Spatial comprehensive Well-Being composite indicators: evidence from Italian provinces

Abstract
This paper proposes spatial comprehensive composite indicators to evaluate the well-being levels and ranking of Italian provinces with data from the Equitable and Sustainable Well-Being (BES) dashboard. We use a method based on Bayesian latent factor models, which allow us to include spatial dependence across Italian provinces, quantify uncertainty in the resulting estimates, and estimate data-driven weights for elementary indicators. The results reveal that the inclusion of spatial information changes the resulting composite indicator rankings compared to those produced by traditional composite indicators' approaches. Estimated social and economic well-being is unequally distributed among southern and northern Italian provinces. In contrast, the environmental dimension appears less spatially clustered, and its composite indicators also reach above average levels in the southern provinces. The time series of well-being composite indicators of Italian macro-areas shows clustering and macro-areas discrimination on larger territorial units.

KEYWORDS
well-being, composite indicator, spatial analysis, Bayesian factor analysis, Italian provinces
JEL Classification C11, I31, D63

1. Introduction

In the socioeconomic literature, we observe a strong consensus regarding the idea that well-being encompasses multiple dimensions, and that looking only at economic aspects may distort perceptions, leading to inadequate policy actions.

The 2011 report by the Sen-Stiglitz-Fitoussi commission on the Measurement of Economic Performance and Social Progress marked a milestone in this debate, requiring researchers across the globe to develop new tools for the multidimensional monitoring of well-being. Since then, the set of tools used to measure multidimensional well-being has flourished in Europe and beyond. The standard of living, quality of life, quality of services and many other aspects of well-being have been measured and monitored since then with an increasing number of specialized indicators. More recently, climate awareness has created new imperatives for the private and public spheres. Air pollution, water quality, particulate matter and other environmentally related indicators have begun to be assessed throughout Europe, expanding the definition of well-being with an environmental dimension. In many European countries, these indicators have been integrated in national accounts, expanding the information policy makers can access when designing policies.

Providing a unique definition of well-being remains a challenge, both on the macro and individual levels. Over the years, scholars have worked to create theoretical models reflecting such multidimensional ideas. On the macro level, advanced theoretical models are mainly based on a set (or dashboard) of indicators of demonstrated consistency with the well-being construct. Well-known examples include the OECD Better Life Index (BLI) and the Canadian Index of Wellbeing.

In Italy, the first qualitative framework developed in this debate was the 'Equitable and

Sustainable Well-Being ('BES')' jointly proposed in 2013 by the National Council for Economics and Labor (CNEL) and the Italian National Institute of Statistics (ISTAT).

The emergence of a new multi-dimensional paradigm of well-being has been revolutionary but not without drawbacks. Comparing nations or sub-regions in terms of their multiple and arbitrary sub-dimensions of well-being has become a daunting task (Kasparian and Rolland, 2012). This hurdle gives rise to the need for synthesis. Composite indicators have fulfilled this requirement for synthesis by reducing complex systems into lower dimension spaces, thus allowing the performance of an individual unit to be evaluated across space and time.

The state of the art of aggregation methods for constructing composite indicators (CI) entails a broad list of different approaches, from simple ones such as the linear aggregation, to more refined ones. Refined empirical indices are built on non-substitutable and non-compensatory indicators and allow for comparison across territorial units (see, e.g., Mazziotta and Pareto, 2013, Mazziotta and Pareto, 2018 and Scaccabarozzi et al., 2022).

Although they effectively fulfill their synthesis requirement, most CI approaches require researchers to rely on several structural assumptions (Ciommi et al., 2017). In this paper, we address mainly three of them. First, we argue that the normative selection of indicator weights is problematic. For several CIs, the choice of weights comes from expert judgments or is neutral by setting all indicators equally weighted (Mazziotta and Pareto, 2013). This approach exposes indicator weights to the subjectivity of those involved in constructing the CI, which could arbitrarily assign equal weights if they believe all indicators have equal importance.

Second, we question the assumption of the spatial independence of elementary indicators across areas. In current approaches, information about well-being depends exclusively on variables from the area analyzed, and not on variables from neighboring areas. However, economically speaking, the neighborhood is not random (Fusco et al., 2018), but rather describes a common culture among enterprises, a common set of administrative rules on the provincial or regional level and so on, creating spatially aligned clusters, not to mention the detrimental influence of neighboring factors on the validity of model estimates. In the linear regression framework, the presence of spatial correlation creates duplicate information and inflates the variance of the statistical model, damaging the validity of the estimated standard errors (Anselin and Griffith, 1988). As suggested by Fusco et al. (2018) (Fusco et al., 2018), when elementary indicators are well clustered, spatial composite indicators bring out inherent local differences by identifying spatial clusters. Moreover, the lack of attention to the spatial dimension of the variables considered may then have significant consequences when assigning weights (Sarra and Nissi, 2020).

Third, traditional indices lack a posterior measure of uncertainty. This last feature can be problematic, for example, if decisions about policies or resource allocation are based on cutoff values or index percentiles (Hogan and Tchernis, 2004).

Researchers solve the weights selection problem relying on data-driven statistical models such as principal component analysis (PCA), factor analytic models (Chelli et al., 2015), and Bayesian latent class models (Hogan and Tchernis, 2004; Machado et al., 2009; Ciommi et al., 2020). These weighting methods are useful when dealing with large data sets to reduce data dimensionality and find common patterns. One critique of this method is that it can accommodate only linear relationships among variables, while it would be reasonable to have non-linear underlying patterns (Canning et al., 2013). Anyhow, when used within the field of well-being CIs, the factor analytic model offers a straightforward interpretation: the elementary indicators are manifestations of an underlying latent construct interpreted as the well-being and factor loadings represent the contribution of each indicator to the well-being construct (Rijpma, 2016; Ciommi et al., 2020).

Here we follow the above-outlined appraoch based on factor models, but we also assume that well-being spillovers occur among neighboring provinces, creating well-being levels that are spatially correlated. Since we are dealing with spatial analysis, we must reformulate the traditional factor analytic model to incorporate spatial co-variation. We follow Hogan et al. (2004) (Hogan and Tchernis, 2004) and David et al. (2021) (Davis et al., 2021) and propose a Bayesian latent factor model for spatially correlated multivariate data. Our Bayesian model confers the distinct advantage of summarizing the distribution of well-being for each province instead of relying on single-point estimates, thus providing a measure for the uncertainty surrounding our estimates. Another advantage of the Bayesian setting is that it can handle missing values with a posterior imputation procedure. In this way, the model directly incorporates the uncertainty caused by missing data into the resulting model's estimates.

In this paper we will analyze the well-being of Italian provines by means of a composite indicator that includes spatial correlation. Starting from the hypothesis that neighboring areas influence each other, our proposed method conceives a better use of the elementary indicators by leveraging the spatial information from neighboring provinces.

The paper is organized as follows. Section 2 describes the data and summarizes the results from the exploratory spatial analysis. Section 3 explains the statistical methodology. Section 4 presents the estimates from implementing statistical models to 'Province' BES data. Section 5 is devoted to concluding remarks.

2. Data

Our analysis is based on data from the Province BES dashboard ('BES at the local level').[1]The Province BES data contains 55 elementary indicators of well-being grouped into 11 macro-domains for the 110 Italian provinces over the period 2004-2021 (ISTAT, 2021). This important data source enables monitoring of well-being in the Italian territories over time. The presence of missing values, especially in the early and later years, lead us to restrict the analysis to 2012 to 2019. We hold elementary indicators with at least one non-missing value for each remaining year. The final set counts 34 elementary indicators. We list and report descriptive statistics for the selected elementary indicators in Appendix A.

Our set of indicators resulted in a missing value percentage of 0.7%, which was then imputed with a posterior imputation procedure, as explained in section 3.

As in Ciommi et al. (2020) (Ciommi et al., 2020), we partition the elementary indicators into three well-being domains: social, economic, and environmental. In doing so, we aim to build composite indicators for each Italian province that summarize the level of well-being in each of these domains.

As mentioned in the introduction, our prior hypothesis is that neighboring provinces have spatially correlated levels of well-being. To test this assumption, we explore the spatial correlation of Province BES indicators through a spatial exploratory data analysis (SEDA). Specifically, we estimate the Moran I test of global spatial correlation, and an indicator of the local spatial association (LISA). Both analysis test the hypothesis of spatial randomness against the alternative of spatial clustering across each Italian province and elementary indicators. [2]

We perform these prior spatial assessments for each year from 2012 to 2019. The results

[1]For more referecens see https://www.istat.it/en/well-being-and-sustainability/the-measurement-of-well-being/bes-at-local-level

[2]We implemented the *lisa* function from the 'ncf' package in R (Anselin, 1995 and Moran, 1950).

from the exploratory spatial assessment outlined above are found in section Appendix B .

Summarizing the results, the spatial association appears on different statistically significant levels, and the well-being domain with a more significant spatial correlation is the economic domain. On the other hand, the environmental indicators only have a weak spatial association. This empirical evidence favors our hypothesis that neighboring provinces share information on socioeconomic development levels. Thus, we estimate factor analytic statistical models for spatially comprehensive composite indicators.

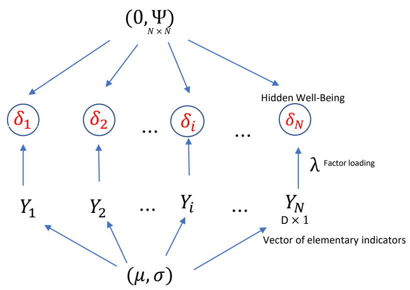
3. Methodology: Bayesian factor model for spatially correlated data

We incorporate spatial information following the Bayesian factor model proposed by Hogan et al. (2004). This model is based on a latent variable framework, where elementary indicators act as manifestation of an hidden counstruct- the provinces well-being.

For province i, where $i = 1, \ldots, N$, with $N = 110$ Italian provinces, let Y_{id} denote the elementary indicator d in province i. The lenght D of the observed vector $\boldsymbol{Y}_i = (Y_{i1}, \ldots, Y_{iD})$ depends on the well-being domain considered: the social domain has $D = 20$ indicators, the economic domain has $D = 9$ indicators, and the environmental domain has $D = 5$ indicators.

For each observation i, the latent factor model assumes an L dimensional $(L < D)$ latent variable δ_i that fully characterizes socioeconomic characteristics, which in turn manifest themselves through $\boldsymbol{Y}_i$. Here, we assume $L = 1$, hence reducing the model to one latent factor for each province, and represent the model in a hierarchical form as in Figure 1.

Figure 1. A graphical representation of a Bayesian hierarchical latent variable model



On the level of observed data, the likelihood is:

$$\boldsymbol{Y}_i \mid \boldsymbol{\mu}, \delta_i, \Sigma \sim \text{Multivariate Normal}\left(\boldsymbol{\mu} + \boldsymbol{\lambda}\delta_i, \Sigma\right), \tag{1}$$

where $\boldsymbol{\mu}$ is a $D \times 1$ mean vector, $\boldsymbol{\lambda}$ is a $D \times 1$ vector of factor loading, and $\Sigma = \text{diag}\left(\sigma_1^2, \ldots, \sigma_D^2\right)$ is a diagonal matrix measuring residual variation in $\boldsymbol{Y}_i$, implying independence among the elements of $\boldsymbol{Y}_i$ conditionally on δ_i.

On the second level, let $\boldsymbol{\delta} = (\delta_1, \ldots, \delta_N)^T$ be the vector of province latent indexes. The prior distribution is:

$$\boldsymbol{\delta} \sim \text{Multivariate Normal}\left(\mathbf{0}_n, \Psi\right), \tag{2}$$

where Ψ is a $N \times N$ spatial covariance matrix with 1's on the diagonal and $\psi_{is} = corr(\delta_i \delta_s)$ on the off-diagonal. When $\Psi = I_N$, the model assumes spatial independence.

The well-being composite index for province i is summarized by the posterior distribution of the latent factor δ_i given $\boldsymbol{Y}$ and $\boldsymbol{\mu}, \boldsymbol{\lambda}, \Sigma$.

The prior distributions for the remaining parameters in (1) are:

$$\lambda_d \sim \text{Normal}(g, G)(\lambda_1 > 0); \tag{3}$$
$$\sigma_d^2 \sim \text{Inverse-Gamma}(\alpha/2, \beta/2); \tag{4}$$
$$\mu_d \sim \text{Normal}(0, V_\mu). \tag{5}$$

The primary scope of prior distributions is to include subjective opinions on the parameters of interest. However, to let the data speak for themselves and simplify the derivation of posterior distributions, we use conjugate diffuse priors by choosing $g = 0$, $G = 10000$, $\alpha = 1/1000$, $\beta = 1/1000$, and $V_\mu = 1000$.

To include spatial dependence, we work on the spatial covariance matrix Ψ, parametrizing it both marginally and conditionally.

The first marginal specification assumes that the generic element ψ_{is} of the prior covariance matrix is

$$\psi_{is} = corr(\delta_i \delta_s) = \exp(-\omega d_{is}), \tag{6}$$

where ω models spatial correlation and $\omega \geq 0$ ensures that $\psi_{is} < 1$; d_{is} is the Euclidean distance between centroids of area i and s and $d_{ii} = 0$ by definition; see Hogan and Tchernis (2004) (Hogan and Tchernis, 2004).

The second way to parametrize the covariance matrix Ψ is through conditional autoregressive (CAR) specifications of spatial dependency (see, e.g., (Besag et al., 1991)). The more general structures are the Gaussian CAR models. These models first requires construction of a set $\mathscr{R}_i$ of areas that are neighbors of area i. Thus, if we assume the conditional distribution of each δ_i to be

$$\delta_i \mid \{\delta_s : s \in \mathscr{R}_i\} \sim \text{Normal}\left(\sum_{s \in \mathscr{R}_i} \beta_{is}\delta_s, \frac{1}{\alpha_i}\right),$$

then the joint marginal distribution of $\boldsymbol{\delta} = (\delta_1, \ldots, \delta_N)^T$ follows a $\text{Multivariate}-\text{Normal}(\mathbf{0}, B^{-1})$, where B is $N \times N$ spatial covariance matrix with $\{\alpha_1, \ldots, \alpha_N\}$ along the diagonal and $-\alpha_i\beta_{is}$ on the off-diagonal, provided that B is symmetric and positive definite; see Besag (1974) (Besag, 1974). The β_{is} are general weights defining the influence of province s on the prior mean of δ_i, while α_i represents area-level characteristics such as the number of neighborhoods (Hogan and Tchernis, 2004).

To ensure that B is positive definite and symmetric, one or more parameters in the CAR models should be constrained. Here we consider two different CAR specifications.

Model CAR A defines $\mathscr{R}_i$ as the set of adjacent indicator tracts. R is an adjacency (weight) matrix with $R_{ii} = 0$, $R_{is} = I(s \in \mathscr{R}_i)$ and $R_{is} = R_{si}$. Thus, the model assumes $\beta_{is} = \omega R_{is}$ and $\alpha_i = 1$ (constant), where ω measures the degree of spatial correlation. This leads to the definition

$$B = I_N - \omega R. \tag{7}$$

One necessary condition for ensuring that B is positive definite and symmetric is that the ordered eigenvalues $\xi_1, \ldots, \xi_N$ of R satisfy: $\xi_1^{-1} < \omega < \xi_N^{-1}$.

Model CAR B, defines $\mathscr{R}_i$ in the same way as CAR 3A but here $\beta_{is} = \omega R_{ij}(n_s/n_i)^{1/2}$ and $\alpha_i = n_i$ (n_i number of neighbors of area i).

For this model

$$B = \mathrm{diag}(n_i) - \omega(n_i * n_s)^{(1/2)} R. \tag{8}$$

We estimate the model posterior distribution using Markov Chain Monte Carlo methods. Specifically, we use a Gibbs sampling algorithm that includes Metropolis Hasting steps for the estimation of spatial parameter ω. At each step of the sampling algorithm, we obtain a draw from the conditional posterior distribution of the model parameters and the latent well-being $\boldsymbol{\delta}$. We use these draws to build the posterior distributions of all models parameters after accounting for a burn-in period prior to convergence. We simulate 6000 draws and "burn" 3000 of them. To obtain our distribution of well-being ranking, we rank the estimates of δ in each sampling iteration, and the province posterior mean ranking is the mean of the provinces rank across all iteration. A key advantage of this model is that it can handle missing values through a posterior imputation procedure. The procedure replaces missing elementary indicator values with "draws" from the first level equation conditional on current iterations' "draws" of the latent factor and the other models' parameters (for more details, see Davis et al., 2021).

We carried out a sensitivity analysis to assess the impact of our prior choices on: (a) the parameters μ_ω and V_ω of the spatial parameter ω prior distribution, (b) the prior mean and variance, g and G, of the factor loading λ_j, and (c) the prior variance V_μ of the mean μ. We also changed the seed or initial values. Finally, we modified the definition of the spatial topology in the CAR models by increasing the number of neighborhoods and defining the spatial weight matrix R differently. In each case, the resulting estimates remained stable.

The results from this assessment prove the stability of the estimated values to variation in prior choices with a slight degree of instability in the marginal correlation model when changing the prior distribution on the spatial parameter. Data are available upon request.

4. Results from the empirical application

In this section, we compare and comment on results from the application of the Bayesian factor model described above. We first focus on each of the three well-being domains separately. Then we assemble the three well-being dimensions into an overall well-being indicator. Finally, we aggregate provincial composite indicators into macro areas (NUTS 1) and estimate the well-being of the Italian macro-areas across the years.

4.1. Economic, social and environmental well-being

We first summarize the posterior distributions of the factor loadings and residual standard deviation for each well-being domain. Second, we rank composite indicator estimates to analyze the degree of divergence in the provincial well-being ranking. We also illustrate the composite indicator results using maps that intuitively describe well-being heterogeneity on the spatial surface. Finally, we compare our data-driven posterior well-being rankings to a set of rankings produced using the Mazziotta-Pareto methodology and discuss how well both measures agree. To summarize the well-being composite indicator for the provinces, we compute the mean posterior value of each latent parameter distribution, i.e. $\mathrm{E}(\delta_i \mid \boldsymbol{Y}, \boldsymbol{\mu}, \Lambda, \Psi, \Sigma)$.[3]

[3] We perform Markov Chain Monte Carlo simulations, reproducing the vector $\{\boldsymbol{\delta} \mid \boldsymbol{Y}, \boldsymbol{\mu}, \Lambda, \Psi, \Sigma\}$ 6000 times and burn 3000 of these iterations, therefore taking the average of the 3000 simulations.

Tables 1, 2 and 3, illustrate the estimates mean and standard deviation of the posterior distributions of model CAR B in the year 2019. We choose this model and this year for illustrative purposes, as results are similar across the three spatial models and years (see results in Appendix C).

Looking at the mean posterior loadings in Table 1 we find that the leading indicator in the economic domain is *Employment rate*, followed by *Non-participation rate*, *Youth non-participation rate*, and *Pensioners with low pension*. When looking at the posterior standard deviations of residuals (column 2), we observe that these are relatively small and similar, indicating equal ability among indicators to explain variation in the latent economic factor. For the environmental domain (Table 2), the most significant positive correlation is among the indicator *Waste recycling services* and *Separate collection of municipal waste*. Their standard deviation posterior estimates are small, indicating a good ability to explain latent environmental well-being variation. The remaining indicators have much higher standard deviations.

Finally, Table 3 shows that, for the social latent factor , the indicator with the strongest positive correlation is *Graduates mobility*, followed by *People not in education employment or training (neet)* and *Participation in lifelong learning*. For this domain, the residual standard deviations differ greatly across all elementary indicators and are much higher than in the economic domain.

Contrary to some traditional approaches that equally weigh all indicators, our data-driven approach shows that indicators have a different weight in explaining latent well-being in all domains. Correcting their weight, as we suggest, will lead to more efficient resource allocation to improve well-being.

Table 1. Economic well-being: posterior mean and and residual standard deviations with 95% credibility intervarls, on CAR B model, in 2019

Indicator (d)	Factor Loadings (95% CI)	Standard Deviation (95% CI)
Employment rate (20–64 years)	1.92 (1.66, 2.20)	0.02 (0.01 , 0.03)
Non-participation rate	-1.92 (-2.21, -1.66)	0.02 (0.01 , 0.03)
Youth non-participation rate (15–29 years)	-1.88 (-2.17, -1.63)	0.05 (0.04, 0.07)
Pensioners with low pension	-1.80 (-2.09, -1.53)	0.14 (0.10, 0.18)
Youth employment rate (15–29 years)	1.79 (1.52, 2.09)	0.15 (0.11, 0.20)
Average yearly earnings of employee	1.58 (1.30, 1.91)	0.42 (0.32, 0.56)
Working days of paid of employee	1.54 (1.29, 1.81)	0.38 (0.28, 0.49)
Average yearly per-capita pension income	1.48 (1.18, 1.82)	0.42 (0.32, 0.56)
Rate of bank's non-performing loans to households	-1.40 (-1.74 , -1.08)	0.50 (0.38, 0.66)

Note: Each row corresponds to one of the elementary indicators used in the composite indicator's construction. Factor loadings represent the posterior mean of each in our statistical model. The number in parenthesis are the left and right thresholds of the mean's 95% confidence intervals. In a Bayesian framework, these values do not have a significance level as in the frequentist approach. Instead, they represent the boundary within which rely 95% of the posterior probability.

Figures 2, 3, and 4 illustrate the well-being latent parameter posterior mean estimates

Table 2. Environmental well-being: posterior mean and and residual standard deviations with 95% credibility intervarls, on CAR B model, in 2019

Indicator (d)	Factor Loadings (95% CI)	Standard Deviation (95% CI)
Waste recyclying services	1.46 (1.28, 1.64)	0.01 (0.00, 0.08)
Separate collection of municipal waste	1.35 (1.17, 1.57)	0.16 (0.10 0.22)
Collection of urban waste	0.27 (0.00, 0.55)	0.99 (0.75, 1.30)
Density of historical green areas	0.16 (-0.12, 0.44)	1.03 (0.79, 1.36)
Availability of urban green areas	-0.07 (-0.36, 0.21)	1.04 (0.79, 1.36)

and the posterior credibility intervals for each Italian province in 2012 and 2019 as estimated by the spatial model CAR 3B. Here, we evaluate the variation in the well-being trend and ranking of the Italian provinces compared to the common mean (vertical dotted line at 0). In Appendix D, we report the posterior distribution quantiles for the three composite well-being indicators.

The well-being distribution appears stable over time for the social and economic domains, Figure 2 and 3. The social domain counts a few above-average provinces, with more provinces concentrating around the mean (vertical dotted line); this suggests a lower degree of polarization in the social domain compared to the economic domain, hence a more equal well-being distribution across Italian provinces. In turn, the economic domain has a large number of provinces with above and below-average values; the polarization in this domain is stronger, suggesting a higher degree of economic inequality on the Italian surface. Figure 4 shows the posterior mean estimates for the environmental composite indicator, which reveal more significant variations across years: from 2012 to 2019, most Italian provinces worsened their environmental well-being, resulting in a more polarized situation.

Finally, the figures show the impact of having elementary indicators missing values on the composite indicator's estimates. When there are multiple missing values, as seen in the case of the province of Sud Sardegna, our model takes into account this uncertainty by producing wider confidence intervals around the composite indicator estimates.

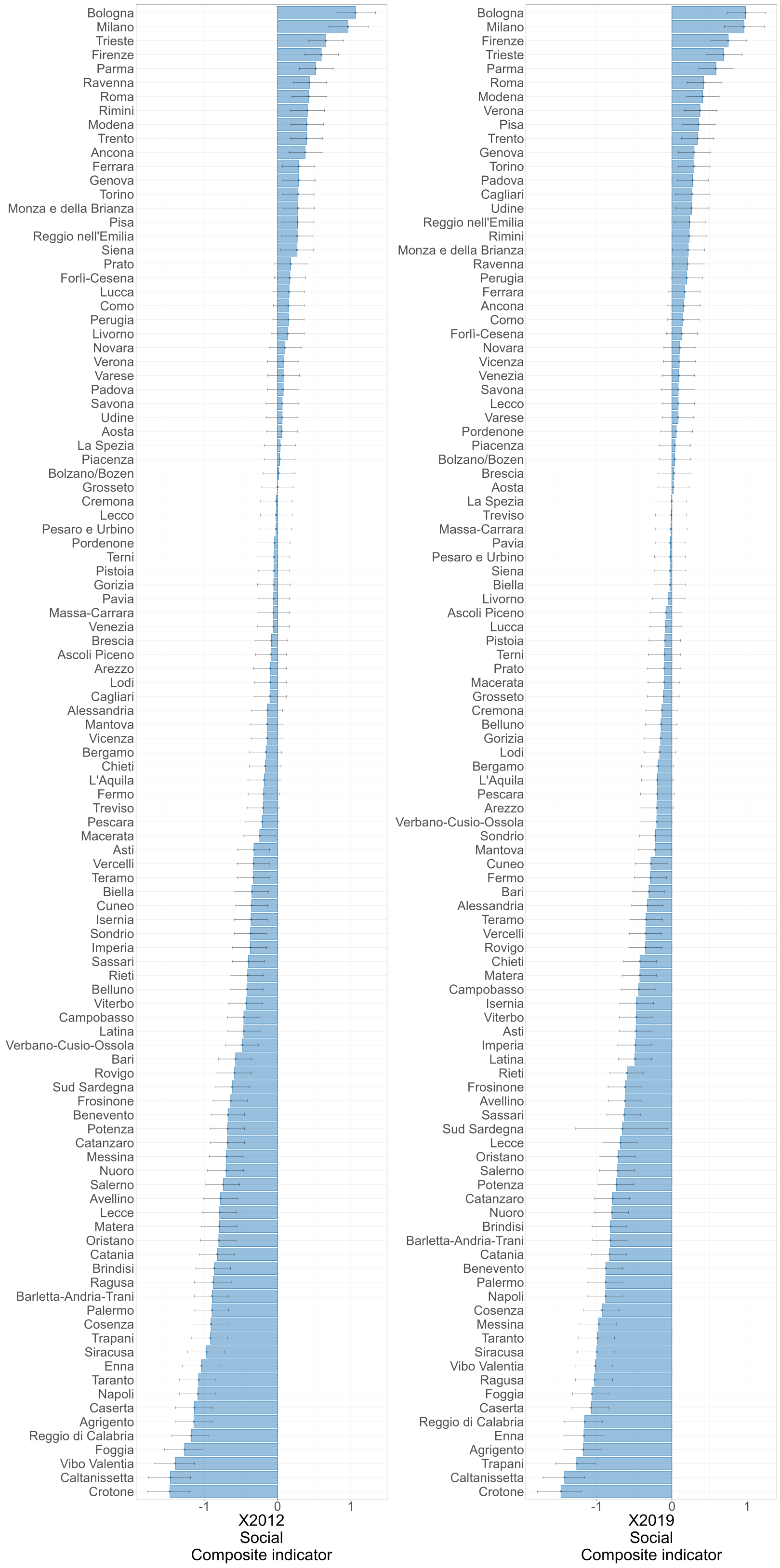
Next, we map the composite indicators' estimates for all provinces at the beginning (year 2012) and end (year 2019) of the period of analysis (Figure 5 and Figure 6). Consistently with our previous findings, spatial distributions of the social (see Figure 5) and the economic well-being do not significantly change over time. Social well-being is higher in some of the Northern provinces, particularly in the regional capitals. Northern and southern provinces are highly polarized in the economic domain, with the northern provinces persistently wealthier. The environmental well-being in Figure 6 seems not to polarize clearly northern provinces vs southern ones. Over time, northern provinces seem to be improving their levels, while the blackening color in Southern provinces highlights a sweeping decline throughout the years.

Finally, for each well-being domain, we compare the correlation between the ranking based on the mean posterior well-being and the rankings based on the Mazziotta-Pareto methodology. The Mazziotta-Pareto index is among Italy's most widely used indicators for policy decision-making. The Mazziotta-Pareto index consists of the arithmetic mean of standardized elementary indicators. It includes a penalization term to account for the

Table 3. Social well-being: posterior mean and and residual standard deviations with 95% credibility intervarls, on CAR B model, in 2019

Indicator (d)	Factor Loadings (95% CI)	Standard Deviation (95% CI)
Graduates mobility (25–39 years)	1.72 (1.41, 2.04)	0.18 (0.12 0.26)
People not in education employment or training (neet)	-1.61 (-1.96, -1.30)	0.28 (0.20 0.39)
Participation in lifelong learning	1.51 (1.20, 1.86)	0.38 (0.28 0.50
People with at least upper secondary education level (25–64 years)	1.50 (1.19,1.83)	0.36 (0.27 0.49)
Irregular electricity services	-1.49 (-1.84,-1.17)	0.39 (0.28, 0.52)
People having completed tertiary education (25–34 years)	1.46 (1.15, 1.81)	0.40 (0.30 0.55)
Children who benefited of early childhood services	1.39 (1.06, 1.75)	0.48 (0.35, 0.64)
Life expectancy at birth	1.31 (0.97, 1.68)	0.52 (0.39 0.70)
Public transportation network	0.97 (0.63, 1.33)	0.76 (0.58 1.01)
Widespread crimes reported	0.95 (0.58, 1.33)	0.77 (0.58 1.03)
Mortality rate in extra-urban road accidents	-0.86 (-1.24, -0.50)	0.82 (0.63,1.08)
Youth (< 40 years old) political representation	-0.71 (-1.09, -0.35)	0.89 (0.67 1.17)
Specialized doctors	0.68 (0.32 1.05)	0.91 0.69 1.20
Women's political representation in municipalities	0.66 (0.29, 1.02)	0.88 (0.67 1.15)
Voluntary murders	-0.65 (-1.02 -0.28)	0.92 0.69 1.21
Health services outflows admittance	-0.63 (-1.03, -0.27)	0.92 (0.70 1.20)
Hospital beds in high care wards	0.49 0.12 0.86	0.96 (0.73 1.28)
Roads accidents mortality rate (15–34 years)	-0.38 (-0.76, 0.01)	0.99 (0.76 1.29)
Prison density	0.33 (-0.04, 0.72)	1.00 (0.76 1.31)
Other reported crimes	0.29 (-0.09, 0.67)	1.00 (0.77 1.32)

Figure 2. Social well-being: composite indicator estimates for Italian provinces in 2012 (left panel) and 2019 (right panel)

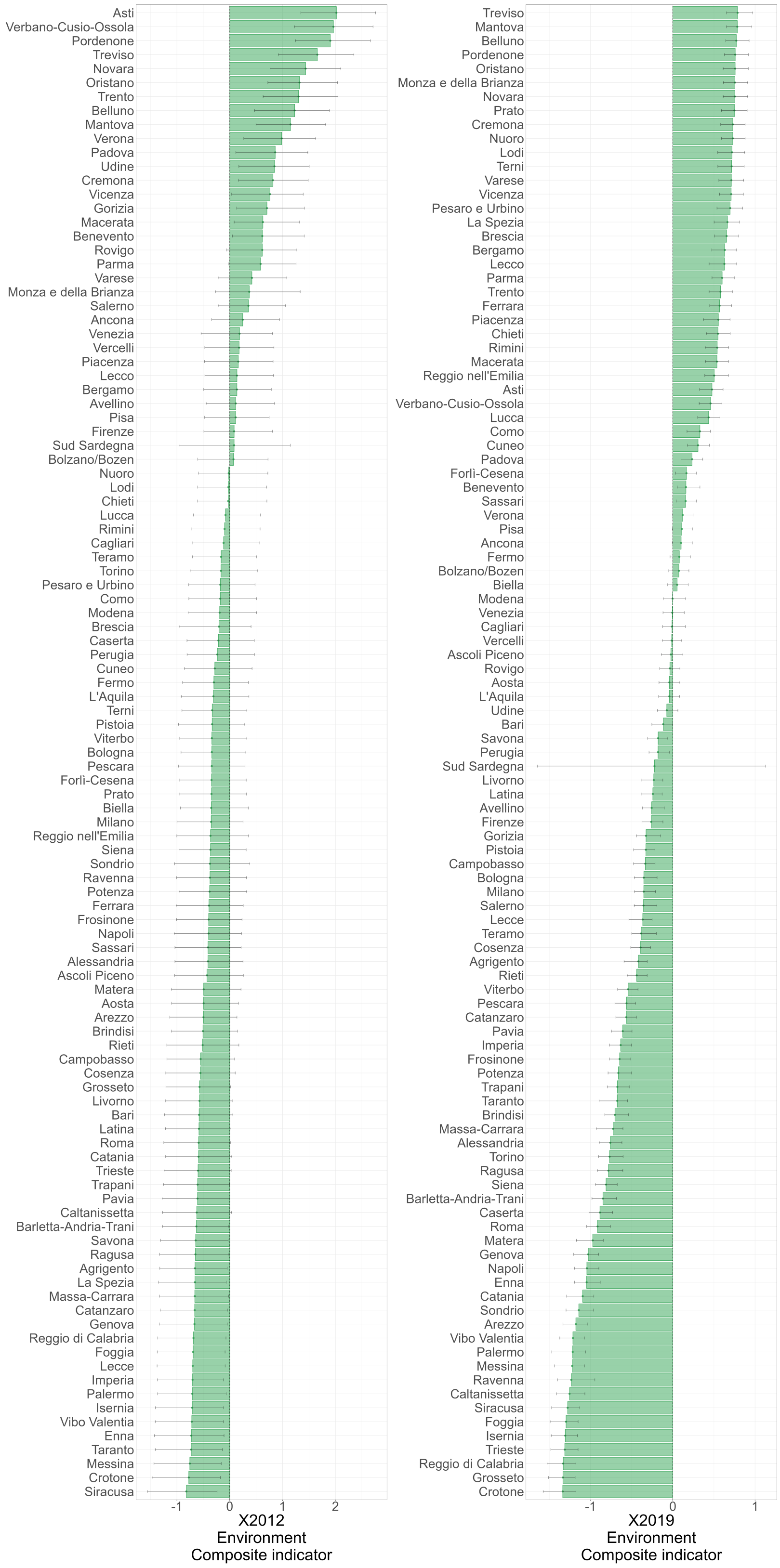


Note: In each panel, the bars indicate mean posterior composite indicator value for each province. The horizontal black line corresponds to the 90% posterior credibility interval. The vertical bar at 0 indicates the italian average of the entire period 2012–2019. *Source*: Our elaboration of ISTAT“Province BES” data.

Figure 3. Economic well-being: composite indicator estimates for Italian provinces in 2012 (left panel) and 2019 (right panel)

Note: see figure 2

Figure 4. Environmental well-being: composite indicator estimates for Italian provinces in 2012 (left panel) and 2019 (right panel)



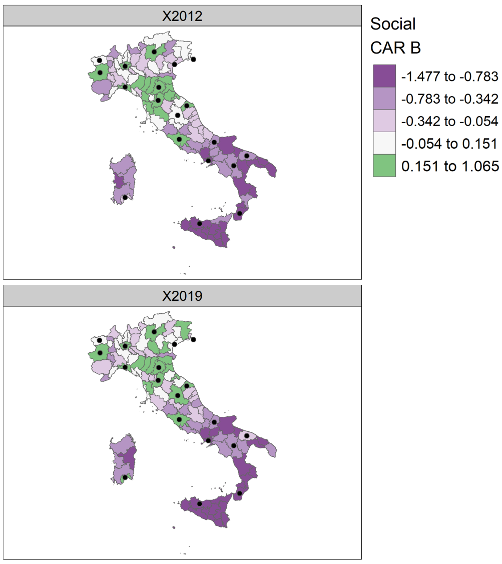
Note: see figure 2

variability of each indicator, and all indicators have equal weights.

Figures 7 and 8 show the rankings with a 90% confidence interval estimated by our Bayesian model on the x-axes, and the corresponding Mazziotta-Pareto rankings on the y-axes. The diagonal line indicates perfect agreement between the Mazziotta-Pareto rank and our mean posterior rank. The farther the provinces locate from this line, the higher the disagreement between the two methodologies.

First, we notice high agreement (Pearson correlation coefficients (ρ) > 0.8) between the two methodologies, more pronounced at the bottom 20% of the rank distribution in all three domains. For the bottom 20%, the estimated posterior confidence intervals indicates a stronger degree of certainty around the rank estimates. The economic domain has the highest ranking agreement ($\rho = 0.96$), followed by the social ($\rho = 0.92$) and the environmental domains ($\rho = 0.86$). We observe more disagreement towards the middle to the top of the distribution. This disagreement across the rankings concerns the difference in our model's elementary indicators weights and the equally valued weights of the Mazziotta-Pareto indicator. This result suggests that alternative methods to evaluate provincial well-being may significantly change the provincial ranks. In light of the use of composite indicators to design and allocate resources that may be scarce, our results suggest the existence of areas with more certain needs hence requiring more targeted interventions.

Figure 5. Maps of provincial Social well-being, for 2012 (top panel) and 2019 (bottom panel)

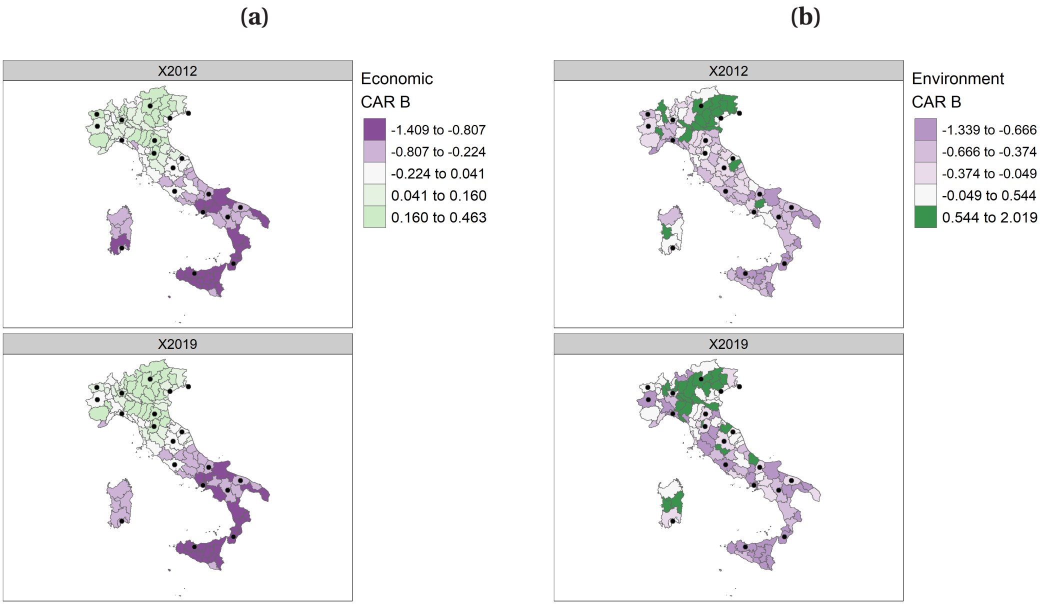


Note: Itaian provinces are grouped in well-being quintiles.The more 'purple' colors refer to worse-off provinces, while 'greener' shades indicate better-off provinces. The black horizontal dotted line indicates the provincial capitals.

4.2. *Overall well-being*

We now further summarize the three composite indicators described above into a single value representing each province's overall well-being. Since we have already included spatial correlation among the Italian provinces in each of the three composite indicators, we apply a spatially independent factor model on the posterior estimate of the three well-being composite indicators estimated above. Using $\hat{\boldsymbol{\delta}}_i = (\hat{\delta}_{i1}, \hat{\delta}_{i2}, \hat{\delta}_{i3})$ to indicate the 3-dimensional vector of composite well-being indicators for each province i, i.e. $\hat{\boldsymbol{\delta}}_i = E(\boldsymbol{\delta}_i \mid$

Figure 6. Maps of provincial Economic (left) and Environmental (right) well-being, for 2012 (top panel) and 2019 (bottom panel)



Note: see figure 5

$\boldsymbol{Y}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \Sigma$), we consider the following Bayesian factor model:

$$\begin{aligned} \hat{\boldsymbol{\delta}}_i \mid \boldsymbol{\mu}, z, \boldsymbol{\lambda}, \sigma &\sim (\boldsymbol{\mu} + \boldsymbol{\lambda} z_i, \Sigma) \\ z_i &\sim N(0,1) \end{aligned}$$

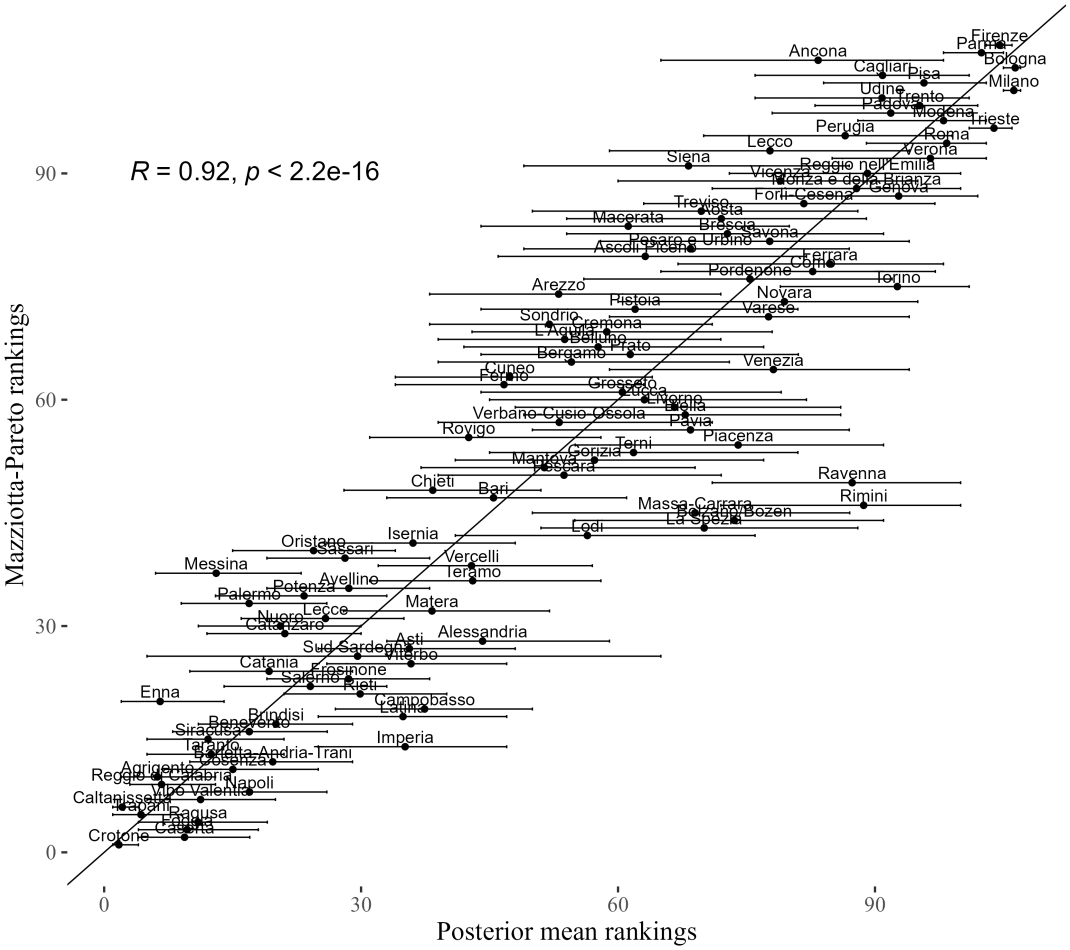
As before, we estimate the posterior distribution of factor loadings (see Table 4). From this table, two insights arise. First, we notice the strongest correlation between z_i, interpreted as overall well-being, and social and economic well-being. The factor loading estimates for these domains are persistently higher than zero and dominate the environmental domain.

Figure 9 maps the overall well-being distribution across Italy. We observe similarities between this illustration and the map of economic composite indicators. Overall well-being is not randomly distributed. The northern provinces share similar high levels of well-being, and the southern provinces experience low well-being. Moreover, we notice a slight improvement in overall well-being over time in some southern and central provinces.

Table 4. Overall well-being: posterior mean and and residual standard deviations with 95% credibility intervarls in 2019

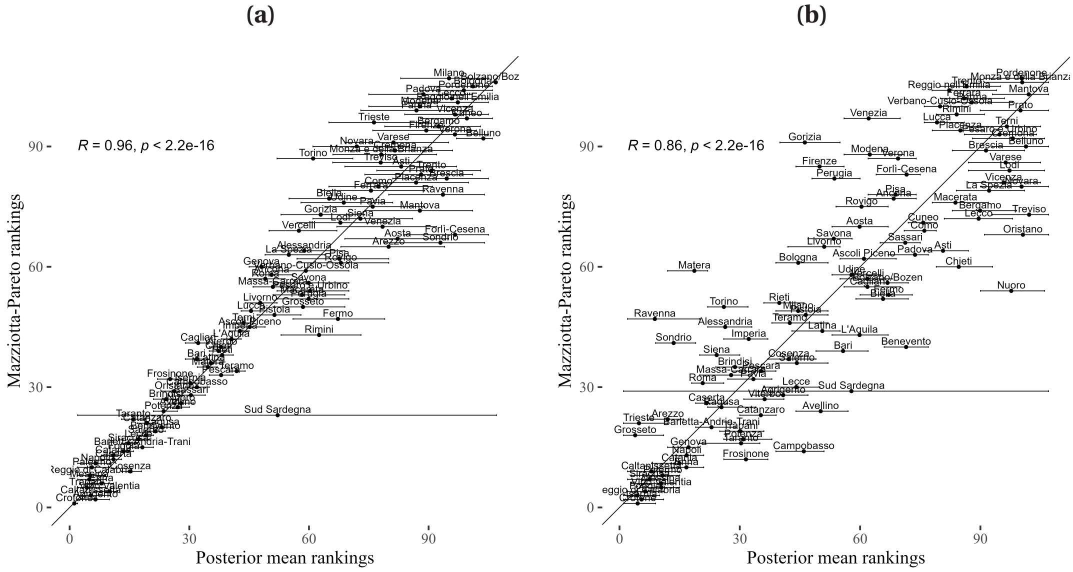
Domain (d)	Factor Loadings (95% CI)	Standard Deviation (95% CI)
Social	0.77 (0.68 ,0.85)	0.06 (0.05, 0.08)
Economic	0.98 (0.92, 0.99)	0.006 (0.0006, 0.03)
Environmental	0.34 (0.19, 0.49)	0.31 (0.25, 0.4)

Figure 7. Social well-being posterior mean rankings and Mazziotta-Pareto rankings for 2019, and 90% confidence interval (CI).



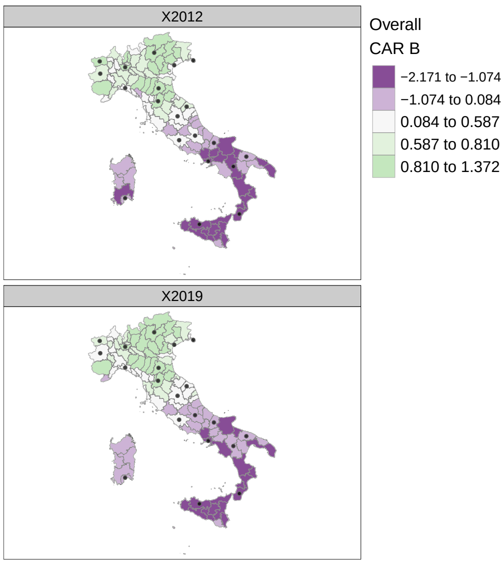
Note: Posterior mean rankings produced by model CAR B. The R in the left corner is the Pearson correlation coefficient between posterior mean ranking and the Mazziotta-Pareto rankings

Figure 8. Economic well-being (a) and Environmental well-being (b) posterior mean rankings and Mazziotta-Pareto rankings for 2019, and 90% confidence interval (CI).



Note: see figure 7

Figure 9. Maps of provincial overall well-being, for 2012 (top panel) and 2019 (bottom panel)

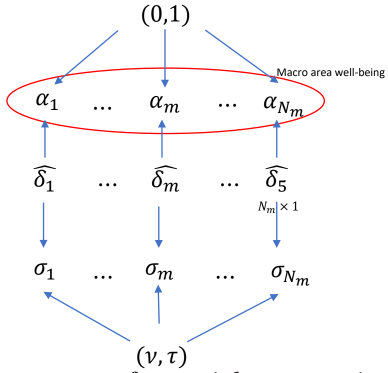


Note: see 5

4.3. *Macro area well-being*

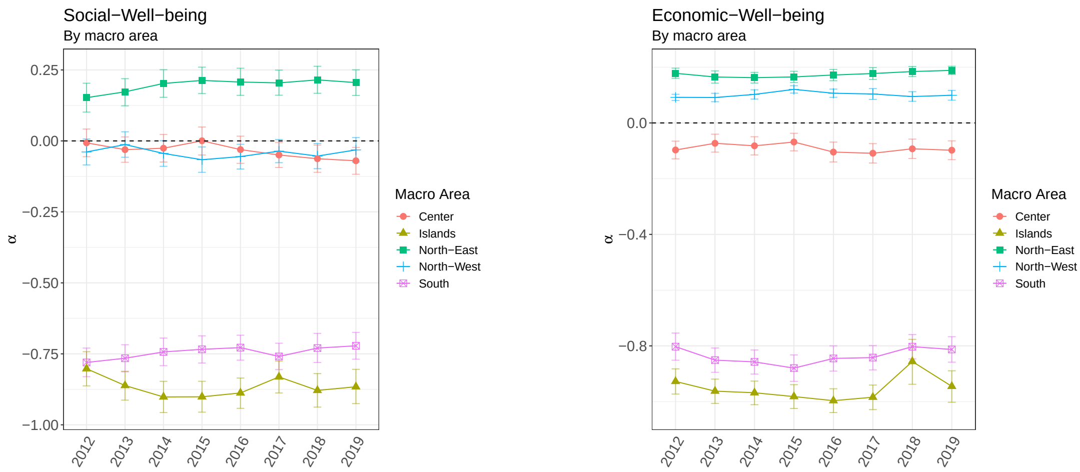
Finally, we aggregate provinces belonging to the same macro-region, i.e., Northwest, Northeast, Center, South, and Islands, and assess the evolution of the Italian macro-region well-being over time. Again, we compare estimates from the spatial independence model and CAR model B. We consider hierarchical models, which require specifying a prior distribution for the mean α of the latent variable $\hat{\delta}_i$. The index for α indicates the macro-area m, $m = 1,\dots,5$. We also assume the variance σ to vary across macro-areas. As standard practice, we chose a normal distribution as the prior distribution for the mean and a Cauchy distribution for the standard deviation (Gelman et al., 2013) of the latent factor distribution. More formally, for the three well-being domains, the model becomes: [4]

$$
\begin{aligned}
\hat{\delta}_i &\sim N(\alpha_{m[i]}, \sigma_{m[i]}) \quad i = 1,\dots,N \\
\alpha_{m[i]} &\sim N(0,1) \quad m = 1,\dots,5 \\
\sigma_{m[i]} &\sim \text{cauchy}(\nu,\tau)
\end{aligned}
$$



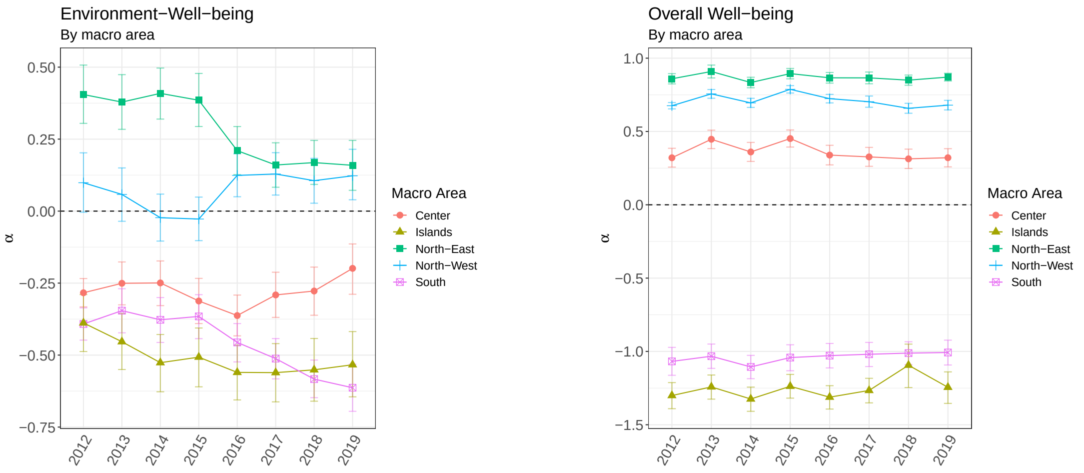
Figures 10 and 11 show the time series for each macro area for social, economic, environmental, and overall well-being. The results highlight persistent macro-territorial division characterizing the Italian territory throughout the period analyzed: the South and Islands fall below the average, while the Center, Northwest, and Northeast remain above the average, intersecting each other in some years and for specific well-being domains. The economic well-being trend is flat over time, and we notice a stable ranking of macro areas across the years. The social well-being trend, shown on the left in Figure 10, presents more interaction among macro-areas throughout the years. The Center intersected the Northwest and remained aligned with it up to 2019. The North-East has a slight upward trend over time. The Islands' social well-being deteriorated over time, reaching, in 2019, a lower level than at the beginning of the series. Only environmental well-being has a non-flat trend over time among the four estimated time series. Finally, in the overall domain, the α estimate for each macro-area combines the social and economic time series linearly. The environmental domain adds just a small contribution to determining the overall well-being trend.

Figure 10. Social well-being (left) and economic well-being (right) for Italian macro territorial areas (black dotted line indicates the Italian average)



[4] We estimate the hierarchical models above using STAN interfaces in R (Carpenter et al., 2017). The code for implementing the Hierarchical models is available on GitHub.

Figure 11. Environmental well-being (left) and overall well-being (right) for Italian macro territorial areas (black dotted line indicates the Italian average)



5. Concluding remarks

This paper proposes well-being composite indicators and rankings for all Italian provinces from 2012 to 2019, applying a Bayesian spatial factor analysis model. Our approach differs from traditional composite indicators methodologies in several ways. First, we modeled the spatial dependence of elementary indicators, capturing potential socioeconomic spillover effects. Second, we incorporate a measure of composite indicators uncertainty related to missing data. Third, we estimate data-driven weights for elementary indicators, thus avoiding an arbitrary selection of weight exposed to subjective opinion.

In the empirical application, we draw elementary indicators from the ISTAT'Province BES" dataset. Therefore, we investigated the general assumption of spatial independence in the elementary indicators by performing global and local tests of spatial association. This first assessment ensures the existence of positive spatial association in the 'Province BES" elementary indicators. We then divided the elementary indicators into three sustainable development well-being domains: social, economic, and environmental. Following the Bayesian approach, we estimated the posterior distribution of the vector of latent variables whose expected value we interpret as the hidden Italian provincial well-being.

The study found significant differences in the social and economic well-being between northern and southern regions, with the former persistently enjoying higher levels of well-being. In contrast, the environmental dimension appears less persistently polarized, and its composite indicators also reach above-average levels in the South. One potential interpretation of such results is that environmental consciousness has only risen recently compared to that socioeconomic aspects. As a result, both northern and southern provinces are experiencing an increase in climate awareness, and provincial investments in these fields are growing at approximately the same rate. Compared to the Mazziotta-Pareto approach, our rankings diverge, especially at the top of the provincial well-being distribution and for the environmental domain. For better-off provinces, the uncertainty in the ranking estimates is also higher. Our findings suggest that the government could allocate resources more effectively by targeting provinces at the bottom of the well-being ranking, which not only need more interventions but also have more certain estimates.

Subsequently, for each Italian province, we further reduced the well-being dimensions from three to one, constructing what we have called the overall well-being indicator. The resulting composite indicator combines the three well-being levels of each province into a single composite well-being indicator. The provincial levels of overall well-being remain stable and clustered throughout the period analyzed, with the economic domain as the leading driver of the overall well-being and the environmental well-being having a minimum weight.

Finally, we extended the analysis at the NUTS-1 level, i.e., Northwest, Northeast, Center, South, and Island, to provide well-being trends across the period analyzed. The results of the analysis show degrees of heterogeneity among the well-being macro areas.

The primary limitation we encounter in this study is the reduced number of indicators within the environmental dimension compared to the social and economic dimensions, also more subject to missing observations. As long as the data on environmental aspects remains limited, it will be difficult for researchers to provide evidence in favor of climate policy interventions.

In future research, we would like to enrich the environmental dashboard by integrating more advanced sensor measurements of air pollution, water quality, and soil temperature into national accounts. In addition, we intend to add a subjective dimension regarding citizens' perceptions of their life satisfaction.

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Appendix A. Descriptive statistics

Table A1. Descriptive statistics of selected elementary indicators, all years

Domain	Indicator	mean	median	sd	Unit
Social	Graduates mobility (25-39 years)	-9.18	-6.13	13.04	Ratio
	People not in education, employment, or training (neet)	23.28	21.00	8.35	%
	Participation in lifelong learning	7.45	7.20	2.21	%
	People with at least upper secondary education level (25–64 years)	58.97	60	7.51	%
	Irregular electricity services	2.27	1.88	1.28	Average number for user
	People having completed tertiary education (25-34 years)	23.38	23.00	5.57	%
	Children who benefited from early childhood services	13.22	12.10	7.65	%
	Life expectancy at birth	82.56	82.5	0.83	Years
	Public transportation network	2618.30	2187.45	2037.70	Seat-km per capita
	Widespread crimes reported	190.74	179.40	72.02	For10.000 inhabitants
	Mortality rate in extra-urban road accidents	5.58	5.10	2.84	%
	Youth (< 40 years old) political representation	30.81	30.70	5.36	%
	Specialized doctors	27.04	24.7	7.46	For10.000 inhabitants
	Women's political representation in municipalities	28.16	29.00	6.73	%
	Voluntarily murders				
	Health services outflows admittance	7.96	6.30	5.07	%
	Hospital beds in high care wards	2.95	2.7	1.24	For10.000 inhabitants
	Road accidents mortality rate (15–34 years)	0.75	0.70	0.41	For 10.000 inhabitants
	Prison density	128.55	126.70	41.55	%
	Other reported crimes	16.47	15.60	5.03	For 10.000 inhabitants
Economic	Employment rate (20–64 years).	61.54	65.90 9.85	%	
	Non-participation rate	18.36	14.30	10.84	%
	Youth non-participation rate (15–29 years)	33.43	30.45	16.72	%
	Pensioners with low pension	10.97	9.47	3.21	%
	Youth employment rate (15–29 years)	35.97	36.15	10.90	%
	Working days of paid of employees	75.16	76.61	5.52	%
	Average yearly earnings of employee	18302.73	18123.38	3077.61	Euro
	Average yearly per-capita pension income	16028.68	15981.43	1597.06	Euro
	Rate of bank non-performing loans to households	1.30	1.20	0.54	%
Environmental	Waste recyclying services	45.05	30.01	77.21	mq for inhabitant
	Separate collection of municipal waste	37.52	37.60	20.17	%
	Collection of urban waste	37.52	37.60	20.17	%
	Density of historical green areas	2.49	1.60	3.26	mq for 100 mq res.areas
	Availability of urban green areas	45.05	30.01	77.21	mq for inhabitant

Source: our elaboration on "Province BES', ISTAT 2019

Appendix B. Spatial Exploratory Data Analysis

Table B1.

Domain	Indicator	**Moran I** 2012	**p value**	**Moran I** 2019	**p value**
Soc.	Graduates mobility (25–39 years)	0.59	<0.001	0.68	<0.001
	People not in education employment or training (neet)	0.72	< 0.001	0.74	< 0.001
	Participation in long life learning	0.21	<0.001	0.33	<0.001
	People with at least upper secondary education level (25–64 years)	0.40	<0.001	0.45	<0.001
	Irregular electricity services	0.67	<0.001	0.64	<0.001
	People having completed tertiary education (25–39 years)	0.26	<0.001	0.18	<0.001
	Children who benefited of early childhood services	0.70	<0.001	0.65	<0.001
	Life expectancy at birth	0.53	<0.001	0.60	<0.001
	Public transport network	-0.06	0.81	-0.03	0.67
	Widespread crimes reported	0.28	<0.001	0.21	<0.001
	Mortality rate in extra urban road accidents	0.29	<0.001	0.35	<0.001
	Youth (<40 years old) political representation in municipalities	0.49	<0.001	0.39	<0.001
	Specilized doctors	0.04	0.23	0.03	0.26
	Women s political representation in municipalities	0.81	<0.001	0.64	<0.001
	Voluntary murders	0.22	<0.001	0.08	0.07
	Health services outflows admittances	0.39	<0.001	0.43	<0.001
	Hospital beds in high care wards	-0.06	0.77	-0.09	0.90
	Roads accidents mortality rate (15–34 years)	0.10	0.05	0.04	0.23
	Prison density	0.09	0.05	0.18	<0.001
	Other reported crimes	0.14	0.01	0.10	0.04
Eco.	Employment rate (20–64 years)	0.82	<0.001	0.82	<0.001
	Non participation rate	0.82	<0.001	0.81	<0.001
	Youth non participation rate (15–29 years)	0.79	<0.001	0.80	<0.001
	Pensioners with low pension	0.78	<0.001	0.80	<0.001
	Youth employment rate (15–29 years)	0.74	<0.001	0.77	<0.001
	Working days of paid employee	0.65	<0.001	0.62	<0.001
	Average yearly earnings of employee	0.65	<0.001	0.68	<0.001
	Average yearly per-capita pension income	0.54	<0.001	0.61	<0.001
	Rate of bank's non performing loans to households	0.35	<0.001	0.52	<0.001
Env	Waste recyclying services	0.53	<0.001	0.34	<0.001
	Separate collection of municipal waste	0.67	0.00	0.47	<0.001
	Collection of urban waste	0.51	<0.001	0.57	<0.001
	Density of historical green areas	-0.05	0.78	-0.04	0.70
	Availability of urban green areas	0.08	0.05	0.03	0.21

Note: Each row corresponds to one of the 34 elementary indicators used in our model. The table reports the results from Moran's test of spatial autocorrelation. The second and fourth columns reports the value of the observed Moran's I coefficient in 2012 and 2019. The third and fifth columns reports the p-value of the test. When p-value is < 0.001, we reject the null hypothesis of spatial randomness at 1% significance level.

Table B2. Proportion of provinces with statistically significant p-value ($p < 0.005$) for the LISA statistic, for each BES elementary indicator, for 2012 and 2019

Dom.	Indicator	2012	2019
Soc.	Prison density	0.14	0.12
	Other reported crimes	0.13	0.12
	Youth (<40 years old) political representation	0.20	0.19
	Women s political representation in municipalities	0.22	0.25
	Children who benefited of early childhood services	0.24	0.20
	Widespread crimes reported	0.17	0.10
	Regional health services outflows hospital admittances	0.21	0.19
	People not in education employment or training (neet)	0.17	0.18
	Irregular electricity services	0.20	0.15
	People having completed tertiary education (25–39 years)	0.10	0.10
	Graduates mobility (25–39 years)	0.22	0.26
	Roads accidents mortality rate	0.10	0.08
	Mortality rate in extra urban road accidents	0.17	0.19
	Participation in long life learning	0.18	0.19
	People with at least upper secondary education level (25–64 years)	0.18	0.15
	Public transport network	0.07	0.07
	Life expectancy at birth	0.23	0.19
	Specilized doctors	0.11	0.13
	Voluntary murders	0.08	0.06
	Hospital beds in high care wards	0.07	0.03
Eco.	Employment rate (20–64 years)	0.21	0.21
	Non-participation rate	0.19	0.20
	Youth non participation rate (15–29 years)	0.22	0.21
	Pensioners with low pension	0.20	0.20
	Youth employment rate (15–29 years)	0.25	0.25
	Average yearly earnings of employee	0.21	0.20
	Average yearly per capita pension income	0.20	0.21
	Rate of bank's non performing loans to households	0.07	0.15
	Working days of paid of employees	0.23	0.24
Env	Waste recyclying services	0.12	0.19
	Separate collection of municipal waste	0.21	0.20
	Collection of urban waste	0.19	0.21
	Density of historical green areas	0.06	0.04
	Availability of urban green areas	0.07	0.08

Note: these are results from the function that estimates the (non-centered) local indicators of spatial association modified form proposed in (Anselin, 1995). The p-value is the permutation two-sided p-value for each observation.

Appendix C. Factor Loadings across spatial models and years

Figure C1. Social well-being: posterior mean and and residual standard deviations with 95% credibility intervarls, for the three spatial model, in 2012, 2015 and 2019

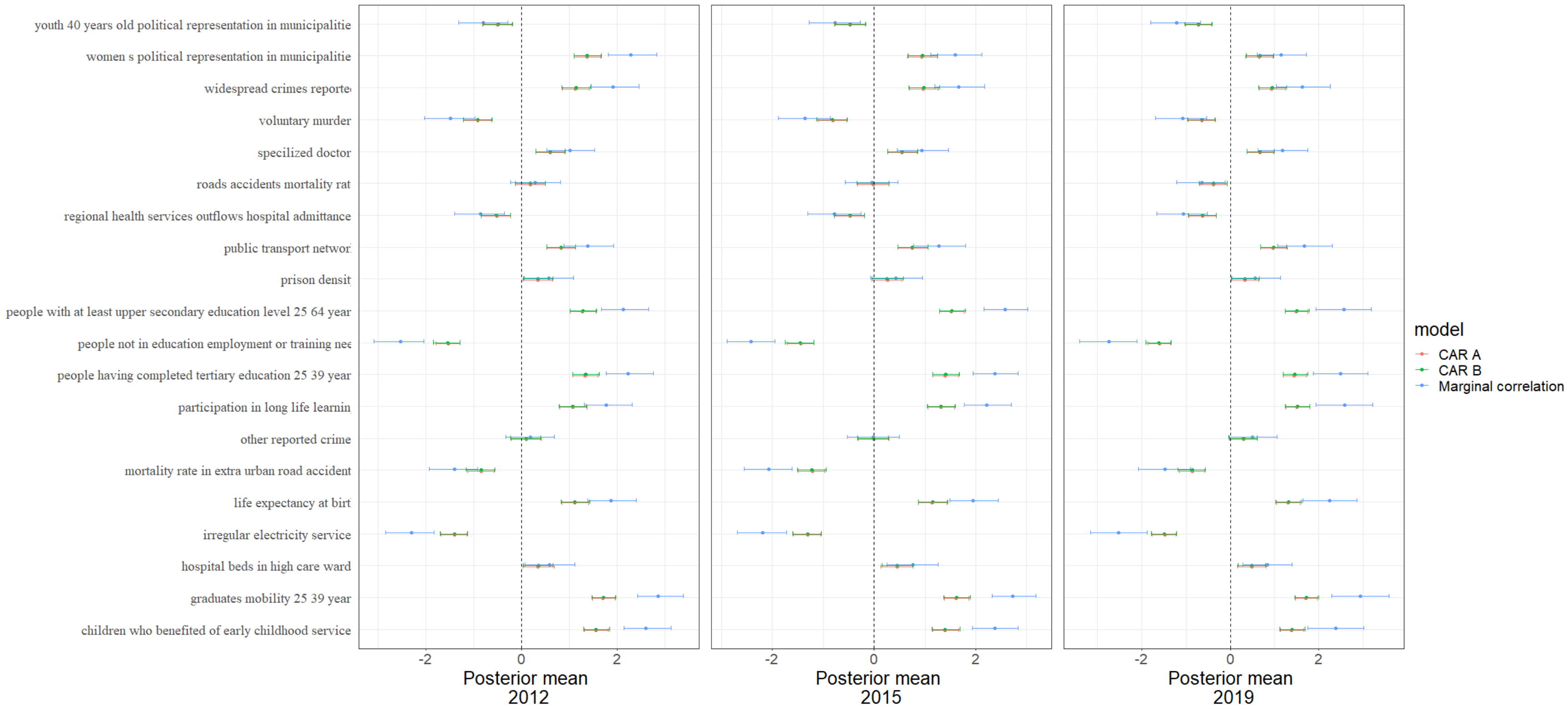


Figure C2. Economic well-being: posterior mean and and residual standard deviations with 95% credibility intervarls, for the three spatial model, in 2012, 2015 and 2019

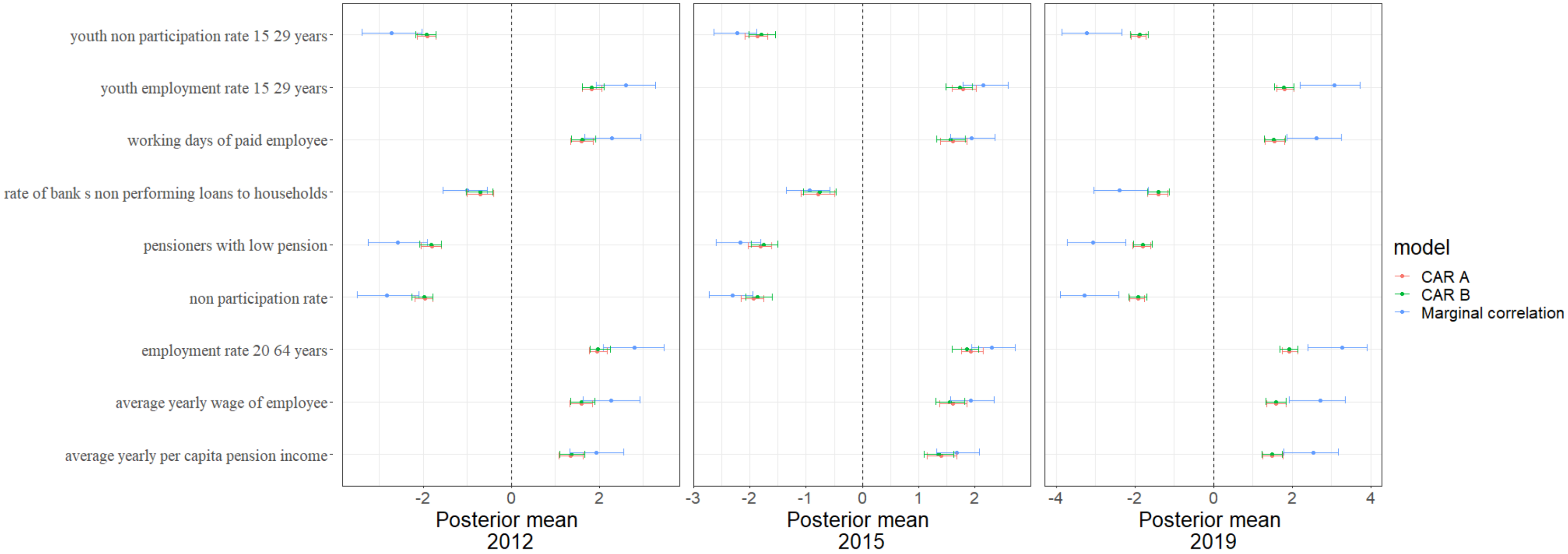
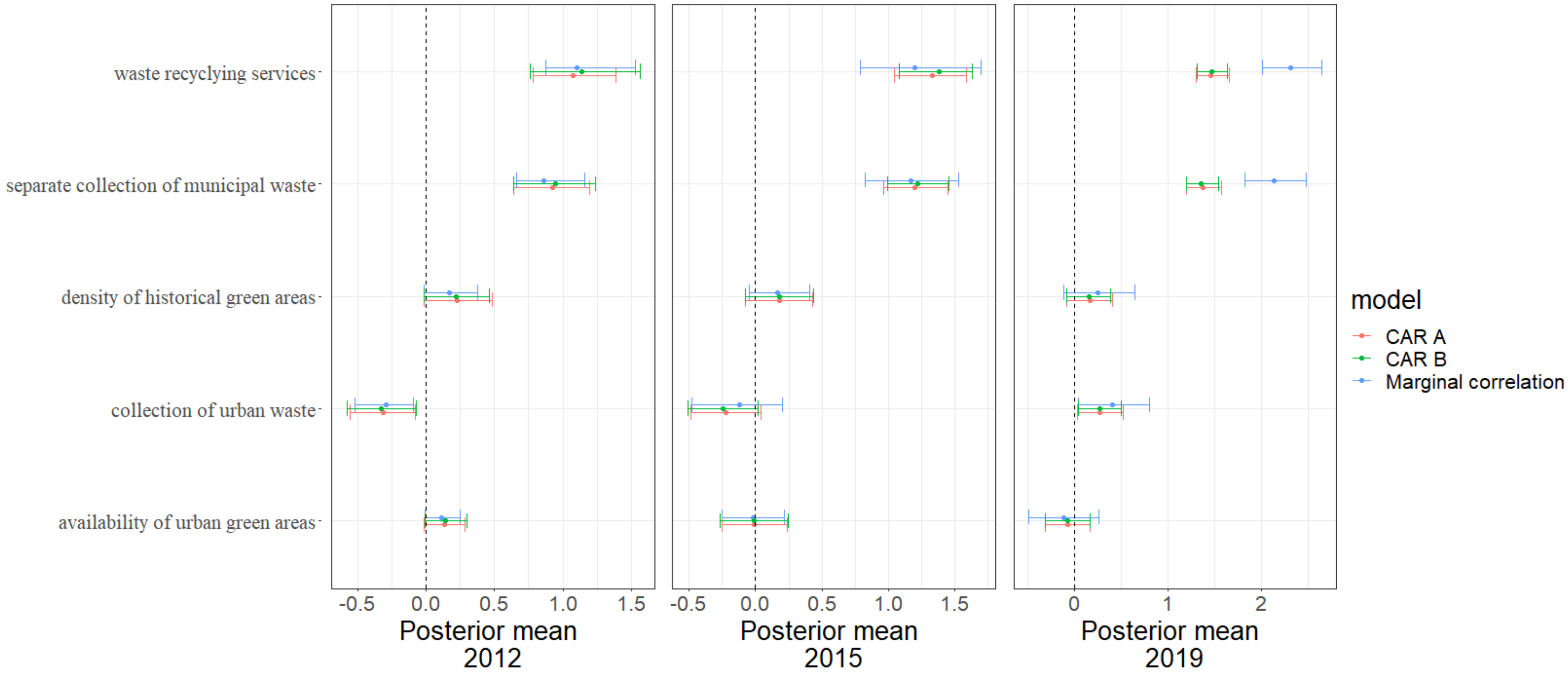


Figure C3. Environmental well-being: posterior mean and and residual standard deviations with 95% credibility intervarls, for the three spatial model, in 2012, 2015 and 2019



Appendix D. Full distribution of composite indicators

Table D1. Summary of posterior distribution of the composite indicator for the social dimension. Model CAR B. Year 2019.

	CAR (model B)																
Province	mean	median	25%	75%	IQR	Province	mean	median	25%	75%	IQR	Province	mean	median	25%	75%	IQR
Agrigento	-1.18	-1.18	-1.50	-0.89	0.21	Foggia	-1.06	-1.06	-1.39	-0.79	0.21	Pescara	-0.20	-0.19	-0.46	0.07	0.17
Alessandria	-0.33	-0.32	-0.58	-0.09	0.17	Forlì-Cesena	0.13	0.13	-0.11	0.39	0.17	Piacenza	0.04	0.04	-0.21	0.28	0.17
Ancona	0.16	0.15	-0.09	0.44	0.18	Frosinone	-0.62	-0.62	-0.90	-0.36	0.18	Pisa	0.36	0.35	0.11	0.62	0.18
Aosta	0.02	0.02	-0.22	0.26	0.17	Genova	0.30	0.29	0.04	0.56	0.18	Pistoia	-0.09	-0.09	-0.35	0.15	0.17
Arezzo	-0.20	-0.20	-0.47	0.06	0.17	Gorizia	-0.15	-0.15	-0.42	0.11	0.17	Pordenone	0.06	0.05	-0.18	0.31	0.17
Ascoli Piceno	-0.08	-0.08	-0.33	0.18	0.17	Grosseto	-0.11	-0.11	-0.36	0.14	0.17	Potenza	-0.74	-0.73	-1.03	-0.47	0.19
Asti	-0.48	-0.47	-0.75	-0.23	0.18	Imperia	-0.49	-0.48	-0.77	-0.23	0.18	Prato	-0.10	-0.10	-0.37	0.15	0.18
Avellino	-0.62	-0.62	-0.89	-0.37	0.18	Isernia	-0.47	-0.47	-0.74	-0.20	0.18	Ragusa	-1.03	-1.02	-1.33	-0.75	0.21
Bari	-0.31	-0.30	-0.57	-0.05	0.18	L'Aquila	-0.19	-0.19	-0.44	0.05	0.18	Ravenna	0.21	0.20	-0.04	0.47	0.17
Barletta-Andria-Trani	-0.82	-0.82	-1.10	-0.56	0.19	La Spezia	0.00	0.00	-0.25	0.24	0.17	Reggio di Calabria	-1.16	-1.15	-1.49	-0.88	0.20
Belluno	-0.14	-0.14	-0.40	0.11	0.17	Latina	-0.49	-0.49	-0.76	-0.23	0.18	Reggio nell'Emilia	0.23	0.23	-0.01	0.48	0.17
Benevento	-0.88	-0.88	-1.16	-0.61	0.19	Lecce	-0.69	-0.69	-0.97	-0.41	0.18	Rieti	-0.60	-0.59	-0.88	-0.34	0.18
Bergamo	-0.18	-0.18	-0.45	0.06	0.18	Lecco	0.08	0.08	-0.16	0.35	0.17	Rimini	0.23	0.23	-0.02	0.49	0.18
Biella	-0.03	-0.03	-0.28	0.22	0.17	Livorno	-0.04	-0.05	-0.30	0.21	0.17	Roma	0.42	0.42	0.16	0.70	0.18
Bologna	0.98	0.97	0.69	1.29	0.21	Lodi	-0.16	-0.16	-0.41	0.09	0.17	Rovigo	-0.35	-0.35	-0.62	-0.09	0.18
Bolzano/Bozen	0.04	0.04	-0.22	0.29	0.17	Lucca	-0.08	-0.09	-0.33	0.16	0.17	Salerno	-0.72	-0.72	-1.01	-0.46	0.19
Brescia	0.03	0.03	-0.22	0.28	0.17	Macerata	-0.10	-0.10	-0.36	0.14	0.17	Sassari	-0.64	-0.63	-0.92	-0.38	0.18
Brindisi	-0.82	-0.81	-1.11	-0.56	0.18	Mantova	-0.22	-0.22	-0.50	0.03	0.17	Savona	0.08	0.08	-0.18	0.35	0.18
Cagliari	0.27	0.26	0.01	0.55	0.18	Massa-Carrara	-0.01	-0.02	-0.26	0.24	0.17	Siena	-0.03	-0.02	-0.27	0.22	0.17
Caltanissetta	-1.43	-1.42	-1.78	-1.12	0.22	Matera	-0.43	-0.42	-0.71	-0.16	0.18	Siracusa	-1.00	-0.99	-1.31	-0.71	0.21
Campobasso	-0.44	-0.44	-0.71	-0.19	0.18	Messina	-0.97	-0.97	-1.27	-0.68	0.19	Sondrio	-0.22	-0.22	-0.47	0.03	0.18
Caserta	-1.07	-1.07	-1.38	-0.79	0.20	Milano	0.96	0.95	0.65	1.30	0.22	Sud Sardegna	-0.66	-0.67	-1.39	0.10	0.48
Catania	-0.83	-0.82	-1.12	-0.57	0.19	Modena	0.41	0.41	0.16	0.68	0.17	Taranto	-0.99	-0.98	-1.30	-0.72	0.19
Catanzaro	-0.79	-0.79	-1.08	-0.52	0.19	Monza e della Brianza	0.22	0.21	-0.03	0.47	0.18	Teramo	-0.35	-0.35	-0.61	-0.08	0.17
Chieti	-0.43	-0.42	-0.69	-0.16	0.18	Napoli	-0.88	-0.88	-1.18	-0.61	0.20	Terni	-0.10	-0.10	-0.35	0.15	0.17
Como	0.15	0.14	-0.09	0.41	0.17	Novara	0.10	0.10	-0.15	0.36	0.17	Torino	0.29	0.29	0.04	0.56	0.18
Cosenza	-0.93	-0.92	-1.24	-0.66	0.20	Nuoro	-0.80	-0.80	-1.08	-0.53	0.19	Trapani	-1.27	-1.26	-1.61	-0.97	0.22
Cremona	-0.13	-0.14	-0.39	0.11	0.17	Oristano	-0.72	-0.72	-1.01	-0.46	0.19	Trento	0.34	0.34	0.09	0.61	0.17
Crotone	-1.48	-1.47	-1.84	-1.16	0.24	Padova	0.28	0.27	0.03	0.53	0.18	Treviso	-0.01	-0.01	-0.26	0.23	0.17
Cuneo	-0.28	-0.28	-0.53	-0.03	0.17	Palermo	-0.88	-0.88	-1.18	-0.62	0.19	Trieste	0.69	0.68	0.41	1.00	0.20
Enna	-1.17	-1.16	-1.49	-0.88	0.21	Parma	0.58	0.58	0.33	0.87	0.18	Udine	0.26	0.26	0.01	0.53	0.17
Fermo	-0.29	-0.29	-0.55	-0.02	0.17	Pavia	-0.02	-0.02	-0.27	0.23	0.17	Varese	0.08	0.08	-0.17	0.33	0.18
Ferrara	0.17	0.17	-0.08	0.42	0.17	Perugia	0.20	0.20	-0.05	0.45	0.17	Venezia	0.09	0.09	-0.16	0.35	0.18
Firenze	0.75	0.74	0.48	1.05	0.19	Pesaro e Urbino	-0.02	-0.02	-0.27	0.22	0.17	Verbano-Cusio-Ossola	-0.20	-0.20	-0.46	0.04	0.18
												Vercelli	-0.35	-0.35	-0.61	-0.09	0.17
												Verona	0.37	0.37	0.12	0.64	0.18
												Vibo Valentia	-1.02	-1.01	-1.34	-0.75	0.20
												Vicenza	0.10	0.09	-0.15	0.35	0.17
												Viterbo	-0.47	-0.47	-0.75	-0.21	0.17

Table D2. Summary of posterior distribution of the latent variable (composite indicator) for the economic dimension. CAR model B. Year 2019.

	CAR (model B)																
Province	mean	median	25%	75%	IQR	Province	mean	median	25%	75%	IQR	Province	mean	median	25%	75%	IQR
Agrigento	-1.25	-1.25	-1.46	-1.07	0.14	Foggia	-1.07	-1.07	-1.26	-0.90	0.12	Pescara	-0.39	-0.39	-0.50	-0.28	0.07
Alessandria	0.01	0.01	-0.08	0.10	0.06	Forlì-Cesena	0.24	0.24	0.14	0.34	0.07	Piacenza	0.18	0.18	0.09	0.28	0.06
Ancona	-0.08	-0.08	-0.17	0.02	0.06	Frosinone	-0.73	-0.73	-0.88	-0.59	0.10	Pisa	0.07	0.07	-0.02	0.16	0.06
Aosta	0.16	0.16	0.06	0.25	0.06	Genova	-0.12	-0.12	-0.21	-0.02	0.06	Pistoia	-0.07	-0.07	-0.16	0.02	0.06
Arezzo	0.14	0.14	0.05	0.24	0.06	Gorizia	0.04	0.04	-0.05	0.13	0.06	Pordenone	0.26	0.25	0.16	0.35	0.06
Ascoli Piceno	-0.18	-0.18	-0.27	-0.09	0.06	Grosseto	0.01	0.01	-0.09	0.10	0.06	Potenza	-0.77	-0.77	-0.91	-0.64	0.10
Asti	0.16	0.16	0.07	0.26	0.06	Imperia	-0.24	-0.24	-0.34	-0.15	0.07	Prato	0.19	0.19	0.09	0.29	0.07
Avellino	-0.68	-0.68	-0.82	-0.55	0.09	Isernia	-0.60	-0.60	-0.74	-0.48	0.09	Ragusa	-0.78	-0.78	-0.94	-0.64	0.10
Bari	-0.56	-0.56	-0.69	-0.45	0.08	L'Aquila	-0.31	-0.31	-0.42	-0.21	0.07	Ravenna	0.22	0.22	0.13	0.31	0.06
Barletta-Andria-Trani	-0.93	-0.93	-1.10	-0.77	0.11	La Spezia	-0.03	-0.03	-0.12	0.07	0.06	Reggio di Calabria	-1.28	-1.27	-1.49	-1.08	0.14
Belluno	0.31	0.31	0.21	0.41	0.07	Latina	-0.46	-0.46	-0.58	-0.36	0.07	Reggio nell'Emilia	0.24	0.24	0.15	0.34	0.06
Benevento	-0.83	-0.83	-0.99	-0.68	0.10	Lecce	-0.96	-0.96	-1.13	-0.80	0.11	Rieti	-0.39	-0.38	-0.50	-0.28	0.07
Bergamo	0.21	0.21	0.12	0.31	0.07	Lecco	0.23	0.23	0.15	0.33	0.06	Rimini	0.04	0.04	-0.06	0.13	0.06
Biella	0.05	0.05	-0.04	0.15	0.06	Livorno	-0.12	-0.12	-0.22	-0.03	0.07	Roma	-0.10	-0.10	-0.19	0.00	0.06
Bologna	0.28	0.28	0.18	0.38	0.07	Lodi	0.07	0.07	-0.02	0.16	0.06	Rovigo	0.07	0.07	-0.02	0.17	0.06
Bolzano/Bozen	0.45	0.45	0.35	0.55	0.07	Lucca	-0.17	-0.17	-0.27	-0.07	0.06	Salerno	-0.91	-0.90	-1.06	-0.76	0.11
Brescia	0.23	0.23	0.14	0.32	0.06	Macerata	0.00	0.00	-0.09	0.09	0.06	Sassari	-0.60	-0.60	-0.73	-0.47	0.09
Brindisi	-0.76	-0.75	-0.90	-0.62	0.10	Mantova	0.19	0.18	0.10	0.28	0.06	Savona	0.02	0.02	-0.07	0.11	0.06
Cagliari	-0.55	-0.55	-0.68	-0.44	0.08	Massa-Carrara	-0.07	-0.07	0.02	-0.16	0.06	Siena	0.10	0.10	0.19	0.01	0.06
Caltanissetta	-1.27	-1.27	-1.48	-1.08	0.14	Matera	-0.49	-0.48	-0.61	-0.37	0.08	Siracusa	-1.03	-1.03	-1.21	-0.87	0.12
Campobasso	-0.56	-0.56	-0.68	-0.45	0.08	Messina	-1.28	-1.28	-1.49	-1.08	0.14	Sondrio	0.22	0.22	0.12	0.31	0.07
Caserta	-1.16	-1.16	-1.35	-0.98	0.13	Milano	0.23	0.23	0.14	0.33	0.07	Sud Sardegna	-0.30	-0.31	-1.44	0.84	0.93
Catania	-1.16	-1.16	-1.35	-0.98	0.13	Modena	0.19	0.18	0.09	0.28	0.06	Taranto	-1.00	-0.99	-1.17	-0.83	0.12
Catanzaro	-0.90	-0.90	-1.06	-0.75	0.11	Monza e della Brianza	0.13	0.13	0.04	0.23	0.07	Teramo	-0.27	-0.27	-0.37	-0.17	0.07
Chieti	-0.41	-0.41	-0.52	-0.31	0.07	Napoli	-1.25	-1.25	-1.46	-1.07	0.14	Terni	-0.22	-0.22	-0.32	-0.12	0.07
Como	0.13	0.13	0.04	0.22	0.06	Novara	0.10	0.10	0.01	0.19	0.06	Torino	0.03	0.03	-0.07	0.12	0.06
Cosenza	-1.02	-1.01	-1.20	-0.85	0.12	Nuoro	-0.66	-0.66	-0.80	-0.54	0.09	Trapani	-1.30	-1.29	-1.52	-1.09	0.15
Cremona	0.15	0.15	0.06	0.25	0.06	Oristano	-0.70	-0.70	-0.84	-0.58	0.09	Trento	0.20	0.20	0.11	0.30	0.06
Crotone	-1.41	-1.41	-1.64	-1.20	0.16	Padova	0.19	0.19	0.10	0.29	0.06	Treviso	0.13	0.13	0.04	0.23	0.06
Cuneo	0.26	0.26	0.17	0.36	0.07	Palermo	-1.27	-1.26	-1.48	-1.08	0.14	Trieste	0.12	0.12	0.03	0.22	0.06
Enna	-1.23	-1.22	-1.43	-1.04	0.14	Parma	0.18	0.18	0.09	0.28	0.06	Udine	0.08	0.08	-0.01	0.17	0.06
Fermo	0.07	0.07	-0.03	0.16	0.06	Pavia	0.12	0.12	0.03	0.21	0.06	Varese	0.15	0.15	0.06	0.24	0.06
Ferrara	0.12	0.12	0.03	0.21	0.06	Perugia	0.02	0.02	-0.07	0.10	0.06	Venezia	0.14	0.14	0.04	0.23	0.07
Firenze	0.20	0.19	0.10	0.29	0.06	Pesaro e Urbino	0.02	0.02	-0.07	0.11	0.06	Verbano-Cusio-Ossola	0.01	0.01	-0.08	0.10	0.06
												Vercelli	0.00	0.00	-0.10	0.09	0.06
												Verona	0.24	0.24	0.15	0.34	0.06
												Vibo Valentia	-1.18	-1.18	-1.38	-1.00	0.13
												Vicenza	0.24	0.24	0.15	0.34	0.07
												Viterbo	-0.40	-0.39	-0.51	-0.29	0.08

Table D3. Summary of posterior distribution of the latent variable (composite indicator) for the environmental dimension. CAR model B. Year 2017

	CAR (model B)																
Province	mean	median	25%	75%	IQR	Province	mean	median	25%	75%	IQR	Province	mean	median	25%	75%	IQR
Agrigento	-0.77	-0.90	-0.44	-1.23	0.79	Foggia	-0.32	-0.26	0.26	-0.84	1.10	Pescara	-0.43	-0.49	-0.05	-0.80	0.76
Alessandria	-0.82	-0.87	-0.42	-1.22	0.80	Forlì-Cesena	-0.21	-0.24	0.12	-0.54	0.66	Piacenza	-0.03	0.00	0.30	-0.36	0.66
Ancona	0.21	0.17	0.57	-0.16	0.73	Frosinone	-0.83	-0.92	-0.41	-1.32	0.91	Pisa	-0.75	-0.80	-0.32	-1.20	0.89
Aosta	-0.43	-0.45	-0.10	-0.77	0.67	Genova	0.29	0.44	1.05	-0.28	1.33	Pistoia	0.12	0.16	0.51	-0.25	0.76
Arezzo	-0.73	-0.80	-0.35	-1.13	0.78	Gorizia	0.17	0.08	0.59	-0.35	0.94	Pordenone	1.04	1.01	1.40	0.67	0.73
Ascoli Piceno	-0.32	-0.30	0.06	-0.68	0.75	Grosseto	-0.36	-0.30	0.04	-0.75	0.79	Potenza	-0.14	-0.28	0.22	-0.63	0.86
Asti	0.07	0.04	0.45	-0.35	0.80	Imperia	-0.84	-0.80	-0.48	-1.21	0.73	Prato	0.35	0.29	0.72	-0.04	0.76
Avellino	0.15	0.22	0.56	-0.26	0.81	Isernia	-1.41	-1.46	-1.01	-1.80	0.79	Ragusa	-0.42	-0.35	-0.05	-0.79	0.74
Bari	-0.84	-0.83	-0.49	-1.20	0.71	L'Aquila	-0.05	-0.06	0.27	-0.36	0.63	Ravenna	-0.25	-0.31	0.13	-0.62	0.75
Barletta-Andria-Trani	0.11	0.25	0.71	-0.35	1.05	La Spezia	-0.11	-0.15	0.28	-0.50	0.78	Reggio di Calabria	-0.70	-0.83	-0.33	-1.21	0.88
Belluno	0.68	0.66	1.04	0.29	0.75	Latina	-0.73	-0.76	-0.40	-1.07	0.67	Reggio nell'Emilia	0.82	0.80	1.15	0.50	0.66
Benevento	-0.24	-0.28	0.16	-0.69	0.85	Lecce	-0.27	-0.21	0.29	-0.79	1.07	Rieti	-0.68	-0.64	-0.35	-1.01	0.66
Bergamo	0.35	0.32	0.70	-0.01	0.72	Lecco	-0.06	-0.10	0.31	-0.44	0.75	Rimini	-0.09	-0.14	0.25	-0.47	0.72
Biella	0.26	0.28	0.63	-0.11	0.74	Livorno	-0.69	-0.70	-0.35	-1.02	0.67	Roma	1.36	1.48	2.16	0.67	1.49
Bologna	0.18	0.19	0.51	-0.15	0.66	Lodi	1.05	1.07	1.41	0.72	0.69	Rovigo	-0.07	-0.10	0.29	-0.42	0.71
Bolzano Bozen	0.93	1.00	1.43	0.47	0.96	Lucca	0.01	-0.05	0.37	-0.37	0.74	Salerno	-0.31	-0.37	0.05	-0.69	0.74
Brescia	1.55	1.66	2.16	1.02	1.14	Macerata	0.02	-0.01	0.41	-0.42	0.84	Sassari	-0.42	-0.46	-0.07	-0.76	0.68
Brindisi	-0.23	-0.19	0.13	-0.62	0.75	Mantova	0.74	0.69	1.13	0.32	0.80	Savona	-0.81	-0.82	-0.42	-1.19	0.78
Cagliari	-0.32	-0.40	0.10	-0.78	0.89	Massa-Carrara	-0.68	-0.66	-0.33	-1.05	0.72	Siena	-0.30	-0.29	0.08	-0.66	0.74
Caltanissetta	-0.54	-0.49	-0.14	-0.95	0.81	Matera	0.15	0.02	0.47	-0.35	0.82	Siracusa	-1.18	-1.14	-0.79	-1.58	0.78
Campobasso	-0.90	-0.86	-0.56	-1.22	0.66	Messina	-0.99	-0.96	-0.67	-1.33	0.66	Sondrio	-0.11	-0.23	0.23	-0.59	0.82
Caserta	0.20	0.18	0.53	-0.12	0.65	Milano	1.19	1.31	1.81	0.68	1.13	Sud Sardegna	-0.99	-1.11	-0.66	-1.44	0.78
Catania	-1.28	-1.33	-0.90	-1.65	0.75	Modena	1.12	1.16	1.49	0.75	0.74	Taranto	-1.44	-1.48	-1.03	-1.84	0.81
Catanzaro	-0.39	-0.48	0.00	-0.80	0.81	Monza e della Brianza	0.78	0.75	1.13	0.42	0.71	Teramo	0.18	0.16	0.53	-0.18	0.71
Chieti	-0.84	-0.89	-0.40	-1.27	0.87	Napoli	-0.68	-0.74	-0.35	-1.03	0.68	Terni	0.39	0.30	0.86	-0.16	1.02
Como	1.91	1.97	2.50	1.34	1.16	Novara	-0.13	-0.18	0.22	-0.49	0.72	Torino	0.34	0.38	0.72	-0.06	0.77
Cosenza	0.52	0.58	0.99	0.06	0.94	Nuoro	0.88	0.91	1.25	0.50	0.75	Trapani	-1.18	-1.11	-0.76	-1.59	0.83
Cremona	0.10	0.06	0.47	-0.28	0.75	Oristano	0.21	0.17	0.64	-0.27	0.92	Trento	0.63	0.52	1.04	0.15	0.90
Crotone	-2.45	-2.46	-2.11	-2.80	0.69	Padova	0.22	0.20	0.56	-0.11	0.67	Treviso	0.80	0.78	1.21	0.43	0.78
Cuneo	0.23	0.20	0.58	-0.12	0.69	Palermo	-1.17	-1.12	-0.84	-1.51	0.67	Trieste	0.35	0.41	0.74	-0.02	0.76
Enna	-1.34	-1.30	-0.97	-1.69	0.73	Parma	0.39	0.45	0.82	0.05	0.77	Udine	0.15	0.10	0.49	-0.19	0.67
Fermo	-0.19	-0.24	0.23	-0.60	0.83	Pavia	-0.24	-0.17	0.11	-0.58	0.69	Varese	0.10	0.03	0.48	-0.29	0.77
Ferrara	0.15	0.09	0.55	-0.24	0.80	Perugia	-0.01	-0.08	0.40	-0.47	0.86	Venezia	0.91	0.92	1.24	0.58	0.67
Firenze	0.29	0.28	0.65	-0.07	0.72	Pesaro e Urbino	-0.36	-0.40	-0.01	-0.74	0.73	Verbano-Cusio-Ossola	0.07	-0.02	0.49	-0.39	0.88
												Vercelli	0.11	0.08	0.50	-0.24	0.74
												Verona	-0.04	-0.07	0.30	-0.39	0.69
												Vibo Valentia	-0.49	-0.49	-0.14	-0.83	0.69
												Vicenza	0.67	0.67	1.04	0.29	0.75
												Viterbo	-0.68	-0.71	-0.31	-1.03	0.71

Table D4. Summary of posterior distribution of the latent variable (composite indicator) for the overall well-being dimension. CAR model B. Year 2019

							CAR (model B)										
Province	mean	median	25%	75%	IQR	Province	mean	median	25%	75%	IQR	Province	mean	median	25%	75%	IQR
Agrigento	-1.84	-1.86	-1.70	-1.98	0.28	Foggia	-1.52	-1.53	-1.39	-1.66	0.27	Pescara	-0.21	-0.22	-0.11	-0.33	0.22
Alessandria	0.46	0.47	0.57	0.36	0.21	Forlì-Cesena	0.95	0.95	1.05	0.85	0.21	Piacenza	0.85	0.84	0.95	0.74	0.21
Ancona	0.40	0.39	0.50	0.29	0.21	Frosinone	-0.86	-0.87	-0.74	-0.98	0.24	Pisa	0.68	0.67	0.78	0.57	0.21
Aosta	0.78	0.78	0.89	0.68	0.21	Genova	0.32	0.31	0.42	0.21	0.21	Pistoia	0.37	0.37	0.47	0.27	0.20
Arezzo	0.70	0.72	0.81	0.60	0.21	Gorizia	0.55	0.56	0.66	0.45	0.21	Pordenone	0.98	0.98	1.08	0.88	0.21
Ascoli Piceno	0.20	0.19	0.29	0.09	0.21	Grosseto	0.48	0.48	0.58	0.38	0.20	Potenza	-0.95	-0.96	-0.83	-1.07	0.24
Asti	0.73	0.75	0.85	0.63	0.22	Imperia	0.00	0.01	0.11	-0.10	0.21	Prato	0.84	0.84	0.95	0.74	0.21
Avellino	-0.76	-0.78	-0.65	-0.88	0.23	Isernia	-0.63	-0.63	-0.53	-0.74	0.21	Ragusa	-1.02	-1.01	-0.89	-1.13	0.23
Bari	-0.51	-0.53	-0.40	-0.63	0.23	L'Aquila	-0.06	-0.07	0.03	-0.17	0.20	Ravenna	0.89	0.89	1.00	0.79	0.20
Barletta-Andria-Trani	-1.24	-1.25	-1.12	-1.37	0.25	La Spezia	0.48	0.47	0.58	0.38	0.20	Reggio di Calabria	-1.90	-1.91	-1.77	-2.04	0.27
Belluno	1.04	1.05	1.15	0.94	0.21	Latina	-0.37	-0.38	-0.27	-0.48	0.21	Reggio nell'Emilia	0.98	0.97	1.08	0.87	0.21
Benevento	-1.05	-1.06	-0.93	-1.17	0.24	Lecce	-1.26	-1.28	-1.14	-1.40	0.26	Rieti	-0.25	-0.26	-0.16	-0.36	0.20
Bergamo	0.87	0.87	0.98	0.76	0.22	Lecco	0.94	0.94	1.04	0.84	0.21	Rimini	0.62	0.61	0.72	0.51	0.21
Biella	0.60	0.60	0.70	0.50	0.20	Livorno	0.29	0.28	0.39	0.18	0.20	Roma	0.38	0.36	0.47	0.26	0.21
Bologna	1.13	1.10	1.23	0.99	0.24	Lodi	0.63	0.63	0.73	0.53	0.20	Rovigo	0.59	0.60	0.70	0.49	0.20
Bolzano Bozen	1.29	1.30	1.42	1.18	0.23	Lucca	0.21	0.20	0.31	0.10	0.20	Salerno	-1.17	-1.18	-1.05	-1.30	0.25
Brescia	0.92	0.92	1.03	0.82	0.21	Macerata	0.52	0.51	0.61	0.41	0.20	Sassari	-0.61	-0.62	-0.51	-0.73	0.22
Brindisi	-0.93	-0.94	-0.82	-1.05	0.23	Mantova	0.82	0.82	0.93	0.72	0.20	Savona	0.55	0.54	0.65	0.44	0.20
Cagliari	-0.40	-0.44	-0.29	-0.56	0.27	Massa-Carrara	0.37	0.36	0.46	0.27	0.20	Siena	0.66	0.67	0.77	0.56	0.21
Caltanissetta	-1.94	-1.94	-1.79	-2.08	0.29	Matera	-0.41	-0.42	-0.31	-0.53	0.22	Siracusa	-1.45	-1.46	-1.32	-1.58	0.26
Campobasso	-0.54	-0.55	-0.44	-0.65	0.21	Messina	-1.88	-1.88	-1.74	-2.03	0.29	Sondrio	0.83	0.84	0.95	0.72	0.22
Caserta	-1.67	-1.68	-1.53	-1.81	0.28	Milano	1.04	1.01	1.14	0.90	0.24	Sud Sardegna	-0.10	-0.10	0.00	-0.20	0.20
Catania	-1.65	-1.66	-1.50	-1.79	0.28	Modena	0.89	0.88	1.00	0.78	0.22	Taranto	-1.38	-1.39	-1.25	-1.50	0.25
Catanzaro	-1.17	-1.18	-1.05	-1.30	0.25	Monza e della Brianza	0.79	0.77	0.89	0.68	0.21	Teramo	-0.01	-0.02	0.08	-0.12	0.20
Chieti	-0.25	-0.25	-0.15	-0.36	0.21	Napoli	-1.81	-1.82	-1.67	-1.96	0.29	Terni	0.14	0.12	0.24	0.03	0.21
Como	0.77	0.75	0.86	0.66	0.20	Novara	0.71	0.70	0.81	0.61	0.21	Torino	0.58	0.57	0.67	0.47	0.20
Cosenza	-1.39	-1.41	-1.26	-1.53	0.27	Nuoro	-0.73	-0.74	-0.62	-0.85	0.23	Trapani	-1.94	-1.94	-1.79	-2.08	0.29
Cremona	0.77	0.77	0.87	0.67	0.20	Oristano	-0.79	-0.81	-0.68	-0.92	0.24	Trento	0.93	0.91	1.02	0.81	0.21
Crotone	-2.17	-2.17	-2.01	-2.32	0.30	Padova	0.89	0.88	0.99	0.78	0.21	Treviso	0.76	0.75	0.86	0.65	0.21
Cuneo	0.93	0.95	1.05	0.83	0.22	Palermo	-1.85	-1.86	-1.70	-1.99	0.29	Trieste	0.79	0.78	0.89	0.68	0.21
Enna	-1.81	-1.82	-1.66	-1.95	0.29	Parma	0.92	0.90	1.03	0.80	0.23	Udine	0.68	0.67	0.78	0.57	0.21
Fermo	0.59	0.60	0.70	0.49	0.21	Pavia	0.71	0.71	0.81	0.61	0.20	Varese	0.80	0.79	0.90	0.70	0.20
Ferrara	0.75	0.74	0.86	0.65	0.21	Perugia	0.56	0.55	0.66	0.45	0.21	Venezia	0.76	0.76	0.86	0.65	0.21
Firenze	0.95	0.93	1.05	0.83	0.22	Pesaro e Urbino	0.56	0.55	0.65	0.46	0.20	Verbano-Cusio-Ossola	0.51	0.51	0.61	0.41	0.20
												Vercelli	0.46	0.46	0.56	0.36	0.20
												Verona	0.99	0.98	1.09	0.88	0.21
												Vibo Valentia	-1.72	-1.72	-1.57	-1.85	0.28
												Vicenza	0.96	0.95	1.06	0.85	0.21
												Viterbo	-0.25	-0.26	-0.15	-0.36	0.21