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A new approach for measuring poverty or social exclusion reduction in European NUTS 2 regions

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ABSTRACT

This paper examines the problem of poverty or social exclusion reduction for NUTS 2 regions in the European Union over the years 2005–2015. To do so, we extend the concept of absolute poverty convergence to conditional poverty β-convergence and use a quantile regression approach to provide a broader assessment of the heterogeneous relationships between poverty and some economic factors. We consider spatial dependence between neighbouring regions using appropriate spatial econometric specification. We focus on regional performance in tackling poverty or social exclusion using a novel indicator based on the efficiency theory and examine potential heterogeneity in regions' ability to fight poverty. These differences are analysed in detail considering instabilities in the relationship between regional performances and a relevant asset for policy effectiveness as the quality of institutions. Our findings can help policy makers to better understand factors behind poverty reductions and develop more responsive policies at different institutional levels.

1. Introduction

Poverty and social exclusion are significant issues that affect individuals and communities. Poverty is a composite phenomenon typically related to low incomes, scarcity of resources, and difficulties for individuals and households to satisfy basic needs [1]. Thus, social exclusion is often an effect of poverty, lack of education, and deprivation. It can assume various forms as discrimination, marginalization, and stigmatization, and it can lead to several negative outcomes as decreased well-being and increased vulnerability [2]. The combination of poverty and social exclusion can create a critical downward spiral, so that disadvantaged people face additional barriers to access resources and opportunities, precluding them from reaching their full potential [3].

The definition of policies to reduce the number of people in state of poverty or social exclusion is one among the main policy goals of the European Union (EU) and its Member States. The *European Pillar of Social Rights* suggests three EU-level targets. Poverty and social exclusion is one of the targets. EU aims to reduce the number of those at risk of poverty or social exclusion by at least 15 million (5 million should be children) by 2030 [4]. To this end, EU has implemented several policies [5,6] and a wide range of actions including improved access to education, better healthcare, essential services, as well as initiatives to promote economic growth, social inclusion and support of disadvantaged groups.[1]

Following this narrative, in the EU, the At Risk of Poverty or Social Exclusion (AROPE) indicator is considered by policy makers as the main measure for observing the multidimensional aspects of poverty and social exclusion. The AROPE is the main measure to keep the EU 2030 target on poverty or social exclusion under surveillance, as well as the principal indicator to monitor the EU 2020 strategy poverty target.

It is worth noting that the AROPE is a composite indicator not strictly representing the level of income of a household. In fact, it is defined as the percentage, in total population, of the persons who are at risk of poverty (after social transfers) and/or severely materially and socially deprived and/or living in a (quasi-) jobless household. People are only considered once even if they are present in two or all the three previous situations. This calculation is made using data from the European Union Statistics on Income and Living Conditions (EU-SILC) survey (see [7,8]).

Figures for the AROPE at European country level have showed some

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[1] For further information on the fight against poverty, social exclusion and discrimination see: https://www.europarl.europa.eu/factsheets/en/sheet/60/the-fight-against-poverty-social-exclusion-and-discrimination.

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decreasing trend over the last years. Nevertheless, it is greatly relevant for policy makers to acknowledge the substantial variations that exist between European regions. For example, at NUTS 2 level, the magnitude of AROPE ranges from less than 10 % in some regions to more than 40 % in others. In essence, Eastern and Southern regions have higher rates of AROPE, while Northern and Western European regions show lower rates. This feature highlights the importance of regional dimension in investigating poverty and social exclusion in EU. The NUTS 2 scale of analysis may shed light on relevant mechanisms useful to attain an in-depth understanding of the economic development of regional economies. Also, it involves local peculiarities and potential interdependences between regions, places and cities.

This paper aims to analyse more comprehensively the target of poverty or social exclusion reduction postulated by the *European Pillar of Social Rights*. To this end, we contribute to the literature in several aspects. First, we extend the poverty convergence models discussed by Ravallion [9] and Crespo-Cuaresma et al. [10] and define a conditional β-convergence model including several factors. Differently from previous contributions, we consider the AROPE indicator and not the mere headcount ratio of people under poverty threshold as the response variable of the convergence model since our focus is on the social targets of EU. Second, our methodological approach is based on the use of quantile regression, and not on the use of linear modelling, to provide a broader assessment of the heterogeneous relationship between poverty and those variables. Third, differently from Ravallion [9] and Crespo-Cuaresma et al. [10] that analyse country data, we estimate a regional convergence model using EU NUTS 2 observations. Fourth, considering the violation of independence for geographically distributed data at NUTS 2 level unlike Bosco [11], we contemplate a spatial augmented quantile approach for the estimation of our conditional convergence model. Fifth, we propose an innovative measure denoted as Poverty or Social exclusion Reduction Performance (PSRP) index, inspired by the contribution of Cartone et al. [12] and based on the quantile estimation of the frontier production function [13]. This indicator aims to assess regional differences in the ability to effectively reduce poverty and social exclusion, monitoring the performances of each NUTS 2 region. Finally, to offer a new useful tool for policy makers, we decide to present an exploratory analysis for studying the spatial association between our indicator of regional performance (i.e., the PSRP index) and a variable reproducing the quality of institutions of European regions. The aim is to understand if a "good" performance in AROPE reduction is always associated to highest levels of the quality of institutions at regional level. The quality of these institutions, in fact, has been recognized as a key asset "*for economic development and deserve to be considered in any development policy*" [14–16]. To do so, we use bivariate Moran's I and, particularly, local bivariate Moran's I [17].

The remainder of the paper follows. In section 2, we introduce the theoretical background on which the paper is based. Section 3 is devoted to the description of the derivation of the economic model and of the methodology adopted. The data and the main results are shown in section 4. Finally, section 5 presents a discussion of the main policy implications of our results and some concluding remarks.

2. Theoretical background

In the recent literature, the concept of poverty convergence emerged as a tool for testing the effective reduction of poverty in a cross-section of countries or regions [9,10]. Technically, poverty convergence is a condition satisfied when countries/regions with higher poverty rates at a starting period face faster reduction of poverty compared to countries/regions with lower levels at the same period. This process is generally supposed to occur through economic development, which leads to higher incomes, better living standards, greater access to education, improved healthcare, welfare and finally reduces poverty [18].

Ravallion [9] and Crespo-Cuaresma et al. [10] both analyse the mechanism of poverty convergence. They develop models of absolute poverty convergence that start from economic $\beta-$ convergence across countries and growth elasticity of poverty reduction [19]. Ravallion [9], using linear/log-linear models and a sample of household data on 90 developing countries between 1977 and 2007, presents evidence that countries starting with higher poverty rates do not show significantly higher proportionate rates of poverty reduction. Conversely, Crespo-Cuaresma et al. [10] test different definitions of elasticity of poverty to verify the specifications provided by Ravallion [9].

Studies on poverty are also carried out using approaches that depart from poverty convergence. Barbero and Rodriguez-Crespo [20], using a standard linear model, analyse if the risk of poverty or social exclusion can be explained on the basis of some economic determinants in 229 European regions during the period 2007–2018. This study finds that the diffusion and quality of ICT investment can have positive effects on poverty reduction.

Reinstadler and Ray [21] use a binary logistic regression, where the probability of being at-risk-of-poverty is explained through a multilevel model that considers time, individuals and regions. They observe that economic growth impacts poverty levels in Europe.

Spada et al. [22] define a linear panel model to study the effect of education and culture on poverty on 34 European countries. In this case, the empirical evidence suggests a relevant and positive effect of education on poverty reduction.

Bosco [11] tries to move a step ahead from linear modelling by using quantile regression. Considering 31 European countries, he shows that quantile regression reveals poverty cross-country differences. When analysing the phenomenon, the use of quantile regression seems particularly suitable to investigate heterogeneous effects across the distribution and go beyond average [23]. Further, the need for going beyond average figures in the analysis of poverty has been early stressed by Ravallion [24].

In our opinion, carrying out regional analyses and going beyond national trends can help policy makers to unmask local peculiarities and fully understand poverty dynamics. To this end, it would be also convenient to consider potential spatial effects [25]. Poverty – as many other socio-economic phenomena – presents a significant geographical dimension and it is likely that occurrences in neighbouring regions may have consequences on poverty levels in one region [26]. Under these circumstances, spatial dependence should be properly considered when analysing NUTS 2 regions [27]. Further, to proper account for heterogeneous effects of the different economic determinants on poverty reduction, an approach based on quantile regression seems more appropriate.

Following this narrative, in the next paragraph, we introduce our model proposal based on spatial quantile regression to test for the presence of AROPE reduction in EU NUTS 2 regions.

3. Methodology

To test for poverty or social exclusion reduction at NUTS 2 level in the EU, a model of poverty convergence is considered [9]. In a cross-sectional framework, a statistical model of poverty convergence can be defined considering two different economic models. The first is the standard absolute β-convergence equation, that at a fixed time t, is defined as [28]:

$$\Delta \mathbf{Y}_t = \alpha \mathbf{i} + \beta \mathbf{Y}_{t_0} + \xi_t \tag{1}$$

where $\Delta \mathbf{Y}_t$ denotes the $N \times 1$ vector of growth rates (in natural logarithm) of the mean output level, between the initial time t_0 and the final time t, $\mathbf{Y}_{t_0}$ is the $N \times 1$ vector of the natural logarithm of the mean output level at the initial time t_0, α is the intercept, $\mathbf{i}$ is the $N \times 1$ vector of ones, and ξ_t is the $N \times 1$ vector of the error terms of zero mean and σ^2_ξ variance, where $i = 1, \ldots, N$ are the regions under investigation. In equation (1), the parameter β associated to the output at the starting point $\mathbf{Y}_{t_0}$ regulates the speed of convergence over the period $t - t_0$. If β is negative and statistically significant, the paradigm of economic convergence is verified.

The second equation [9] concerns the advantage of economic growth (i.e., growth in mean output implies poverty reduction) and it is defined, at a fixed final time t, as:

$$\mathbf{H}_t = \delta\mathbf{i} + \eta\mathbf{Y}_t + \mathbf{v}_t \tag{2}$$

where $\mathbf{H}_t$ is the $N \times 1$ vector of the natural logarithm of the poverty indicator (i.e., in our case the AROPE), $\mathbf{Y}_t$ is the $N \times 1$ vector of the natural logarithm of the mean output level, δ is the intercept, and $\mathbf{v}_t$ is the $N \times 1$ vector of the error terms with σ_v^2 variance. The parameter η is interpretable as the elasticity of poverty to the mean output, as by $\eta < 0$ higher economic growth is associated to high poverty reduction.

Combining the previous Equations (1) and (2), Ravallion [9] defines the model for testing absolute poverty convergence as:

$$\Delta\mathbf{H}_t = \alpha^*\mathbf{i} + \beta^*\mathbf{H}_{t_0} + \varepsilon_t \tag{3}$$

where $\Delta\mathbf{H}_t$ denotes the $N \times 1$ vector of growth rates (in natural logarithm) of the poverty indicator between the initial time t_0 and the final time t, $\mathbf{H}_{t_0}$ is the $N \times 1$ vector of the natural logarithm of the poverty indicator at time t_0 (i.e., the starting point), with $\alpha^* = \alpha\eta - \beta\delta$, $\beta^* = \beta$, and $\varepsilon_t = \eta\xi_t + \mathbf{v}_t - (1+\beta)\mathbf{v}_{t_0}$. Poverty convergence is reached if the estimation of $\beta^* < 0$. The absolute mean income convergence ($\beta < 0$) implies absolute poverty convergence ($\beta^* < 0$).

Linear models are discussed to analyse economic growth, regional economic convergence, poverty convergence, and poverty reduction [28]. However, as noted by Friedman [23], the use of linear regression does not seem suitable to investigate potentially heterogeneous effects across the distribution. Conversely, using quantile regression, researchers can investigate heterogeneous effects and go beyond average effects [29]. The advantage of quantile regression lies in the possibility of estimating a family of regression parameters for the entire conditional distribution, allowing for a broader view of a phenomenon [30,31].

A representation of a quantile regression for the case of absolute poverty convergence can be expressed for every $\boldsymbol{\tau} \in (0,1)$ as [32]:

$$\Delta\mathbf{H}_t = \alpha_\tau^*\mathbf{i} + \beta_\tau^*\mathbf{H}_{t_0} + \mathbf{u}_\tau \tag{4}$$

where α_τ^* is the intercept and β_τ^* is the poverty convergence parameter (expected to be negative for convergence) at each quantile τ, respectively, and $\mathbf{u}_\tau$ is the error term for the quantile τ. Here, no further assumption on disturbs than $Q_\tau(\mathbf{u}_\tau|\mathbf{H}_{t_0}) = 0$, where $Q_\tau(\mathbf{u}_\tau|\mathbf{H}_{t_0})$ denotes the conditional quantile of $\mathbf{u}_\tau$ on the regressor $\mathbf{H}_{t_0}$.

Simple absolute β-convergence in equations (3) and (4) may not accurately capture the complete dynamics of poverty and social exclusion. For this reason, to model poverty and social reduction across regions, it is appropriate to add a set of covariates ($\mathbf{X}$) interpretable as exogenous socio-economic drivers. A quantile conditional β-poverty convergence model can be specified as follows:

$$\Delta\mathbf{H}_t = \alpha_\tau^*\mathbf{i} + \beta_\tau^*\mathbf{H}_{t_0} + \mathbf{X}\theta_\tau + \mathbf{u}_\tau \tag{5}$$

where $\mathbf{X}$ is an $N \times p$ matrix of additional control economic variables with the corresponding $p \times 1$ vector of parameters θ_τ at each quantile.

Considering the nature of our geographical data set, to assess poverty at regional level it is convenient to apply spatial econometric techniques to properly model spatial dependence in the quantile specification [33, 34]. Spatially augmented models have been proposed to embed spatial dependence and address issues resulting from spatial endogeneity, model misspecification and measurement problems. Among others, a widely used specification in the literature of spatial linear regressions is the Spatial Lag Model [35].

McMillen [36] and Cartone et al. [12] offer a spatially augmented specification of quantile regression in analogy with spatial lag linear models. In fact, the problem of the violation of the independence assumption may lead to biased estimates in the case of quantile regression [37]. This spatial specification can be extended to the case of conditional poverty convergence as follows:

$$\Delta\mathbf{H}_t = \alpha_\tau^*\mathbf{i} + \rho_\tau\mathbf{W}\Delta\mathbf{H}_t + \beta_\tau^*\mathbf{H}_{t_0} + \mathbf{X}\theta_\tau + \mathbf{u}_\tau \tag{6}$$

where $\mathbf{W}$ is an $N \times N$ exogenous proximity matrix that measures the degree of closeness between units. Its entries, w_{ij}, are set to zero if two units are not neighbours and set to one conversely. The term ρ_τ is the spatial autocorrelation parameter, which measures the intensity of spatial dependence for each quantile τ.

It can be noted how the spatial quantile specification (6) contains a spatial lag of the dependent variable on the right side of the equation, causing endogeneity in the model. The impact of endogeneity in the estimation process can be analysed through several methods. Chernozhukov and Hansen [38] propose an Instrumental Variable Quantile Regression (IVQR) estimator that is a modified version of the standard quantile regression estimator for dealing with endogeneity.

This estimation strategy is generalized to the case of spatial endogeneity by Kostov [33] and Su and Yang [39], where predicted values $\widehat{\mathbf{W}\Delta\mathbf{H}}_t$ from a regression on a selected set of instruments $\mathbf{Z}$ of $\mathbf{W}\Delta\mathbf{H}_t$ are used as the first step of the procedure. The instrumented variables are then used as explanatory variables for a series of quantile regressions of the dependent variables over the covariates and the instrumented spatially lagged terms. Concerning the choice of instruments, the following set is used:

$$\mathbf{Z} = \left[\mathbf{X}, \mathbf{H}_{t_0}, \mathbf{WX}, \mathbf{WH}_{t_0}, \mathbf{W}^2\mathbf{X}, \mathbf{W}^2\mathbf{H}_{t_0}\right] \tag{7}$$

as suggested by McMillen [36], who grounds on Kelejian and Prucha [40] in analogy with standard linear spatial lag models.

The spatial quantile regression approach can be used to evaluate the performance of each region in reducing poverty and social exclusion. In this paper, we propose an indicator, denoted as Poverty or Social exclusion Reduction Performance (PSRP) index, derived from the study of efficiency [12,13].

The quantile regression represents a suitable alternative to stochastic frontier analysis and data envelopment analysis [41] to study efficiency in production frontier. This frontier describes the maximum output attainable by a firm with given inputs [42]. Quantile regression uses the top firms as a benchmark for the other firms in the sample. In other words, the firms at higher levels of the conditional distribution (say $\tau = 0.90$) realise better performances in terms of output than those at the lowest quantiles [13,43].

In our case study, we can apply this rationale following the idea introduced by Cartone et al. [12] considering spatial units. It is worth noticing that the aim here is to analyse the performance of each region in reducing poverty or social exclusion and not best results in terms of economic growth as in Cartone et al. [12]. The idea is the following. A quantile function (i.e., the frontier) that represents the relationship between the reduction of the AROPE and some exogenous variables is estimated. In this case, the better performing regions are considered with reference to lower levels of conditional distribution (say $\tau = 0.10$), since we aim to find regions with the highest poverty growth reduction or, in other words, the lowest AROPE growth during the period. Therefore, residuals $u_{i\tau=0.1}$ of spatial quantile regression are calculated for each region i from the quantile $\tau = 0.10$ to express the distance from the "efficient" quantile. These residuals represent our PSRP indicator that is a novel measure to inform policy makers about regional ability to tackle poverty.

Lastly, to further assess potential regional differences, we employ exploratory spatial data analysis and, particularly, a bivariate local Moran's I [17,44] to identify spatial heterogeneity in the relationship between regions' ability to reduce poverty and the quality of their institutions. A generalization of Moran's I in the bivariate case can be written as [17,45]:

$$I_{\mathbf{M}_k,\mathbf{M}_l} = \frac{\mathbf{M}^{k'}\mathbf{W}\mathbf{M}^l}{N} \quad (8)$$

where $\mathbf{M}^k$ and $\mathbf{M}^l$ are, respectively, two $N \times 1$ vectors of standardized values, with zero mean and unit variance, of our performance indicator $u_{i\tau=0.1}$ and a variable embedding the quality of the institutions, while $\mathbf{W}$ is a spatial weight matrix.

The global formula in (8) can be manipulated to obtain bivariate local statistics and visualize bivariate LISA clusters using the same rationale of the univariate case. Local bivariate Moran's $I^i_{\mathbf{M}_k,\mathbf{M}_l}$ indices are defined as:

$$I^i_{M_k,M_l} = m_i^k \sum_{j \neq i} w_{ij} m_j^l \quad (9)$$

where m_i^k is the standardized value of $u_{i\tau=0.1}$ at i and m_j^l is the quality of institutions in its neighbours js defined according to a row-standardized spatial matrix $\mathbf{W}$, whose entries are w_{ij}. The statistic in (9) provides evidence of the extent of systematic association between our performance indicator at a fixed location i and the spatial lag of the quality of institutions in its neighbouring sites.

Statistical inference of spatial indicators (9) is implemented by using a permutation approach following the same rationale of Panzera et al. [46] and Rey [47]. To this end, the observed values of the variables in (9) are randomly reassigned to different locations, considering a large number of these permutations (ideally 9999), and the statistic $I^i_{M_k,M_l}$ is calculated for each of these configurations. Given the null hypothesis that each pattern is equally likely, the observed value of $I^i_{M_k,M_l}$ is compared with the reference distribution defined with the permutations, and a pseudo-significance level is calculated by the position of the actual value into the so obtained ranked distribution.

4. Empirical evidence

Data for 223 European regions are collected to estimate our poverty conditional β-convergence model over the period 2005 to 2015. The spatial scale adopted is the NUTS 2 level, as it represents a relevant level for fund assignment by European Union. We decided to use the 2013 NUTS version to consider the largest number of NUTS 2 units and ensure wide coverage for countries. In fact, several years cannot be obtained in the newer NUTS version for many variables. The list of NUTS 2 region studied is provided in Appendix 1.

The years from 2005 to 2015 represent a crucial period for the analysis of poverty dynamics in the EU. Indeed, 2004 was the year of the greatest enlargement of EU, with the consequent entrance of many countries. As well, different economic tendencies have characterised developed areas and joining regions [48]. Besides, the recession and economic crisis has created potential differences [49]. Hence, analysing the regional answers to different dynamics in a cross-section of regions from 2005 to 2015 may represent an interesting example to observe policy implications of the proposed methodologies.

To account for variation of poverty levels, the dependent variable of our model is the growth rate of the AROPE, expressed as percentage in total population. The conditioning variables are: the level of the AROPE at the initial year 2005 (*AROPE_2005*), the average annual growth rate of the gross domestic product *per capita* (*GDP per capita growth rate*) over the period expressed in purchasing power standard (PPS), the ratio between the gross fixed capital formation and the regional GDP (both in PPS) between 2005 and 2015 as a proxy for the relevance of investments (*Investments* [50]), the percentage of the population aged 18–24 having attained at most lower secondary education (i.e., *Early leavers* from the school in 2005), the share of human resources in science and technology (*HRST* in 2005) in the working population [51] and the inequality [19].

The inequality (*Inequality*) is calculated as the natural logarithm of the Gini index obtained using GDP *per capita* NUTS 3 data at the beginning of the period for each NUTS 2 region. As many of the NUTS 2 regions are composed by only one NUTS 3, we assign to these regions a value of the Gini index equal to the average of the Gini index computed for the NUTS 2 regions in the same country [52].

The AROPE, GDP *per capita*, *Early leavers*, and *HRST* are obtained from the ESPON database,[2] while *Investments* derives from the ARDECO Database.[3] Summary statistics for all variables are reported in Table 1.

To observe potential heterogenous effects of poverty drivers, we adopt a quantile regression approach relying on Koenker and d'Orey [53] estimation strategy. Confidence intervals are obtained by inverting rank test method [54], while computation is pursued by quantreg library available in the R environment.

Results for the non-spatial specification (model (5)) are reported in Fig. 1 and Table 2. As expected, the estimated parameter related to the starting point of AROPE (i.e., β^*) is negative over the whole distribution. Hence, poverty convergence is verified. In the upper tail, the magnitude of the estimated parameters corresponding to the initial level of AROPE is a bit lower, so that the speed of convergence is higher in the right side of the distribution.

In Fig. 1, income growth (*GDP per capita growth rate*) seems to have a great influence on poverty reduction, as coefficients for this variable are strictly negative. The lack of school attainment (*Early leavers*) impacts positively on the variation of poverty rates. Moreover, in the non-spatial specification, *Investments* is tested significant at lowest quantiles only, while both *Inequality* and *HRST* do not show significant coefficients (see Table 2).

In a context where observations may not be independent on each other's, the application of non-spatial techniques may lead to biased parameter estimates [25]. To overcome this problem, we move a step ahead in the analysis and propose the use of a spatial quantile regression specification for our poverty convergence model.

To estimate the spatial quantile model (6) at NUTS 2 level, a row-standardized proximity matrix is defined according to a k-nearest rule accounting for the $k = 8$ closest regions as neighbours [52]. Other contiguity matrices were also considered, but the results obtained are not substantially different from those presented in this paper. This empirical evidence is supported by LeSage [55] who posits that different specifications of the spatial weight matrix $\mathbf{W}$ do not have a significant impact on the results obtained.

The estimation of the spatial quantile regression model is performed adopting the McSpatial library available in the R environment. Results are summarized in Fig. 2 and Table 3.

Looking at Fig. 2 and Table 3, we note how poverty convergence is verified over the whole distribution also for the spatial model (all values are negative and significant). However, magnitude of the β^* estimated in the spatial model appears to be lower if compared to the non-spatial specification, especially in the left side of the conditional distribution.

Table 1
Summary statistics for variables included in the conditional poverty convergence model at NUTS 2 level. All variables in natural logarithm.

Variable	Min	1st Q	Mean	Median	3rd Q	Max
AROPE growth rate	−0.070	−0.011	−0.003	0.001	0.008	0.071
AROPE_2005	−2.577	−1.749	−1.487	−1.666	−1.179	−0.277
GDP per capita growth rate	−0.014	0.014	0.023	0.021	0.030	0.081
Investments	−2.018	−1.613	−1.531	−1.523	−1.446	−0.852
Early leavers	−1.877	−1.234	−1.092	−1.053	−0.919	−0.536
HRST	−3.527	−2.331	−2.023	−2.025	−1.730	−0.597
Inequality	−3.042	−2.015	−1.753	−1.764	−1.468	−0.833

[2] https://database.espon.eu/.
[3] https://knowledge4policy.ec.europa.eu/territorial/ardeco-online_en.

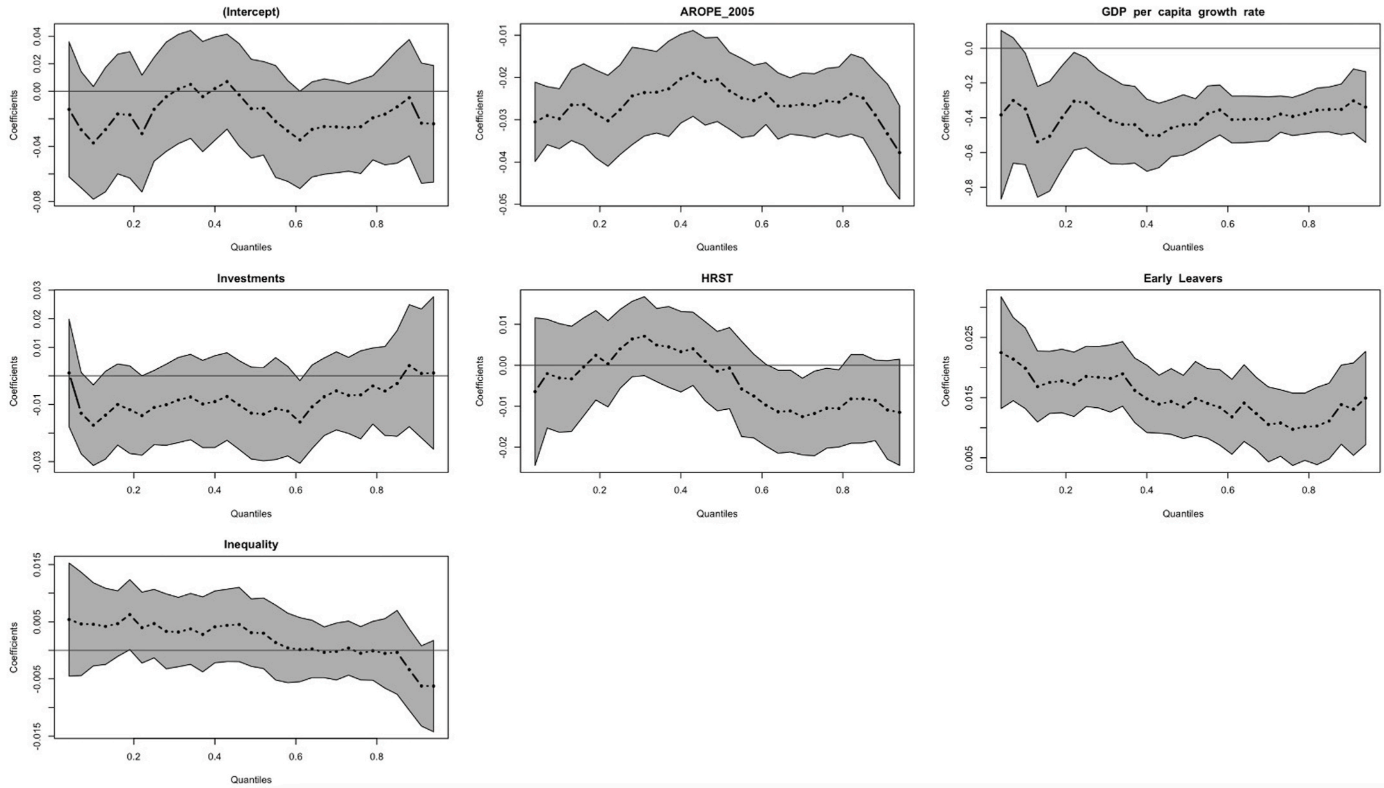

Fig. 1. Quantile regression estimates for conditional poverty convergence model (5). Coefficients are in dashed black, while the 95 % confidence intervals for quantile estimates are highlighted by the grey area.

Table 2
Quantile regression estimates for standard quantile regression model of poverty convergence model (5) at different τ s. *P*-values in brackets.

Variables	0.10	0.25	0.40	0.50	0.60	0.75	0.90
(Intercept)	−0.037 (0.160)	−0.013 (0.628)	0.002 (0.926)	−0.013 (0.575)	−0.030 (0.148)	−0.025 (0.212)	−0.014 (0.588)
AROPE_2005	−0.030 (0.000)	−0.028 (0.000)	−0.020 (0.001)	−0.022 (0.000)	−0.026 (0.000)	−0.026 (0.000)	−0.032 (0.000)
GDP per capita growth rate	−0.349 (0.073)	−0.313 (0.058)	−0.501 (0.000)	−0.437 (0.000)	−0.355 (0.000)	−0.389 (0.000)	−0.335 (0.004)
Investments	−0.017 (0.050)	−0.011 (0.215)	−0.009 (0.338)	−0.014 (0.177)	−0.012 (0.198)	−0.007 (0.427)	0.001 (0.931)
HRST	−0.003 (0.736)	0.004 (0.523)	0.003 (0.551)	−0.001 (0.901)	−0.009 (0.144)	−0.010 (0.118)	−0.009 (0.248)
Early Leavers	0.020 (0.000)	0.019 (0.000)	0.015 (0.000)	0.014 (0.000)	0.014 (0.000)	0.010 (0.006)	0.014 (0.003)
Inequality	0.005 (0.319)	0.005 (0.219)	0.004 (0.303)	0.003 (0.420)	0.000 (0.907)	0.000 (0.894)	−0.005 (0.346)

A negative association between the *GDP per capita growth rate* and the *AROPE growth rate* is also present according to our estimates. However, this impact is only significant for the highest quantiles (see Table 2). This points out how economic growth is a substantial driver of poverty reduction mainly where this reduction is rather low or not happening at all [56,57]. Concerning the *Investments*, an increase in their level has a positive impact on poverty reduction in the spatial model, but this effect is only significant at lower quantiles (see Table 3).

In Tables 3, it can be observed how an increasing number of *Early Leavers* is directly linked to a growth in the poverty rates at all quantile levels. Hence, fostering educational attainment may effectively reduce poverty. For the case of *HRST*, significant negative coefficients at high quantiles indicate how poverty reduction may benefit of highly skilled human capital. Positive influence of education and skilled human capital on poverty is in line with previous studies [22].

In the spatial model, the effect of inequality is verified positive and significant at the lowest levels (e.g., $\tau = 0.10; 0.25$). Thus, differently from the non-spatial quantile regression, inequality can be a driver of poverty for regions where poverty growth rate is lower.

In Fig. 3, estimates for the autocorrelation parameter ρ are shown. It is clear how positive spatial dependence is present among almost the entire distribution (see Table 2). Hence, significant spatial autocorrelation confirms that poverty reduction is a process largely influenced by poverty dynamics in neighbouring regions [49].

In Fig. 4, the two models are compared in terms of goodness of fit by using pseudo-R squared as in Koenker and Machado [58]. Indeed, a gain in representativeness is obtained when the spatial augmented conditional model is estimated, stressing that spatial quantile regression outperforms standard specification in the analysis of poverty convergence.

Moving a step ahead in our analysis, EU regions are classified in 5 classes using our novel PSRP indicator calculated as the distance from the efficient quantile (in our case $\tau = 0.10$, see Fig. 5). This measure is built up to map regions according to their capacity to reduce poverty or social exclusion. On the one side, regions in red show the highest distances from the most efficient quantile, *i.e.*, regions where the poverty reduction is lower. Conversely, regions in green are better performing in terms of poverty reduction during the accounted period.

The PSRP indicator returns us a picture characterised by within countries differences in the fight against poverty at regional level. Italy and Spain show similarities in terms of North-South divide, with the Northern regions standing out more than the Southern ones. With regards to Germany, a clear East-West divide can be spotted. Here, regions in the West, which have shown persistent high growth rates of

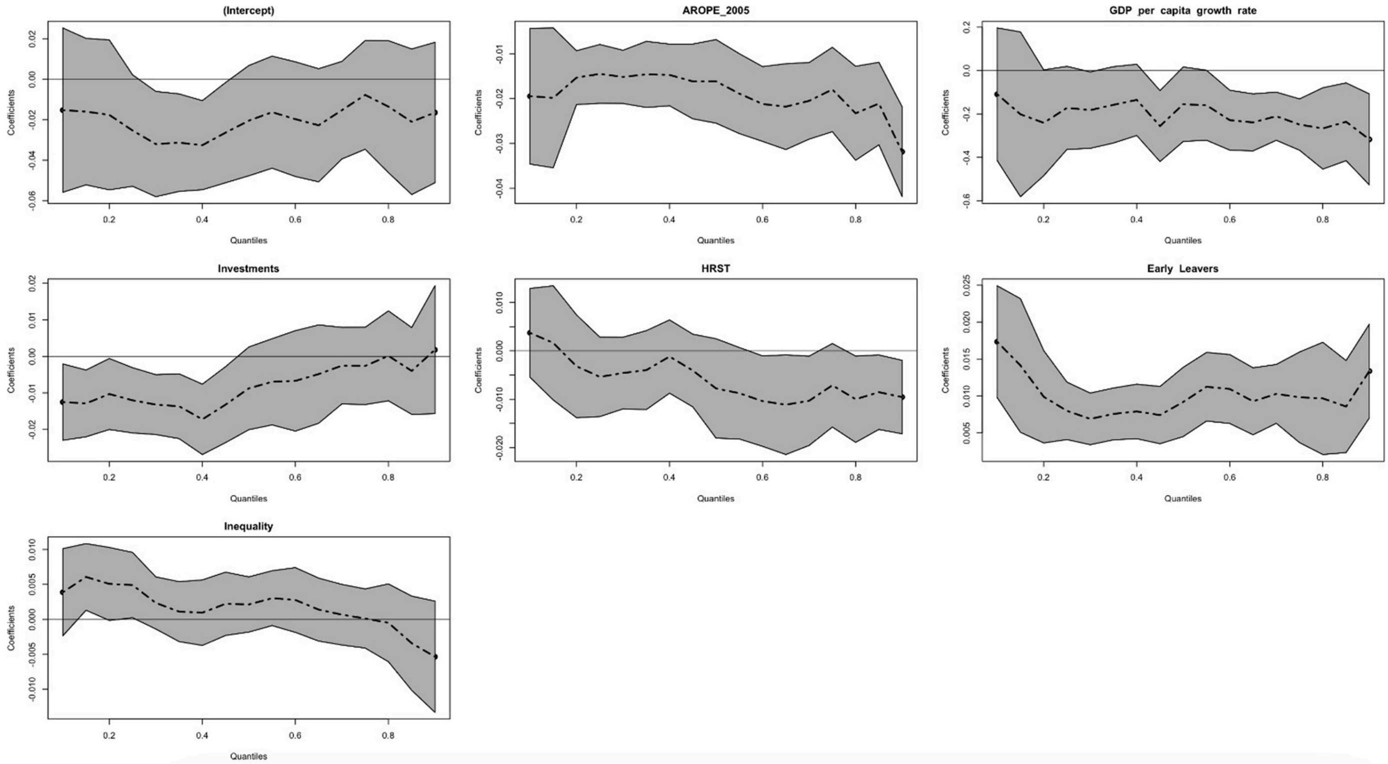

Fig. 2. Spatial quantile regression estimates of conditional poverty convergence model (6). Coefficients are in dashed black, while the 95 % confidence intervals are highlighted by grey area.

Table 3
Quantile regression estimates for spatial quantile regression model of poverty convergence model (6) at different τ s. P-values in brackets.

Variables	0.10	0.25	0.40	0.50	0.60	0.75	0.90
Intercept	−0.015 (0.538)	−0.025 (0.131)	−0.033 (0.015)	−0.021 (0.218)	−0.020 (0.253)	−0.008 (0.636)	−0.017 (0.437)
AROPE_2005	−0.020 (0.035)	−0.015 (0.000)	−0.015 (0.001)	−0.016 (0.005)	−0.021 (0.000)	−0.018 (0.002)	−0.032 (0.000)
GDP per capita growth rate	−0.109 (0.557)	−0.172 (0.140)	−0.135 (0.177)	−0.155 (0.138)	−0.229 (0.007)	−0.249 (0.001)	−0.317 (0.013)
Investments	−0.013 (0.050)	−0.012 (0.027)	−0.017 (0.003)	−0.009 (0.205)	−0.007 (0.424)	−0.003 (0.686)	0.002 (0.865)
HRST	0.004 (0.505)	−0.005 (0.284)	−0.001 (0.800)	−0.008 (0.215)	−0.010 (0.068)	−0.007 (0.177)	−0.010 (0.039)
Early leavers	0.015 (0.000)	0.008 (0.001)	0.008 (0.001)	0.009 (0.001)	0.011 (0.000)	0.010 (0.009)	0.013 (0.001)
Inequality	0.004 (0.008)	0.005 (0.048)	0.001 (0.736)	0.002 (0.374)	0.003 (0.411)	0.001 (0.959)	−0.005 (0.271)
ρ	0.533 (0.067)	0.738 (0.001)	0.688 (0.000)	0.603 (0.000)	0.411 (0.001)	0.331 (0.003)	0.033 (0.908)

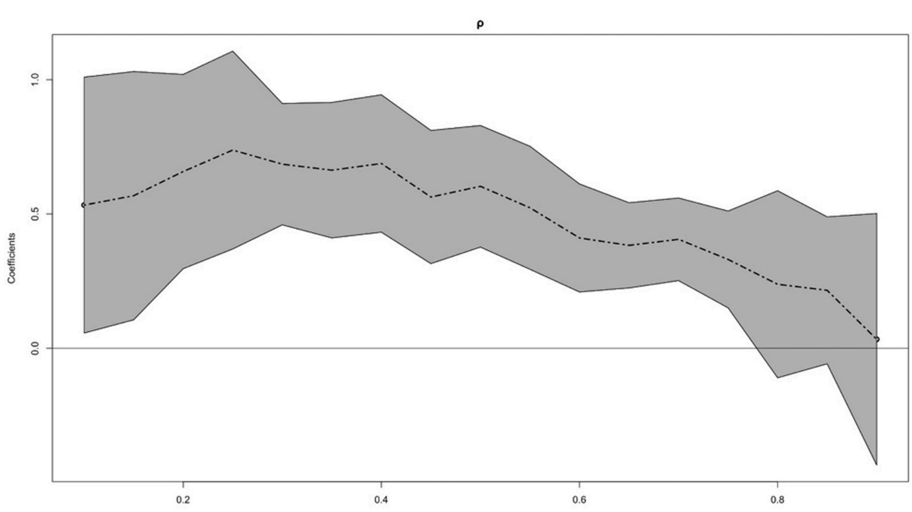

Fig. 3. Quantile regression estimates of the spatial autoregressive parameter ρ. Coefficient is in dashed black, while the 95 % confidence intervals are highlighted by grey area.

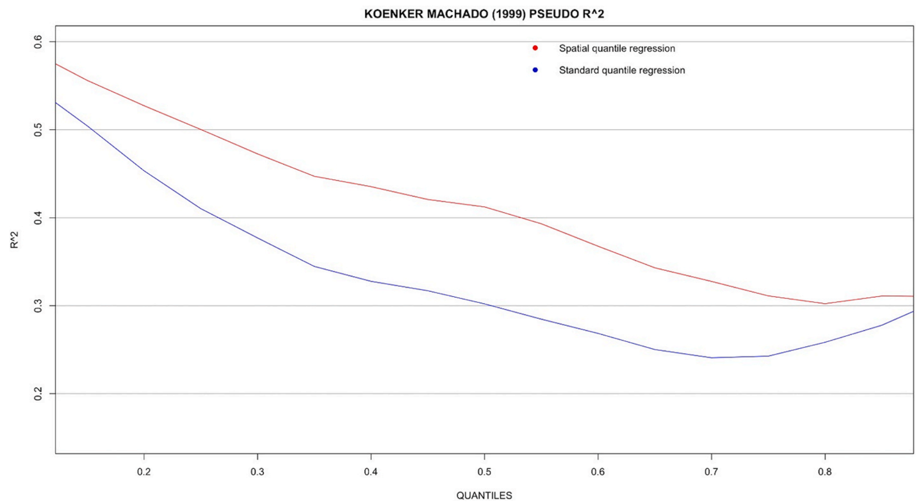

Fig. 4. Pseudo R-squared at different $\tau^{'}$s for conditional poverty convergence by quantile regression (blue) and spatial quantile regression (red).

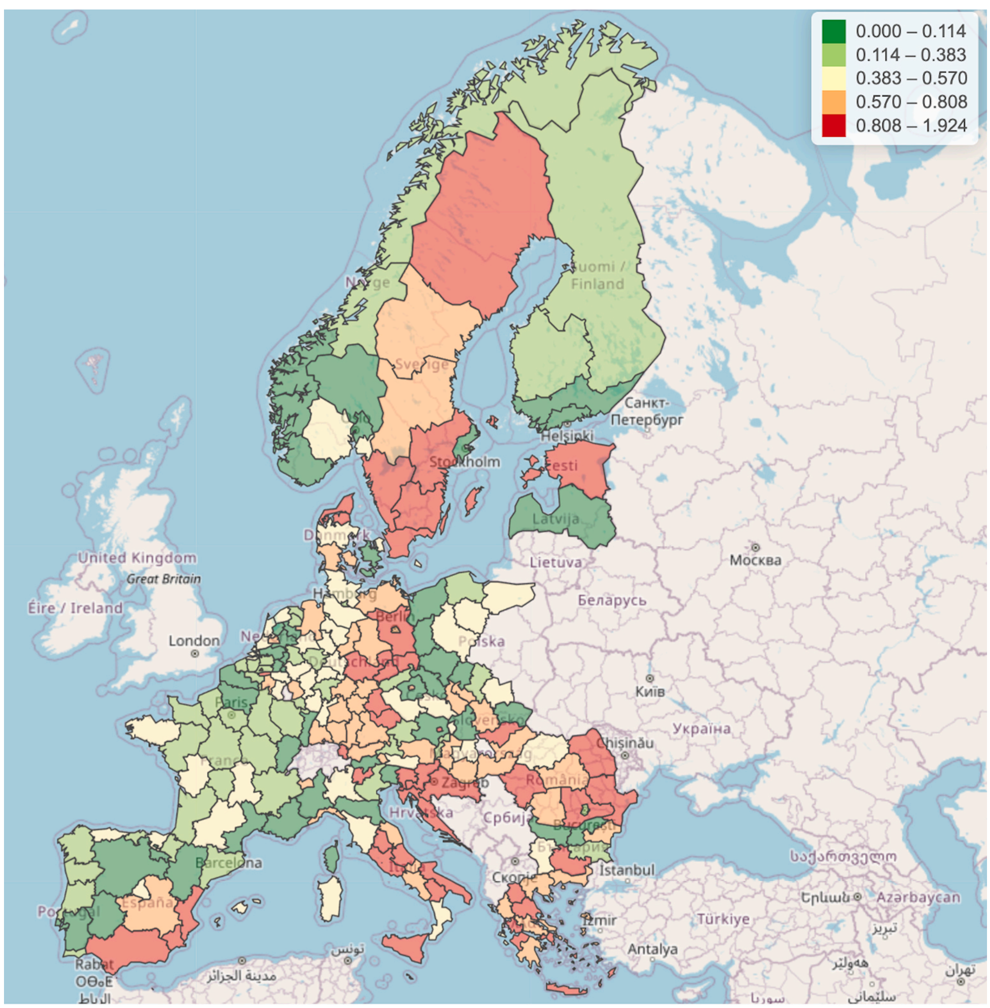

Fig. 5. Quantile map (5 classes) of the PSRP indicator at $\tau = 0.10$.

income, have probably not been able to translate this into an effective reduction of poverty or social exclusion. In the Scandinavian peninsula it becomes evident that there is group of regions not performing well, predominantly concentrated in the Southern regions of Sweden. An exception to this is represented by the Stockholm area (in green).

As the aim of this study is to investigate spatial differences in AROPE reduction dynamics, we lastly focus on the analysis of the spatial heterogeneity in the relationships between our PSRP indicator and an important asset for policy effectiveness such as the quality of institutions. According to previous literature (among others, [59,60]), the quality of institutions has been proxied by the European Quality of Government Index (EQI) for the year2006.[4] This variable is calculated as a regional score, and it is provided by the University of Gothenburg. To visualize spatial instabilities, LISA clusters using bivariate Moran's I are reported in Fig. 6.

In Fig. 6, the *high-high* cluster (red) individuates units characterised by higher distance from the efficient quantile and higher levels of *EQI* in the neighbourhood. Mainly situated in East Germany and Sweden, those regions show high levels of institution in the neighbourhood, but poverty reduction has been low. In opposite, the *low-low* group (light green) includes spatial clusters very close to the efficient quantile of our PSRP indicator and characterised by low levels of *EQI* in the neighbourhood. These are mainly situated in Poland, Czech Republic, and other Eastern regions. Those regions show quite low institutional capital in the neighbourhood, despite regions have been able to reduce poverty.

The units lying in the *low-high* cluster can be described by a short distance from the efficient quantile and high levels of *EQI* in the neighbours. These regions are mainly situated in Baltic Countries, Finland, West Germany, the Netherlands, and Loire regions of France. The *high-low* individuates a group far from efficient quantile of our indicator and characterised by low levels of *EQI* in the neighbours mainly in Central and Southern Italy, Romania and Greece. Here, low institutional capital in neighbour regions pairs with a slack reduction of poverty.

Empirical evidence from the bivariate LISA (see Fig. 6) suggests that the relationship between regional ability in poverty reduction and quality of institutions is different across European regions. Hence, despite the quality of institutions in a region can be widely considered as a pre-condition for development [61], other exogenous factors could promote – at least temporarily – poverty reduction [62]. For instance, some factors could be new access to technology, innovation, foreign investments, and the relative impact of subsides. On the other side, regions with "good" institutions could fail to reduce poverty very effectively if, for example, they are disregarded by policy actors at higher levels (e.g., national, and European [16]).

5. Discussion and concluding remarks

Our study contributes to the literature on poverty at NUTS 2 level in Europe as an attempt to fill the gap with the broader literature at the national level. To offer a comprehensive insight, we focus on regional dynamics that regulate AROPE reduction, as well as the ability of each region to effectively reduce poverty over a decade.

From the methodological point of view, as evidenced by Ravallion [24], the use of averages in the analysis of poverty relationships can be misleading and the same circumstance may apply to models of poverty convergence. The use of standard linear regression, in fact, would return average effects that can hide heterogenous responses across different regions. Moreover, an analysis based on geographically distributed observations, as EU regional data, poses new challenges to properly define appropriate statistical models.

To address these issues, this paper focuses on the use of spatial quantile regression for uncovering main mechanisms underlying poverty reduction in EU regions. The results confirm the presence of heterogeneous quantile effects, similarly to the case of economic convergence [11,12]. The use of a spatial quantile model proposed in this study also provides valuable information for quantile differences in spatial autocorrelation coefficients (i.e., ρ). Further, the evidence highlights the importance of accounting for spatial autocorrelation and geographical interconnections to achieve better representativeness.

In the analysis, regional poverty convergence is tested significant across the 223 European regions. However, this convergence appears to be faster in the higher part of the distribution and lower when a spatially augmented model is considered. At all quantiles, the influence of education (i.e., *Early leavers*) can be recognized as pivotal to reduce poverty. This highlights that school attainment is a key feature, and it is not limited to lower levels of education, as good proportions of skilled human capital (measured in our case by the share of HRST) can have benefits in lowering poverty or social exclusion [63].

Looking at the spatial quantile model, boosting economic growth appears not to be a general answer, but this effect could be leveraged effectively where poverty reduction is low. Instead, controlling the rise of inequality seems more relevant in NUTS 2 regions where poverty reduction is happening faster. Again, this supports how not only economic growth but also poverty reduction is a place-based matter [64].

In the paper, we introduce a novel PSRP indicator based on the efficiency theory to express regions' ability to reduce their level of poverty. This indicator is used to classify regions into different groups, providing policy makers with a broader vision for developing policies and territorial cohesion. Looking at the results, great differences are shown in the way regions deal with poverty reduction, while careful consideration of those differences by policy makers is suggested. The proposed indicator could be thence used to shed more light on the way regional and national policies work at different levels. On the one side, policy makers at European and national levels can benefit from a more careful assessment on the presence of within-country mechanisms [65]. On the other side, regional policy makers could be more aware of what economic factors could be pivotal to improve their performance [66].

The quality of local institutions has been discussed as a crucial element for policy effectiveness, also while addressing poverty reduction [16]. Along this line, we take advantage of our methodology to offer an empirical analysis on the spatial association between our regions' performance (i.e., PSRP index) and the quality of institutions in EU NUTS 2 regions. Results from the bivariate LISA points out how poverty reduction could not be effectively targeted taking into account a single feature equally in all regions. Rather, a careful analysis of spatial heterogeneity reveals us that an "intermediate way" between tailored solutions and EU overall policy is required and that local actions should be based on a multilevel perspective [67].

Overall, our study suggests new implications to reduce poverty or social exclusion and improve cohesion at NUTS 2 level. Poverty or social exclusion, as well as cohesion, are processes involving both interdependencies and local peculiarities and the role of EU institutions will be particularly complex without addressing these spatial features [68]. A look at the structure of the actions provided by the *European Pillar of Social Rights* through our results could be also of some use. The evidence points out the need for strengthening local opportunities along the harmonization in the access to services as education [69]. This could allow well-trained individuals to leverage their capabilities throughout every location of the Union, benefiting from local interdependencies, and aligning to market shifts without facing degradation of economic and social conditions. Besides, the heterogeneous role of institutional capital, different for each NUTS 2 regions, should lead European bodies to focus on a flexible perimeter within which the regional actions can be guided through innovative directions in a more effective way.

It should be emphasised that this article cannot be considered a definitive study on the analysis of poverty or social exclusion in European regions. The main future research challenges will concern both methodological aspects and interpretative analyses. We stress that spatial quantile approach used in this paper is a valid method since it is not based on distributional assumptions on errors, and it is robust to outliers. However, if the data are available for a longer period of time, a spatial panel quantile analysis might be more appropriate to analyse the heterogeneous effects of the covariates on the reduction of poverty.

Besides, in this study we focus on instability in tackling poverty using EQI for reasons of policy relevance, but other factors could be used in future studies and produce more robust information for policy makers. Finally, we are aware that some policies – to be effective in each person's

[4] We consider 2006 for this variable since it is the closest year available to our starting period of analysis (i.e., 2005).

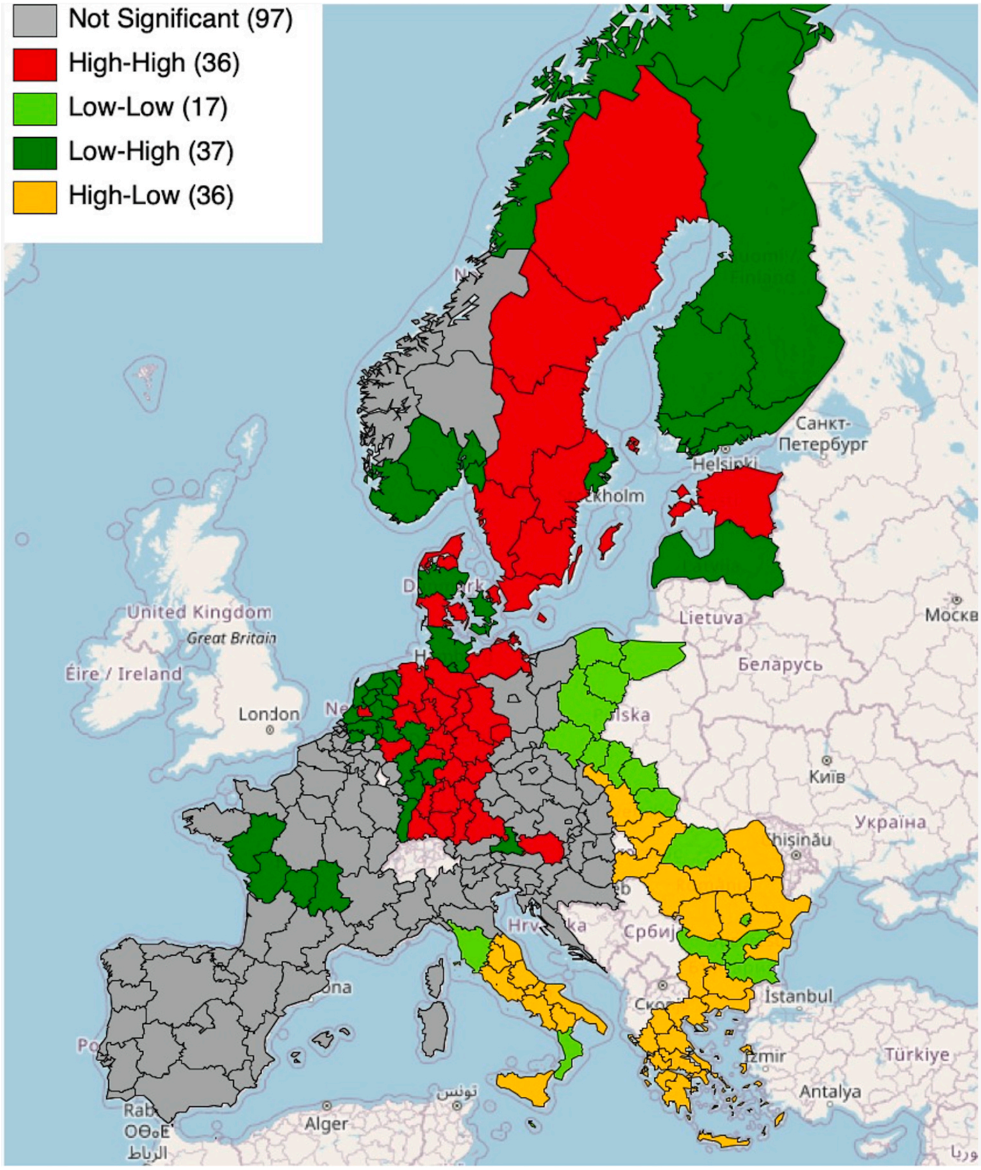

Fig. 6. LISA clusters from a Bivariate Moran's I calculated using the PSRP indicator at $\tau = 0.10$ and the EQI. A $k = 8$ nearest neighbour contiguity matrix is considered.

life – should be defined at a more "local level" than NUTS 2 (i.e., NUTS 3 and/or municipality). To this end, we would need data that are not available with sufficient coverage now. A future challenge is to build data set at a finer territorial level to study poverty reduction and social exclusion in EU localities in order to define locally oriented programs.

CRediT authorship contribution statement

Alfredo Cartone: Writing – original draft, Writing – review & editing, Data curation, Software. **Luca Di Battista:** Data curation, Software. **Paolo Postiglione:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix 1

List of NUTS 2 regions studied in the application.

NUTS_ID	NUTS_NAME
AT11	Burgenland
AT12	Niederösterreich
AT13	Wien
AT21	Kärnten
AT22	Steiermark
AT31	Oberösterreich
AT32	Salzburg
AT33	Tirol
AT34	Vorarlberg
BE10	Région de Bruxelles-Capitale
BE21	Prov. Antwerpen
BE22	Prov. Limburg (BE)
BE23	Prov. Oost-Vlaanderen
BE24	Prov. Vlaams-Brabant
BE25	Prov. West-Vlaanderen
BE31	Prov. Brabant Wallon
BE32	Prov. Hainaut
BE33	Prov. Liège
BE34	Prov. Luxembourg (BE)
BE35	Prov. Namur
BG31	Severozapaden
BG32	Severen tsentralen
BG33	Severoiztochen
BG34	Yugoiztochen
BG41	Yugozapaden
BG42	Yuzhen tsentralen
CZ01	Praha
CZ02	Strední Cechy
CZ03	Jihozápad
CZ04	Severozápad
CZ05	Severovýchod
CZ06	Jihovýchod
CZ07	Strední Morava
CZ08	Moravskoslezsko
DE11	Stuttgart
DE12	Karlsruhe
DE13	Freiburg
DE14	Tübingen
DE21	Oberbayern
DE22	Niederbayern
DE23	Oberpfalz
DE24	Oberfranken
DE25	Mittelfranken
DE26	Unterfranken
DE27	Schwaben
DE30	Berlin
DE40	Brandenburg
DE50	Bremen
DE60	Hamburg
DE71	Darmstadt
DE72	Gieβen
DE73	Kassel
DE80	Mecklenburg-Vorpommern
DE91	Braunschweig
DE92	Hannover
DE93	Lüneburg
DE94	Weser-Ems
DEA1	Düsseldorf
DEA2	Köln
DEA3	Münster
DEA4	Detmold
DEA5	Arnsberg
DEB1	Koblenz
DEB2	Trier
DEB3	Rheinhessen-Pfalz
DEC0	Saarland
DED2	Dresden
DED4	Chemnitz
DED5	Leipzig
DEE0	Sachsen-Anhalt
DEF0	Schleswig-Holstein
DEG0	Thüringen
DK01	Hovedstaden
DK02	Sjælland
DK03	Syddanmark
DK04	Midtjylland

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NUTS_ID	NUTS_NAME
DK05	Nordjylland
EE00	Eesti
EL30	Attiki
EL41	Voreio Aigaio
EL42	Notio Aigaio
EL43	Kriti
EL51	Anatoliki Makedonia, Thraki
EL52	Kentriki Makedonia
EL53	Dytiki Makedonia
EL54	Ipeiros
EL61	Thessalia
EL62	Ionia Nisia
EL63	Dytiki Ellada
EL64	Sterea Ellada
EL65	Peloponnisos
ES11	Galicia
ES12	Principado de Asturias
ES13	Cantabria
ES21	País Vasco
ES22	Comunidad Foral de Navarra
ES23	La Rioja
ES24	Aragón
ES30	Comunidad de Madrid
ES41	Castilla y León
ES42	Castilla-La Mancha
ES43	Extremadura
ES51	Cataluña
ES52	Comunidad Valenciana
ES53	Illes Balears
ES61	Andalucía
ES62	Región de Murcia
ES63	Ciudad Autónoma de Ceuta
ES64	Ciudad Autónoma de Melilla
FI19	Länsi-Suomi
FI1B	Helsinki-Uusimaa
FI1C	Etelä-Suomi
FI1D	Pohjois- ja Itä-Suomi
FI20	Åland
FR10	Île de France
FR21	Champagne-Ardenne
FR22	Picardie
FR23	Haute-Normandie
FR24	Centre
FR25	Basse-Normandie
FR26	Bourgogne
FR30	Nord - Pas-de-Calais
FR41	Lorraine
FR42	Alsace
FR43	Franche-Comté
FR51	Pays de la Loire
FR52	Bretagne
FR53	Poitou-Charentes
FR61	Aquitaine
FR62	Midi-Pyrénées
FR63	Limousin
FR71	Rhône-Alpes
FR72	Auvergne
FR81	Languedoc-Roussillon
FR82	Provence-Alpes-Côte d'Azur
FR83	Corse
HR03	Jadranska Hrvatska
HR04	Kontinentalna Hrvatska
HU21	Közép-Dunántúl
HU22	Nyugat-Dunántúl
HU23	Dél-Dunántúl
HU31	Észak-Magyarország
HU32	Észak-Alföld
HU33	Dél-Alföld
ITC1	Piemonte
ITC2	Valle d'Aosta/Vallée d'Aoste
ITC3	Liguria
ITC4	Lombardia
ITF1	Abruzzo
ITF2	Molise
ITF3	Campania
ITF4	Puglia

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NUTS_ID	NUTS_NAME
ITF5	Basilicata
ITF6	Calabria
ITG1	Sicilia
ITG2	Sardegna
ITH1	Provincia Autonoma di Bolzano/Bozen
ITH2	Provincia Autonoma di Trento
ITH3	Veneto
ITH4	Friuli-Venezia Giulia
ITH5	Emilia-Romagna
ITI1	Toscana
ITI2	Umbria
ITI3	Marche
ITI4	Lazio
LV00	Latvija
MT00	Malta
NL11	Groningen
NL12	Friesland (NL)
NL13	Drenthe
NL21	Overijssel
NL22	Gelderland
NL23	Flevoland
NL31	Utrecht
NL32	Noord-Holland
NL33	Zuid-Holland
NL34	Zeeland
NL41	Noord-Brabant
NL42	Limburg (NL)
NO01	Oslo og Akershus
NO02	Hedmark og Oppland
NO03	Sør-Østlandet
NO04	Agder og Rogaland
NO05	Vestlandet
NO06	Trøndelag
NO07	Nord-Norge
PL21	Malopolskie
PL22	Slaskie
PL41	Wielkopolskie
PL42	Zachodniopomorskie
PL43	Lubuskie
PL51	Dolnoslaskie
PL52	Opolskie
PL61	Kujawsko-Pomorskie
PL62	Warminsko-Mazurskie
PL63	Pomorskie
PT11	Norte
PT15	Algarve
PT16	Centro (PT)
PT17	Área Metropolitana de Lisboa
PT18	Alentejo
RO11	Nord-Vest
RO12	Centru
RO21	Nord-Est
RO22	Sud-Est
RO31	Sud - Muntenia
RO32	Bucuresti - Ilfov
RO41	Sud-Vest Oltenia
RO42	Vest
SE11	Stockholm
SE12	Östra Mellansverige
SE21	Småland med öarna
SE22	Sydsverige
SE23	Västsverige
SE31	Norra Mellansverige
SE32	Mellersta Norrland
SE33	Övre Norrland
SI03	Vzhodna Slovenija
SI04	Zahodna Slovenija
SK01	Bratislavský kraj
SK02	Západné Slovensko
SK03	Stredné Slovensko
SK04	Východné Slovensko

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