QUALITY OF GOVERNMENT AND ENVIRONMENTAL WELLBEING ACROSS EUROPEAN REGIONS

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1. Introduction

As stated in the United Nations General Assembly resolution 66/288 (UN 2012: 2), "to achieve our sustainable development goals, we need institutions at all levels that are effective, transparent, accountable and democratic". Simply put, we need *quality of government* to foster human wellbeing. The vast majority of cross-national comparative studies on the relationship between institutions and wellbeing supports this view, yet extant research has focused primarily on the economic and social aspects of wellbeing. Given that wellbeing is commonly conceived as a tri-dimensional concept consisting of three main pillars – economic, social, and environmental (e.g., Ciommi *et al.*, 2020) – the current literature has neglected the environmental dimension of wellbeing. Furthermore, the few existing studies on the relationship between quality of government and environmental wellbeing remain inconclusive. Depending on the study, this association has been described as positive (e.g., Ríos and Picazo-Tadeo, 2021), negative (e.g., Cole, 2007), or non-significant (e.g., Peiró-Palomino *et al.*, 2020).

This study contributes to the literature on the relationship between institutional quality and human wellbeing, by filling the above gap in the literature. Ultimately, our goal is to investigate if quality of government – defined as "the extent to which states perform their required activities and administer public services in an impartial and uncorrupt manner" (Charron *et al.*, 2015) – is a significant predictor of common dimensions of environmental wellbeing. To shed light on the institutions-environment nexus, we address three major shortcomings in the existing body of scholarship on the topic. We argue that these three limitations may have played an important part in prior inconclusiveness of results.

First, a lion's share of studies has focused on institutional quality and environmental wellbeing at the country-level, disregarding subnational variation within countries. Experts however have recently demonstrated that both quality of government (Charron *et al.*, 2015; Charron *et al.*, 2019) and human wellbeing (Iammarino *et al.*, 2019; OECD 2014) vary significantly within countries. Therefore, we investigate the relationship between quality of government and environmental wellbeing at a subnational level. We focus on NUTS 2 regions in the European Union (EU) because, in the last decades, within-country territorial differences have increased especially in Europe (Iammarino *et al.*, 2019).

Second, present knowledge on the institutions-environment nexus is based on an excessively narrow understanding of the environment. Even some of the most sophisticated studies measure environmental wellbeing through exposure to air pollution by particular matter (Peiró-Palomino *et al.*, 2020) or by a combination of multiple air pollutants (Halkos *et al.*, 2015). Nevertheless, it is self-evident that one or more air pollutants cannot represent environmental wellbeing in its entirety. In the same way that human development is much more than GDP/capita, environmental wellbeing is much more than air pollution. Therefore, we take a multidimensional approach to environmental wellbeing measurement. Following the Italian National Institute of Statistics (ISTAT 2021), we identify six main dimensions, and measure four of them with multiple representative indicators. Specifically, we look at: (1) air quality, (2) water quality, (3) soil quality, and (4) energy and climate change.

Third, somewhat related, instead of using simple indicators to proxy these four dimensions, we construct composite indices to represent each of them as comprehensively as possible. To do so, we take a Bayesian approach to composite indicator construction, which has some important advantages compared to frequentist methods. In particular, our Bayesian latent variable approach, through the incorporation of prior knowledge, results in estimates that are more precise and informs on the uncertainty of these estimates. Moreover, since scholars have shown that regional wellbeing tends to be spatially interdependent (Peiró-Palomino *et al.*, 2020), we assess the magnitude of environmental wellbeing's spatial correlation in EU regions and take into account this information in the newly developed composite indicators. Finally, we use these composite indicators as dependent variables in our subsequent regressions of environmental wellbeing on quality of government.

This paper proceeds as follows. First, we present the data we use in the analysis. Second, we explore the methods. Third, we present and discuss our empirical results. Finally, in the conclusive section, we briefly summarize our main findings.

2. Empirical Approach

2.1. Main Data

Frequently used cross-national measures of environmental wellbeing and quality of government capture these two concepts at the country-level without making any difference among territorial discrepancies within countries. Recently, however, as scholarly interest in subnational development has increased, new subnational data on institutional quality and environmental wellbeing has been published.

To measure subnational quality of government in EU regions, we use arguably the most widely used and well-constructed dataset on the topic: the *European Quality of Government Index Survey Dataset* (Charron *et al.*, 2019). The dataset, published by the Quality of Government Institute at the University of Gothenburg, provides subnational data for EU countries in four years – 2010, 2013, 2017, and 2021. Its *European Quality of Government Index* (EQI) is constructed by first aggregating individual survey question scores into three dimensions of quality of government, and then by synthesising these three component indicators – *Quality*, *Impartiality*, and *Corruption* – into an aggregate index. EQI captures institutional quality at the NUTS 2 level in 238 subnational territories across EU countries. The index runs from low to high on a z-score scale (mean of 0; standard deviation of 1).

As for environmental wellbeing, no comprehensive measure at the subnational EU level exists at the time of this writing. As already stressed, to cope with the lack of subnational data on the environmental pillar of wellbeing, most scholars tend to focus only on measures of air pollution. Yet, these measures are not representative of environmental wellbeing as a whole. For instance, one of the most well-known datasets on subnational wellbeing – OECD's *Regional Wellbeing Dataset* – provides only one measure of environmental wellbeing: air pollution by particulate matter. To tackle the above problems, we (1) scrutinize and collect a battery of subnational indicators of various aspects of environmental wellbeing and (2) develop an original set of composite indicators of air quality, water quality, soil quality, and energy and climate change to comprehensively capture these aspects.

Next, before the actual empirical analysis, we discuss in detail the process of constructing our novel set of composite indicators and specify the regressions used to examine the nexus between quality of government and environmental wellbeing.

2.2. Methods

One of the shortcomings in past subnational studies on the relationship between quality of government and environmental wellbeing is the lack of a comprehensive and synthetic measure of environmental wellbeing. Hence, by means of a data-driven approach based on factor analysis, we construct four environmental composite indicators, one for each of our four environmental pillars – air, water, soil, and energy – summarizing the information of 17 elementary environmental indicators. Then, we run ordinary least squares (OLS) regressions to shed light on the link between quality of government and environmental wellbeing in EU regions.

We hypothesize the existence of spatial spillovers, so that environmental conditions in each region are partially determined by the environmental conditions of its neighboring regions. To verify this initial assumption, we test for spatial autocorrelation in the 17 environmental elementary indicators through the Global Moran I test (Moran, 1950), which provides significant results for all the indicators.

Based on these results, we follow Hogan and Tchernis (2004) and estimate a Bayesian latent factor model for spatially correlated data.

The Bayesian approach naturally adapts to the hierarchical structure of the latent factor model. Moreover, through priors' distribution specification, the Bayesian approach allows providing information on the spatial structure of the data, resulting in more precise latent factors' estimates. Finally, the Bayesian approach has the specific advantage of providing a measure of uncertainty about the latent factor scores, through the information embedded in the posterior parameters' distribution.

For each European region i, where $i = 1, \dots, 235$, let $Y_{i,p}$ denote the elementary environmental indicator p in region i and $p = 1, \dots, 17$. Hence $\boldsymbol{Y}_i = \left(Y_{i,1}, \dots, Y_{iP}\right)^T$ is the vector of the observed outcome variables for region *i*. We assume the existence of a latent variable δ_i, that fully characterizes the environmental wellbeing level, which in turn manifests itself through Y_i. Thus, we represent the model in a hierarchical form. At the first level we have:

$$\mathbf{Y}_\mathrm{i} \mid \mu_i, \delta_i, \mathbf{\Sigma} \sim \textit{Multivariate-Normal}\,(\mu_i + \boldsymbol{\lambda}\delta_i, \mathbf{\Sigma}),$$

where $\boldsymbol{\mu}_i$ is $a\ P \times 1$ mean vector, $\boldsymbol{\lambda}$ is a $P \times 1$ vector of factor loadings, and $\mathbf{\Sigma} = \mathrm{diag}(\sigma_1^2, \dots, \sigma_P^2)$ is a diagonal matrix measuring residual variation in Y_i. Assuming Σ diagonal implies independence among the elements of Y_i conditionally on δ_i. Writing the model compactly, let Y be the $NP \times 1$ stacked vector of manifest variable and $\boldsymbol{\mu}$ the stacked vector of mean defined analogously. Finally, let $\mathbf{\Lambda} = \mathrm{I_N} \otimes \boldsymbol{\lambda}$ the $NP \times N$ matrix of factor loadings where I_N is the identity matrix of dimension N.

Let $\boldsymbol{\delta} = (\delta_1, \dots, \delta_N)^T$ be the vector of regions' latent environmental wellbeing. We add spatial information to the latent factor prior distribution by assuming:

$$\boldsymbol{\delta} \sim \text{Multivariate-Normal}(0_n, \mathbf{\Psi}),$$

where $\mathbf{\Psi}$ is a $N \times N$ spatial variance-covariance matrix having 1's on the diagonal and $\psi_{i,j} = corr\left(\delta_i, \delta_j\right)$ on the off-diagonal. When $\mathbf{\Psi} = I_N$ the model assumes spatial independence across regions' environmental wellbeing levels. To introduce spatial correlation, the literature proposes several alternatives. We choose a marginal parametrization of the spatial variance-covariance matrix $\mathbf{\Psi}$, through specifications of spatial dependency based on distances between regions' centroids (Cressie, 1993). This parametrization assumes $\psi_{i,j} = \exp\left(-\xi d_{i,j}\right)$, where ξ is the spatial correlation parameter, and $\xi \geq 0$ to ensure $\psi_{ij} < 1$; $d_{i,j}$ is the Euclidean distance between the centroid of regions i and j.

The composite index of environmental wellbeing for region i is summarized by the conditional distribution of the latent factor δ_i given Y and μ, λ, Σ. Hence, the posterior distribution of $\boldsymbol{\delta}$ will be a Multivariate normal distribution:

$$(\boldsymbol{\delta} \mid \boldsymbol{Y}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\Sigma}) \sim \text{Multivariate-Normal}(\boldsymbol{d}, \boldsymbol{D}),$$

where

$$\mathbf{D} = \{\Psi + \Lambda^{\mathrm{T}}\Sigma^{-1}\Lambda\}^{-1},$$
$$\mathbf{d} = \mathrm{D}\Lambda^{\mathrm{T}}\Sigma^{-1}(\mathrm{Y} - \mu).$$

Finally, a characteristic of the Bayesian framework is the introduction of prior distributions on all the model's parameters. In our model, we have set $\lambda_p \sim \text{Normal}(g, G)I(\lambda_1 > 0)$, $\sigma_p^2 \sim \text{Inverse-Gamma}(\alpha/2, \beta/2)$, $\mu_p \sim \text{Normal}(0, V_\mu)$. The primary scope of prior distributions is to include subjective opinions on the parameters of interest. Yet, to let the data “speak for themselves”, we use diffuse priors by choosing $g = 0$, $G = 1000$, $\alpha = 1/1000$, $\beta = 1/1000$, and $V_\mu = 1000$.

We estimate the model with a Gibbs sampling algorithm that includes Metropolis Hasting steps for the spatial parameter ξ[1].

Next, we retrieve the mean from the estimated environmental composite indicators’ posterior distributions and use it as an outcome in OLS regressions to analyse the correlation between environmental wellbeing and quality of government. Let $\hat{\delta}_{ik} = E[\delta_{ik} \mid Y, \mu, \lambda, \Sigma]$, where i indicates the European region and k the environmental dimension, i.e. $k = air, energy, water, soil$; the QoG_i is quality of government in region i. Then, our regressions take the following form:

$$\hat{\delta}_{ik} = \theta + \beta * QoG_i + \boldsymbol{\gamma}' * \boldsymbol{x_i} + \epsilon \ \ \forall k$$

The coefficient of interest is β, which captures the correlation between the quality of government and the observed environmental levels in domain k. We add a few region-specific controls in $\boldsymbol{x}_i$, namely GDP/capita and population density.

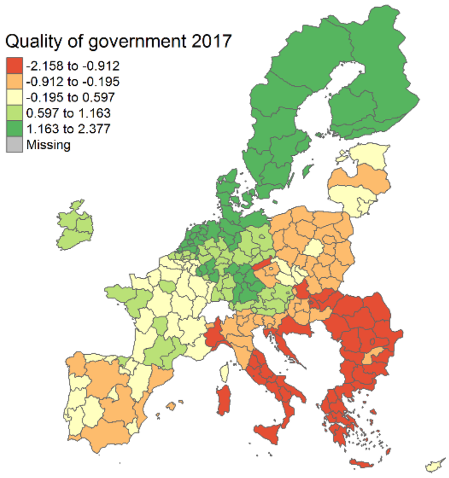
2.3. Results and Discussion

We begin the empirical part and discussion of results by drawing a map of the level of quality of government in all EU regions with available data in 2017 (Figure 1). The map shows clearly that Northern and Western European countries have more quality of government than Southern and Eastern European countries. Yet, the map confirms that there are substantial differences among regions within many countries. To give an example of the nuances that would be missed in a national level approach, let us examine the case of Italy. At the national level, according to EQI, Italy has more quality of government than Bulgaria, Croatia, Greece, and Romania. At the

[1] We have written the sampling algorithm in the R software and made it available on GitHub.

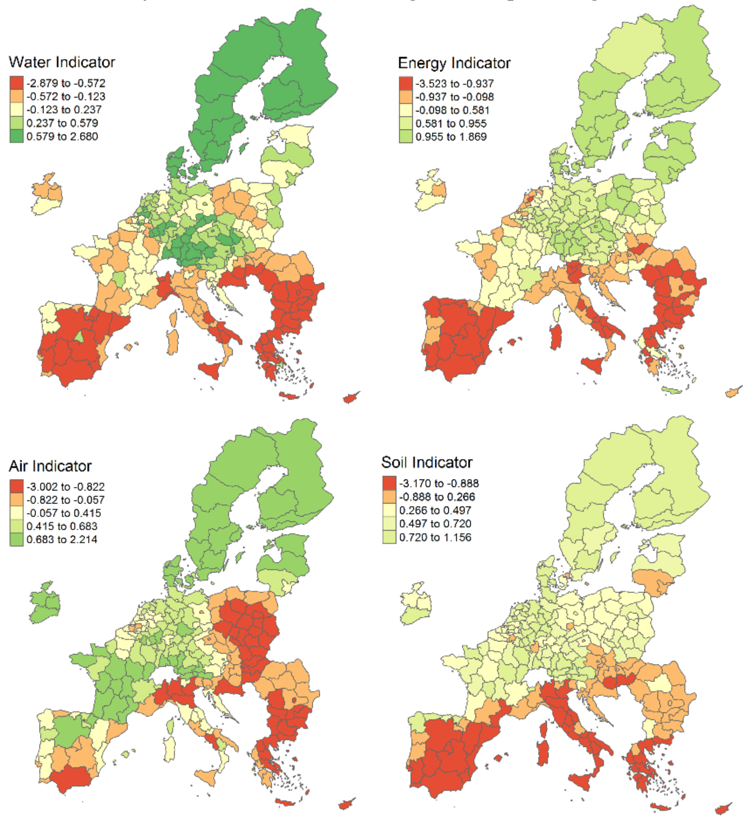
regional level, however, the South Italian region of Calabria has the second lowest level of subnational institutional quality in Europe, whereas the North Italian autonomous provinces of Trento and Bolzano have higher subnational institutional quality than regions such as Catalonia and countries such as Latvia and Poland. These details remain unseen in studies that do not dig deeper into the subnational level. Figure 1 confirms that a complete picture of the effects of quality of government requires taking into account these subnational differences.

Figure 1 – *Quality of government in EU regions.*



Next, we continue our empirical consideration by analyzing the spatial distributions of the estimated composite indicators (latent variable) for each of our four environmental domains. As illustrated by the maps in Figure 2, there seems to be a clear division in environmental wellbeing – regardless of the dimension – between countries in Northern and Western Europe and countries in Southern and Eastern Europe. Citizens of the former group of countries enjoy a considerably greater environmental wellbeing than citizens of the latter group of countries. Nevertheless, our subnational and multidimensional approach allows discovering also interesting nuances and several exceptions to this general trend. By observing Figure 2 and computing the standard deviation of regions within a given country, we can detect that within-country variation is in some cases substantial.

Figure 2 – *Dimensions of environmental wellbeing in European regions.*



As for the dimension of air, the largest within-country variation occurs in Greece (*sd* = 0.82), Italy (*sd* = 0.82), and Croatia (*sd* = 0.77). As for the dimension of water, the largest within-country variation occurs in Denmark (*sd* = 0.73), Greece (*sd* = 0.72), and Belgium (*sd* = 0.71). As for the dimension of soil, the largest within-country variation occurs in Spain (*sd* = 1.18), Portugal (*sd* = 0.98), and Italy (*sd* = 0.95). As for the dimension of energy and climate change, the largest within-country variation occurs in Portugal (*sd* = 1.28), Greece (*sd* = 0.97), and Spain (*sd* = 0.67). These results suggest that in general within-country unevenness in environmental wellbeing is higher in Southern European countries than in the rest of EU countries.

Next, in Table 1 we report the estimated factor loadings. Factor loadings with negative signs imply an inverse association between the elementary indicators and the latent dimension of environmental wellbeing. Conversely, factor loadings with positive signs imply a positive association between the elementary indicators and the latent dimension of environmental wellbeing. When the factor loading distribution is highly centered around zero, we consider the associated indicator not significant for improving wellbeing. All elementary indicators have expected signs.

As shown by factor loadings in Table 1, some elementary indicators are more strongly related to a given latent dimension of environmental wellbeing than others. Indicators of PM10 and PM2.5 based air pollution have the strongest relationships with the latent dimension of *Air*. Urban exposure to PM10 and ozone and NO2 based air pollution are moderately related to Air, whereas the capacity of urban vegetation to remove NO2 is somewhat weakly related to Air. Water productivity and the quality of drinking water instead are relatively strongly related to the latent dimension of *Water*, whereas sewage treatment and freshwater consumption are moderately related to Water. The capacity of ecosystems to avoid soil erosion has by far the strongest correlation with the latent dimension of *Soil*. Severe soil erosion by water and organic farming are moderately related to Soil. Artificial surfaces inside protected areas and land use with heavy environmental impact are weaklier related to *Soil*. Potential vulnerability to climate change instead represents well the latent dimension of *Energy*, whereas energy recovery capacity is only moderately related to Energy.

Table 1 – *Elementary indicators of wellbeing and factor loadings*.

Elementary indicator	Air	Water	Soil	Energy
NO2 Removal capacity by urban vegetation (2020)	-0.092			
Urban population exposed to PM 10 (2020)	-0.431			
Air pollution - PM2.5 (2016)	-0.974			
Air pollution - PM10 (2016)	-1.035			
Air pollution - Ozone (2017)	-0.365			
Air pollution - NO2 (2017)	-0.431			
Water productivity or use efficiency (2020)		0.642		
Drinking water quality (2020)		0.651		
Sewage treatment (2016/2014)		0.424		
Freshwater consumption per capita (2020)		-0.487		
Capacity of ecosystems to avoid soil erosion (2020)			0.976	
Severe soil erosion by water (2016)			-0.412	
Artificial surfaces inside N2000 in km² (2018)			-0.171	
Land use with heavy environmental impact (2018)			0.180	
Organic farming (2016)			0.315	
Energy recovery (R1) capacity per capita (2018)				0.321
Potential vulnerability to climate change (2071-2100)				-1.005

With our composite indicators of environmental wellbeing, we can now assess the multidimensional relationship between environment and quality of government. Table 2 reports a summary of the results of the OLS regressions on the relationship between environmental wellbeing and quality of government. In the baseline models, we do not include any control variables into the regression equation. In the second set of models, we control for potential socioeconomic confounders including GDP/capita and population density. In the third and last set of models, to exclude that the "effects" are driven by other aspects of environmental wellbeing, we control also for the different dimensions of environmental wellbeing.

Table 2 – *Environmental wellbeing and quality of government: regression results.*

	Dependent variable:			
	Air	*Water*	*Soil*	*Energy*
	(1)	(2)	(3)	(4)
Baseline models				
Quality of government	0.672***	0.562***	0.616***	0.547***
	(0.049)	(0.037)	(0.047)	(0.044)
R^2	0.49	0.49	0.38	0.31
N	233	233	233	233
Models with socioeconomic controls	(5)	(6)	(7)	(8)
Quality of government	0.594***	0.471***	0.679***	0.624***
	(0.075)	(0.049)	(0.068)	(0.068)
GDP/capita	0.336	0.322*	-0.264	-0.332
	(0.180)	(0.161)	(0.186)	(0.200)
Population density	-0.0002*	0.0002***	0.0001	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R^2	0.51	0.56	0.39	0.33
N	233	233	233	233
Models with socioeconomic and environmental controls	(9)	(10)	(11)	(12)
Quality of government	0.519***	0.143**	0.283**	0.264**
	(0.090)	(0.054)	(0.091)	(0.094)
GDP/capita	0.277	0.428**	-0.380*	-0.430*
	(0.183)	(0.150)	(0.190)	(0.181)
Population density	-0.0002**	0.0002**	-0.00004	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Air		0.073	0.054	-0.067
		(0.043)	(0.087)	(0.067)
Water	0.165		0.509***	0.547***
	(0.105)		(0.114)	(0.087)
Soil	0.052	0.216***		0.210*
	(0.082)	(0.048)		(0.081)
Energy	-0.061	0.220***	0.199*	
	(0.062)	(0.042)	(0.078)	
R^2	0.52	0.69	0.53	0.49
N	233	233	233	233

*Robust standard errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001.*

The baseline models (1-4) without control variables show that the quality of government is strongly related to each of our four dimensions of environmental wellbeing. The positive sign of the slope coefficients suggests that a higher level of quality of government increases environmental wellbeing. Regardless of the dimension, the result is statistically significant at the 99.9% level of confidence. Additionally, variation in the quality of government alone predicts a relatively important amount of variation in each of the four dimensions of environmental wellbeing – in particular air (R^2 = 0.49) and water (R^2 = 0.49). Nevertheless, more robust evidence on the link between quality of government and environmental wellbeing requires controlling for potential confounding factors.

This is precisely what we do in models 5-8, where we include controls for GDP/capita and population density. As shown by the estimates, adding these two common socioeconomic variables on the right-hand side of the regression equation does not alter substantively the interpretation of the results. Quality of government remains a positive and statistically significant predictor of air (β = 0.59), water (β = 0.47), soil (β = 0.68), and energy (β = 0.62) at the highest conventional level of confidence. In general, environmental wellbeing is better predicted by institutional quality than by economic development or population density. The inclusion of the two socioeconomic controls in the models generates only a negligible increase in model fit.

Finally, in models 9-12 we analyze the predictive power of quality of government on air, water, soil, and energy by controlling for the various dimensions of environmental wellbeing – excluding of course the one used as a dependent variable. At least in theory, the different dimensions of environmental wellbeing are likely to be interrelated. Models 9-12 seem to confirm these theoretical expectations at least in part. The predictive power of quality of government on water (β = 0.14), soil (β = 0.28), and energy (β = 0.26) decreases considerably compared to the previous sets of models. These three slope coefficients are also significant at the lower 99% level of confidence. Interestingly, however, our estimates show that the relationship between quality of government and air quality (β = 0.52) remains essentially unaffected by the inclusion of the controls for water, soil, and energy.

3. Conclusions

The study at hand has investigated the relationship between environmental wellbeing and quality of government across European regions through a multidimensional, comparative, and subnational approach. The main contributions of our study are manifold. First, we have detected the presence of spatial spillovers in environmental levels across EU regions. Second, accounting for this spatial correlation, we have constructed multidimensional composite indicators for four common aspects of environmental wellbeing – air, water, soil, and energy. Third, through a battery of cross-section OLS regression models, we have shown that institutional quality is a significant and positive predictor of each of our dimensions of environmental wellbeing, and it seems to be particularly important for improving air quality. This is reassuring since various measures of air pollution are often used as proxies of environmental wellbeing as a whole. Yet, we have shown that the other three dimensions of environmental wellbeing are important too, suggesting that future studies should not equate simplistically the environment with air pollution and overlook aspects related to water, soil, and energy.

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SUMMARY

Conventional wisdom holds that effective state institutions play a key role for improving sustainable wellbeing. Hence, building quality of government is one of the global targets of the UN Sustainable Development Goals. While empirical evidence indicates that quality of government is indeed crucial for social and economic wellbeing, studies on the environmental impact of effective institutions are scarce and inconclusive. Yet, considering the increasingly severe environmental threats faced by humanity, understanding whether effective institutions are associated with environmental wellbeing should be of primary importance for both researchers and policymakers. In order to shed light on the somewhat neglected institutions-environment nexus, our study addresses three major gaps in the literature. First, instead of focusing on the country level, we focus on the subnational level. Second, instead of considering only a single aspect of environmental wellbeing, our results are based on multiple domains of the environment. Third, given the lack of subnational indices on environmental wellbeing, we develop a new composite index of environmental wellbeing via Bayesian latent variable analysis that takes into account spatial correlation. Our findings show persuasively that quality of government is in general an important and positive determinant of environmental wellbeing at the NUTS 2 level the EU, though we find also that the strength of the institutions-environment nexus depends on the sphere of environmental wellbeing. Policymakers should be aware that environmental destruction can be tackled by building more effective regional institutions.

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