higher levels of well-being. This is consistent with previous findings focused on income, such as that by Crespo-Cuaresma et al. (2014), who find that EU capital cities grow faster. At the same time, the share of GDP devoted to R&D emerges as an important factor in explaining regional differences in well-being. Our estimates reveal that well-being in a particular region is positively influenced by R&D spending, which is consistent with previous observations of the positive effects of R&D on economic growth (Capello & Lenzi, 2013; 2014). Similarly, the estimated positive impact of trust on well-being is in line with the findings of Forte et al. (2015) and Peiró-Palomino (2016) for economic growth.

5.2 | Quality of government and specific well-being dimensions

A clear advantage of using composite indicators is the possibility of comparing regions in terms of overall well-being. In contrast, it considerably complicates the identification of particular channels through which QoG affects well-being. We attempt to address this shortcoming by providing results for each of the 10 dimensions of the composite well-being index, which are reported in Table 5. All the models correspond to spatial SEM models

[10]See Table A2 for the temporal period considered for each variable.

TABLE 4 Estimation results, quality of government and regional well-being

	Dependent variable: Well-being				
Model	(1)	(2)	(3)	(4)	(5)
Quality of government	0.070***	0.070***	0.060***	0.061***	0.051***
	[0.010]	[0.010]	[0.010]	[0.010]	[0.013]
Eco-self rule	0.004**	0.005**	0.002	0.002	-0.008**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.004]
Eco-self rule^2	-0.0001*	-0.0001*	-0.0000	-0.000	0.0001*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Capital city		0.032**	0.012	0.010	0.043***
		[0.019]	[0.018]	[0.020]	[0.018]
Population density		-0.006	-0.003	0.001	-0.003
		[0.008]	[0.008]	[0.009]	[0.007]
R&D			0.025***	0.025***	0.017***
			[0.007]	[0.006]	[0.006]
Trust			0.048	0.038	0.124**
			[0.057]	[0.058]	[0.069]
Infrastructure density			0.000*	0.000***	0.000
			[0.000]	[0.000]	[0.000]
Sectoral specialisation				-0.524*	-0.448
				[0.396]	[0.402]
Agriculture				-0.001	0.001
				[0.001]	[0.001]
Manufactures				0.000	0.001
				[0.001]	[0.001]
$W\varepsilon$	0.587***	0.600***	0.603***	0.601***	0.480***
	[0.090]	[0.086]	[0.087]	[0.088]	[0.137]
Country fixed effects	No	No	No	No	Yes
R^2	0.641	0.653	0.707	0.713	0.811
Adjusted R^2	0.634	0.642	0.693	0.693	0.770
$\hat{\sigma}$	0.003	0.003	0.003	0.003	0.002

Notes: Bayesian heteroskedastic estimates based on 1,100 Markov Chain Monte Carlo (MCMC) draws with a burn-in sample of 100 draws following LeSage (1997). $\hat{\sigma}$ stands for the standard deviation of the estimated residuals, which is an indicator of the model's goodness of fit. The dependent variable is in all cases the measure of well-being described in section 3.1. Standard errors in brackets. All regressions include a constant (not shown). * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

(most comprehensive specification 5 in Table 4, including country fixed-effects). Results show that QoG is positive and significantly associated with the majority of the well-being dimensions, although there are interesting nuances. For instance, no significant effects are found for the dimensions of health and environment. Whereas for the former variable this result stands in stark contrast to previous literature, for the latter it is no surprise, since as we discuss in Section 2 there is very mixed evidence on the link between QoG and environmental performance (see Holmberg et al., 2009). For the rest of the dimensions, large differences are found in the size of the QoG coefficient. The largest impact is seen in the jobs dimension (0.137), indicating that higher QoG helps create a more dynamic job market able to overcome negative tendencies, thereby making regions more resilient (Ezcurra & Rios, 2019). The impact on education and income, two of the pillars of the HDI index, is also non-negligible, although we find larger effects for social features such as civic engagement and community, suggesting that people tend to participate more actively in the community under a reliable institutional setting. Other dimensions such as access to services and housing also benefit from good governance. Finally, the intensity of the spatial effects is similar to the case of the composite well-being indicator, ranging from 0.34 to 0.63 depending on the dimension considered.

There are several potential underlying mechanisms behind these positive associations. Although identifying the particular links operating in each well-being dimension would deserve a specific research,[11] there are some general mechanisms which can be driving the relationships found. First, QoG may lead to increased efficiency of the tax system, which helps generate additional resources that are better allocated to infrastructures (Aghion et al., 2016). Second, governments perceived as fair and corruption-free encourage people to participate in the socio-economic and political life (Chong et al., 2015), as the institutional frame is expected to guarantee that the system works properly. Third, where QoG is high, the possibility that funds are allocated to benefit particular lobbies is much more limited, favouring equality and a broader access to services to all citizens (Gupta et al., 2002). Fourth, QoG can act as a lubricant of the institutional system, increasing flexibility, eliminating duplicities and, in general, reducing transaction costs. This might benefit the economic spheres, as reduced transaction costs increase economic dynamism and absoptive capacity (Rodríguez-Pose & Di Cataldo, 2014).

5.3 | Robustness checks

In order to test the robustness of our results, we perform several additional checks. First, a potential concern relates to the possible endogeneity of QoG. Regional well-being may by determined by QoG, but the latter may, in turn, be influenced by some of the well-being dimensions, giving rise to a reverse causality problem. Moreover, the QoG indicator used in the paper may be affected by measurement errors. Finally, although our baseline specification includes several controls and country dummies, we cannot definitely rule out the possible existence of an omitted determinant of regional well-being correlated with government performance. In view of these potential problems, we now treat QoG as endogenous. That said, it is admittedly difficult to identify variables affecting QoG but not well-being. To tackle this problem, we follow the strategy adopted by Kelejian, Murrel, and Shepotylo (2013) and use as instruments the linearly independent columns of (X, WX, W^2X). Importantly, the exclusion restriction for identification in this context is supported by the spatial Bayesian model selection results of Table 3 showing that the spatial lags of X in the SDM and SDEM specifications have a very low probability of being part of the true data generating process (DGP) of well-being, thus our set of instruments cannot be correlated with the error term in the explanatory equation. Table 6 presents the results for Models 1 to 5, showing that the effect of QoG on well-being holds in all cases.

Second, we estimate model 5, the most comprehensive, using alternative strategies to compute the composite well-being indicator. In particular, we considered six alternative scenarios: (i) DEA-BoD-MCDM, setting $t=1$; (ii) DEA-BoD-MCDM, setting $t=0$; (iii) arithmetic mean of all the dimensions; (iv) geometric mean of all the dimensions; (v) factor analysis based on the principal factors method and regression scoring for prediction over all the dimensions (one factor retained); and (vi) principal components analysis based on the correlation matrix, retaining one component. Table 7 contains the results, which remain qualitatively unaltered, suggesting both the robustness of our composite index and that of the QoG effect on well-being, as it holds regardless of the method used to compute the composite well-being indicator.[12]

Finally, as mentioned in subsection 3.2, the QoG measure used is a three-dimensional concept, including quality, impartiality and the control of corruption in education, public health and law enforcement. Although they are positively correlated, they may have different effects on well-being. To control for that scenario, Table 8 provides separate results for each component in the context of model 5, showing that all three are statistically significant.

[11] It is likely that some well-being dimensions can be affected simultaneously. Also, impacts on some dimensions can finally be seen in other dimensions, being the effects indirect. For example, improvements in QoG can positively affect education, which in turn can boost the income and jobs dimensions.

[12] In addition to the alternative composite indicators of well-being based on multivariate analysis mentioned above, we have also calculated two other indicators. The first one is computed with factor analysis, but prediction is carried out using the Bartlett scoring method; the second is calculated with principal components and the covariance matrix method. Outstandingly, the results regarding the effect of the QoG on well-being are also robust to these two additional indicators.

TABLE 5 Quality of government and dimensions of well-being

	Dependent variable: Well-being dimensions									
	Education	Jobs	Income	Safety	Health	Environment	Civic	Access	Housing	Community
Quality of government	0.050***	0.137***	0.044***	0.042**	0.019	-0.031	0.080***	0.034**	0.023*	0.057**
	[0.015]	[0.028]	[0.011]	[0.023]	[0.022]	[0.032]	[0.020]	[0.014]	[0.016]	[0.02]
Eco-self rule	-0.003	-0.003	-0.005	0.001	-0.003	-0.004	0.009*	-0.008*	-0.002	-0.021**
	[0.006]	[0.010]	[0.004]	[0.007]	[0.009]	[0.011]	[0.007]	[0.005]	0.005]	[0.013]
Eco-self rule^2	0.0001	0.0002***	0.0002**	0.000	0.0001	0.0001	-0.0002*	0.0001	0.0001	0.0003
	[0.0001]	[0.0002]	[0.0001]	[0.0001]	[0.0002]	[0.0002]	[0.0001]	[0.0001]	[0.0001]	[0.0002]
Capital city	0.070***	0.097***	0.069***	0.010	0.037*	-0.030	0.078***	0.058***	-0.004	0.008
	[0.026]	[0.038]	[0.018]	[0.031]	[0.029]	[0.047]	[0.029]	[0.022]	[0.021]	[0.041]
Population density	-0.013*	-0.035**	-0.001	-0.002	0.014	-0.031**	0.006	0.003	-0.024***	0.000
	0.010]	0.016]	0.009]	0.012]	0.013]	0.017]	0.011]	0.008]	0.008]	0.015]
R&D	0.013**	0.018*	0.009*	0.002	0.029***	-0.024*	0.013*	0.015**	-0.012*	0.023*
	[0.007]	[0.013]	[0.006]	[0.011]	[0.012]	[0.015]	[0.010]	[0.007]	[0.007]	[0.014]
Trust	0.068	0.341***	0.153**	0.088	0.259**	-0.294*	0.118	0.142**	-0.193***	0.159
	[0.096]	[0.145]	[0.070]	[0.123]	[0.118]	[0.180]	[0.124]	[0.084]	[0.082]	[0.167]
Infrastructure density	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000	[0.000]
Sectoral specialisation	0.113	0.077	-0.088	-0.463	-0.950	0.069	-1.289**	0.317	0.078	-0.071
	[0.502]	[1.017]	[0.369]	[0.735]	[0.760]	[1.086]	[0.675]	[0.493]	[0.475]	[0.895]
Agriculture	-0.002*	0.003	-0.003***	0.002	0.002	-0.001	0.000	-0.003**	0.000	0.004*
	[0.002]	[0.003]	[0.001]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.001]	[0.003]
Manufactures	0.001	0.003	0.000	0.004**	-0.003	-0.004	0.003*	0.002*	0.002	0.001
	[0.001]	[0.003]	[0.001]	[0.002]	[0.002]	[0.003]	[0.002]	[0.001]	[0.001]	[0.003]
$W\varepsilon$	0.587***	0.592***	0.630***	0.486***	0.486***	0.629***	0.477***	0.346***	0.535***	0.220
	[0.104]	[0.108]	[0.087]	[0.145]	[0.127]	[0.094]	[0.140]	[0.149]	[0.112]	[0.182]
Country fixed effects	Yes	Yes	Yes	Yes	Yes					
R^2	0.926	0.860	0.899	0.485	0.912	0.735	0.930	0.853	0.946	0.573
Adjusted R^2	0.909	0.830	0.877	0.372	0.893	0.677	0.915	0.821	0.934	0.480
$\hat{\sigma}$	0.003	0.008	0.002	0.006	0.006	0.012	0.005	0.003	0.002	0.011

Notes: Bayesian heteroskedastic estimates based on 1,100 Markov Chain Monte Carlo (MCMC)draws with a burn-in sample of 100 draws following LeSage (1997). $\hat{\sigma}$ stands for the standard deviation of the estimated residuals, which is an indicator of the model's goodness of fit. The dependent variable is in all cases the measure of well-being described in section 3.1. Standard errors in brackets. All regressions include a constant (not shown). * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

TABLE 6 Robustness (I), endogeneity of quality of government

Dependent variable: Well-being					
Model	(1)	(2)	(3)	(4)	(5)
Quality of government	0.099***	0.071***	0.069***	0.071***	0.058**
	[0.036]	[0.030]	[0.021]	[0.022]	[0.026]
Eco-self rule	0.004*	0.006**	0.002	0.002	-0.008**
	[0.003]	[0.003]	[0.002]	[0.002]	[0.005]
Eco-self rule^2	0.000*	0.000**	0.000	0.000	0.000*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Capital city		0.035*	0.019	0.017	0.044**
		[0.021]	[0.019]	[0.021]	[0.019]
Population density		-0.005	-0.003	0.001	-0.003
		[0.009]	[0.009]	[0.010]	[0.008]
R&D			0.023***	0.022***	0.017***
			[0.008]	[0.008]	[0.006]
Trust			0.025	0.019	0.106*
			[0.068]	[0.070]	[0.079]
Infrastructure density			0.000**	0.000**	0.000
			[0.000]	[0.000]	[0.000]
Sectoral specialisation				-0.539*	-0.424
				[0.386]	[0.436]
Agriculture				0.000	0.001
				[0.001]	[0.001]
Manufactures				0.000	0.001
				[0.001]	[0.001]
$W\varepsilon$	0.719***	0.700***	0.624***	0.597***	0.517***
	[0.071]	[0.075]	[0.088]	[0.084]	[0.142]
Sargan	2.894	6.566	29.045	29.045	25.333
Hansen	0.568	0.577	0.995	0.995	0.440
Country fixed effects	No	No	No	No	Yes
R^2	0.584	0.584	0.674	0.675	0.798
Adjusted R^2	0.576	0.571	0.657	0.652	0.754
$\hat{\sigma}$	0.004	0.004	0.003	0.003	0.002

Notes: Bayesian heteroskedastic estimates based on 1,100 Markov Chain Monte Carlo (MCMC) draws with a burn-in sample of 100 draws following LeSage (1997). $\hat{\sigma}$ stands for the standard deviation of the estimated residuals, which is an indicator of the model's goodness of fit. Quality of government is treated as endogenous in columns (1) to (4) using as instruments the linearly independent columns of (X, WX, W^2X) as in Kelejian et al. (2013). The dependent variable is in all cases the measure of well-being described in section 3.1. All regressions include a constant (not shown). Standard errors in brackets. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

This indicates that the observed connection between QoG and well-being is not driven by a particular dimension of QoG. On the contrary, different aspects/measures of QoG seem to capture a broader and more all-encompassing concept, as shown by Versteeg and Ginsburg (2017).

6 | CONCLUSIONS AND PROSPECTS FOR FUTURE RESEARCH

In this paper we calculate a composite indicator of global well-being, which allowed to rank objectively 168 European regions according to their well-being level. This indicator is built using information on 10 well-being domains provided by the OECD Regional Well-being Database. The resulting ranking shows that regional well-being disparities are sizeable. These findings underline the fact that EU regional policies should mantain a focus on a wide variety of

TABLE 7 Robustness (II), alternative composite well-being indicators

	Dependent variable: Alternative well-being indicators					
Model	DEA-BoD-MCDM $t = 1$	DEA-BoD-MCDM $t = 0$	Arithmetic Mean	Geometric Mean	Factor Analysis	Principal Component
Quality of government	0.042***	0.051***	0.045***	0.057***	0.307***	0.644***
	[0.016]	[0.012]	[0.010]	[0.021]	[0.075]	[0.142]
Eco-self rule	-0.003	-0.008**	-0.005*	-0.013	-0.037	-0.074
	[0.005]	[0.004]	[0.003]	[0.011]	[0.025]	[0.045]
Eco-self rule squared	0.0001	0.0001**	0.0001*	0.0001	0.001*	0.002*
	[0.0001]	[0.0000]	[0.0001]	[0.0002]	[0.000]	[0.001]
Capital city	0.032*	0.045***	0.045***	0.065**	0.327***	0.633***
	[0.021]	0.019	[0.013]	[0.032]	[0.094]	[0.192]
Population density	-0.003	-0.006	-0.008*	-0.013	-0.022	-0.059
	[0.009]	[0.008]	[0.006]	[0.013]	[0.047]	[0.086]
R&D	0.008	0.016***	0.009**	0.017*	0.078**	0.126*
	[0.007]	[0.006]	[0.005]	[0.011]	[0.035]	[0.071]
Trust	0.111*	0.115*	0.087*	0.074	0.877**	1.497*
	[0.082]	0.072	[0.054]	[0.134]	[0.387]	[0.828]
Infrastructure density	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Sectoral specialisation	-0.438	-0.454	-0.313	-1.026	-1.716	-4.854
	[0.491]	[0.386]	[0.300]	[0.866]	[2.339]	[4.675]
Agriculture	0.001	0.001	0.000	-0.002	0.000	0.000
	[0.002]	0.001	[0.001]	[0.002]	[0.006]	[0.013]
Manufactures	0.0027**	0.001	0.0005	0.0000	0.004	0.015
	[0.0014]	0.001	[0.0009]	[0.0024]	[0.007]	[0.014]
$W\varepsilon$	0.487***	0.492***	0.589***	0.422***	0.575***	0.555***
	[0.134]	[0.127]	[0.110]	[0.139]	[0.114]	[0.118]
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.635	0.813	0.916	0.764	0.941	0.939
Adjusted R^2	0.556	0.770	0.898	0.712	0.928	0.926
$\hat{\sigma}$	0.003	0.002	0.001	0.007	0.055	0.229

Notes: Bayesian heteroskedastic estimates based on 1,100 Markov Chain Monte Carlo (MCMC) draws with a burn-in sample of 100 draws following LeSage (1997). $\hat{\sigma}$ stands for the standard deviation of the estimated residuals, which is an indicator of the model's goodness of fit. All regressions include a constant (not shown). Standard errors in brackets. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

well-being dimensions, apart from purely economic indicators such as income. While it is essential to reduce the income gap, a much more egalitarian EU can only be achieved if disparities in other important well-being dimensions decrease.

The ultimate responsibility of governments is to achieve higher living standards for their citizens and, in that regard, we find that government quality substantially improves well-being. These results suggest some guidelines for the design of future policies, which should follow two different paths: on the one hand, they should be aimed at improving particular well-being domains; while on the other hand, they should seek to enhance the quality of government, which might have an indirect effect on the application and effectiveness of other policies. Moreover, spatial dependence has been proved to play an important role in these processes and should also be considered when quantifying the impact of government quality on well-being.

Apart from providing evidence for the aggregate composite well-being indicator, the multidimensional nature of well-being makes it advisable to analyse the effects of particular dimensions, in order to unveil more specific mechanisms by which government quality can influence well-being. This decomposition showed that with the

TABLE 8 Robustness (III), dimensions of quality of government and well-being

Model	Dependent variable: Well-being (5_a)	(5_b)	(5_c)
Quality of public services	0.056***		
	[0.019]		
Impartiality		0.035**	
		[0.016]	
Corruption			0.063***
			[0.015]
Eco-self rule	-0.008**	-0.009**	-0.008**
	[0.005]	[0.005]	[0.005]
Eco-self rule^2	0.0002*	0.0002*	0.0001*
	[0.0001]	[0.0001]	[0.0001]
Capital city	0.038**	0.038**	0.041**
	[0.018]	[0.018]	[0.019]
Population density	-0.004	-0.004	-0.005
	[0.008]	[0.008]	[0.008]
R&D	0.017***	0.017***	0.017***
	[0.007]	[0.007]	[0.006]
Trust	0.131**	0.144**	0.116*
	[0.075]	[0.072]	[0.071]
Infrastructure density	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Sectoral specialisation	-0.729*	-0.576*	-0.406
	[0.443]	[0.449]	[0.430]
Agriculture	0.000	0.001	0.001
	[0.001]	[0.001]	[0.001]
Manufactures	0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]
$W\varepsilon$	0.467***	0.501***	0.479***
	[0.139]	[0.131]	[0.127]
Country fixed effects	Yes	Yes	Yes
R^2	0.802	0.791	0.811
Adjusted R^2	0.758	0.745	0.769
$\hat{\sigma}$	0.002	0.002	0.002

Notes: Bayesian heteroskedastic estimates based on 1,100 Markov Chain Monte Carlo (MCMC) draws with a burn-in sample of 100 draws. $\hat{\sigma}$ stands for the standard deviation of the estimated residuals, which is an indicator of the model's goodness of fit. The dependent variable is in all cases the measure of well-being described in section 3.1. Standard errors in brackets. All regressions include a constant (not shown). * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. For the case of corruption, higher values of the indicator correspond to better performance in that dimension.

exception of the health and environment dimensions, quality of government is positively associated with many well-being spheres, in line with country-level findings in the literature. However, although we went a step further than previous analyses with this dimension-level analysis, a more detailed exploration focusing on specific government actions could lead to even more informative policy prescriptions. As a robustness check, we provided evidence of a positive effect for the three components of institutional quality of the EQI index, namely corruption, impartiality and quality. However, there are other dimensions which are not considered in the index, such as democratic or political quality. At the country level, different effects are found for institutional and political quality; thus, efforts should also be targeted at improving the availability of this information at a regional level.

In addition, the multidimensionality of well-being represents a crucial handicap when it comes to isolating particular effects. Several differences could be attributed to the development level. Given that we have included several control variables and country dummies, and have specifically accounted for endogeneity and spatial spillovers, our estimates are expected to be relatively robust, although we acknowledge that there might be several links in effect among the different dimensions, making it especially difficult to disentangle all the causal effects. 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 at the regional level, on these and other closely related issues.

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APPENDIX A

TABLE A1 Well-being ranking of European regions

Region	Well-being score	Region	Well-being score	Region	Well-being score
Western Finland (FI)	1.000	Luxembourg (LU)	0.941	Severovchod (CZ)	0.838
Basque Country (ES)	1.000	Abruzzo (IT)	0.940	Picardy (FR)	0.835
Midi-Pyres (FR)	0.999	South Holland (NL)	0.939	Malopolskie (PL)	0.835
Saxony (DE)	0.998	Southern and Eastern (IR)	0.939	Jihozpad (CZ)	0.833
Bavaria (DE)	0.998	North Holland (NL)	0.939	Podlaskie (PL)	0.829
South East England (UK)	0.994	Lower Austria (AT)	0.937	Wielkopolskie (PL)	0.825
Baden-Wrttemberg (DE)	0.992	Vlaams Gewest (BE)	0.934	Balearic Islands (ES)	0.819
Salzburg (DE)	0.991	Languedoc-Roussillon (FR)	0.932	Sicily (IT)	0.813
Styria (AT)	0.991	Yorkshire and The Humber (UK)	0.932	Jihovchod (CZ)	0.812
Tyrol (AT)	0.989	Scotland (UK)	0.931	Lazio (IT)	0.812
South West England (UK)	0.988	West Midlands (UK)	0.931	Mazowieckie (PL)	0.811
Rhne-Alpes (FR)	0.988	North Brabant (NL)	0.928	La Rioja (ES)	0.806
Aquitaine (FR)	0.987	Southern Denmark (DK)	0.928	Extremadura (ES)	0.803
Thuringia (DE)	0.985	Burgundy (FR)	0.925	Stredn Morava (CZ)	0.798
South (FI)	0.982	Centre (FR)	0.924	Pomorskie (PL)	0.795
Pays de la Loire (FR)	0.979	Province of Bolzano-Bozen (IT)	0.921	Bratislava Region (SK)	0.793
Franche-Comt (FR)	0.978	Friesland (NL)	0.921	Opolskie (PL)	0.790
Mecklenburg-Vorpommern (DE)	0.975	Overijssel (NL)	0.920	Kujawsko-Pomorskie (PL)	0.788
Auvergne (FR)	0.975	North West England (UK)	0.920	Rgion wallonne (BE)	0.788
Svealand (SE)	0.974	Asturias (ES)	0.918	Andalusia (ES)	0.784
Greater London (UK)	0.973	Brandenburg (DE)	0.915	Lubelskie (PL)	0.783
Brittany (FR)	0.973	Flevoland (NL)	0.913	East Slovakia (SK)	0.776
Madrid (ES)	0.972	Liguria (IT)	0.910	Central Slovakia (SK)	0.774
Norrland (SE)	0.972	Lorraine (FR)	0.909	land (FI)	0.772
Navarra (ES)	0.971	Northern Ireland (UK)	0.904	Veneto (IT)	0.768
Hamburg (DE)	0.971	Zealand (NL)	0.900	Warminsko-Mazurskie (PL)	0.765
Rhineland-Palatinate (DE)	0.970	North East England (UK)	0.899	Zachodniopomorskie (PL)	0.763
Upper Austria (AT)	0.969	Upper Normandy (FR)	0.897	Lisbon (PT)	0.761
East of England (UK)	0.969	Saarland (DE)	0.896	West Slovakia (SK)	0.761
Drenthe (DE)	0.969	Bremen (DE)	0.892	Aosta Valley (IT)	0.754
East (FI)	0.968	Gelderland (NL)	0.891	Kzp (HU)	0.753

TABLE A1 Continued

Region	Well-being score	Region	Well-being score	Region	Well-being score
North (FI)	0.968	Vienna (AT)	0.889	Brussels-Capital Region (BE)	0.752
Gtaland (SE)	0.966	Apulia (IT)	0.889	Moravskoslezsko (CZ)	0.752
Schleswig-Holstein (DE)	0.965	Limburg (NL)	0.889	Slaskie (PL)	0.748
Vorarlberg (AT)	0.964	Aragon (ES)	0.886	EmiliaRomagna (IT)	0.746
Carinthia (AT)	0.964	Castile and Len (ES)	0.885	Severozpad (CZ)	0.739
Limousin (FR)	0.962	Podkarpackie (PL)	0.885	Dolnoslaskie (PL)	0.736
Saxony-Anhalt (DE)	0.960	Border, Midland and Western (IR)	0.884	Swietokrzyskie (PL)	0.735
Utrecht (NL)	0.960	Province of Trento (IT)	0.880	Stredn Cechy (CZ)	0.709
Burgenland (AT)	0.957	Zeeland (NL)	0.880	Dunnt (HU)	0.706
East Midlands (UK)	0.955	Sardinia (IT)	0.877	Ldzkie (PL)	0.705
Capital (DK)	0.953	Calabria (IT)	0.875	Friuli-Venezia Giulia (IT)	0.702
Groningen (NL)	0.951	Catalonia (ES)	0.870	Corsica (FR)	0.693
Cantabria (ES)	0.950	Basilicata (IT)	0.869	Alfd s szak (HU)	0.690
North Rhine-Westphalia (DE)	0.949	Piedmont (IT)	0.866	Umbria (IT)	0.684
Wales (UK)	0.949	Campania (IT)	0.865	Lubuskie (PL)	0.677
Lower Normandy (FR)	0.949	Provence-Alpes-Cte d'Azur (FR)	0.864	Estonia (EE)	0.668
Central Jutland (DK)	0.948	Castile-La Mancha (ES)	0.858	North (PT)	0.665
Alsace (FR)	0.948	Galicia (ES)	0.858	Attiki (GR)	0.647
Northern Jutland (DK)	0.947	Nord-Pas-de-Calais (FR)	0.858	Central Portugal (PT)	0.625
Hesse (DE)	0.946	Tuscany (IT)	0.856	Nisia Aigaiou, Kriti (GR)	0.604
Poitou-Charentes (FR)	0.946	Lombardy (IT)	0.854	Voreia Ellada (GR)	0.593
Lower Saxony (DE)	0.944	Praha (CZ)	0.851	Alentejo (PT)	0.580
Berlin (DE)	0.941	Valencia (ES)	0.849	Kentriki Ellada (GR)	0.565
le-de-France (FR)	0.941	Murcia (ES)	0.841	Algarve (PT)	0.562
Molise (IT)	0.941	Champagne-Ardenne (FR)	0.839	Marche (IT)	0.480

Notes: Well-being scores computed with DEA-BOD-MCDM, integer scenario. A score of 1 represents the highest well-being. Country abbreviations are in parentheses.

TABLE A2 Description, sources and descriptive statistics for control variables

Variable	Mean	Sd	Definition	Source
Governance factors				
Eco-self rule	13.76	14.84	Index capturing the extent of politically effective	Sorens (2014)
			regional autonomy in economic policy and taxation	
			$ESR_i = [PS_i \times FA_i \times PR_i]\ \forall\ ID_i = 3$	
			$ESR_i = \frac{[PS_i \times FA_i \times PR_i]}{2} \rightarrow ID_i \neq 3$	
			where: PS denotes policy scope, FA fiscal autonomy,	
			PR political representation, and ID stands for institutional depth	
Socio-demographic factors				
Capital city	0.11	0.31	Dummy that takes a value of 1 if the capital of the country is located in the region and 0 otherwise	
Population density	0.34	0.83	Population (in thousands) per square kilometre	Eurostat
Knowledge and innovation				
R&D	1.37	0.95	Ratio of R&D spending to GDP (%)	Eurostat
Trust	0.34	0.14	Proportion of all respondents that chose the answer 'Most people can be trusted'	European Values Study
			(as opposed to 'Can't be too careful') when responding to the survey question	
			"Generally speaking, would you say that most people can be	
			trusted or that you can't be too careful in dealing with people?"	
Infrastructure density	1159.36	814.29	Number of kilometres of motorways and railways network on usable land	Eurostat
Sectoral composition and specialisation				
Sectoral specialisation	0.23	0.02	Herfindahl index of regional specialisation calculated from	Cambridge Econometrics
			employment shares in agriculture,	
			manufacturing, construction, construction, distribution,	
			financial services, and non-market services	
			$SPE_i = \sum_{s=1}^{S} e_{is}^2$ where e_{is} is the employment share of region i in sector s	
Agriculture	6.89	6.50	Employment in agriculture (% of total employment)	Cambridge Econometrics
Manufactures	18.71	6.60	Employment in manufacturing (% of total employment)	Cambridge Econometrics

Notes: All variables are calculated as the mean during the 2000-2007 interval. The only exceptions are the indicator of regional autonomy, which refers to the period 2000-2005, and the trust index, measured in 2008.