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ORIGINAL RESEARCH

Unveiling multidimensional poverty across Italian Provinces using small area estimation and penalized power means

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Abstract
This paper aims to examine the impact of the Covid-19 pandemic on multidimensional poverty in Italy and its provinces by comparing household poverty levels before and after the outbreak. To capture the multidimensionality of poverty, we analyze various dimensions, including economic well-being, health status, education, neighborhood quality, and subjective well-being. The empirical analysis relies on micro-data from Istat's aspects of daily life (AVQ) survey, covering the years 2018–2021. As the survey's direct estimates are reliable only at the regional level (NUTS 2), we apply small area estimation techniques to produce accurate estimates of provincial (NUTS 3) deprivation incidences. Subsequently, we aggregate the deprivation headcounts across the elementary indicators using penalized power mean composite indicators. The empirical findings indicate that overall multidimensional poverty worsened in most of the Italian provinces, particularly during the second year of the pandemic, with higher levels persisting in southern areas. The various dimensions of poverty exhibited different trends, with education, subjective well-being, and health emerging as the most negatively affected in numerous provinces.

Keywords Multidimensional poverty index · Small area estimation · EBLUP estimator · Power mean composite indicator

1 Introduction

In recent years, there has been a growing consensus among scholars, policymakers, and practitioners that poverty is a complex and multidimensional phenomenon. This perspec-

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tive emphasizes that poverty cannot be fully understood or addressed by focusing solely on monetary indicators, such as income or consumption levels. Instead, it requires considering a broader range of factors, including access to education, healthcare, housing, social inclusion, political participation, and environmental sustainability. This holistic approach highlights the interplay between economic, social, and structural dimensions of poverty, underscoring the need for comprehensive strategies to address its root causes and varied manifestations. The multidimensional approach to analyzing poverty has garnered significant attention over the past decades (see, among others, Atkinson and Bourguignon (1982), Bourguignon and Chakravarty (2003), Tsui (2002), Deutsch and Silber (2005), Duclos et al. (2006), Chakravarty et al. (2009), Bossert et al. (2013)).

The 2009 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 (Stiglitz et al., 2009).

Atkinson (2003) confirms the existence of significant mismatches between monetary poverty and multiple deprivations and, therefore, the need to include many dimensions of poverty, such as health, education, housing, satisfaction with life, security.

Over the years, scholars have worked to create theoretical frameworks reflecting this multidimensional approach (see, e.g., Bourguignon and Chakravarty (2003), Alkire and Foster (2011)). Composite indicators fulfill this requirement 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 aggregation methods for constructing composite indicators entail with a broad list of approaches, from simple ones, such as 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.

In addition, there has been a growing interest in the literature in estimating poverty and well-being at the local level, to help plan local policies aimed at reducing poverty and social exclusion. Only a limited number of empirical studies have investigated multidimensional poverty in Italy at the sub-national level, including De Rosa (2022), Coromaldi and Zoli (2012), and Betti et al. (2008). Our aim is to contribute further to this field by examining changes in multidimensional poverty at the provincial level resulting from the Covid-19 pandemic. Additionally, the paper offers a spatial analysis of the distribution of multidimensional poverty at a highly detailed territorial level, providing insights to assist policymakers in effectively targeting resources to the most vulnerable areas.

It is well known that social indicators at the regional level often fall short of providing the granularity needed to design effective social policies, as they may fail to capture the nuanced disparities and localized needs within smaller areas (Carley, 1981). In fact, regional averages can obscure significant intra-regional disparities. For example, a region may have an overall moderate poverty rate, but certain areas or communities within the region could experience extreme poverty. This drawback brings out the necessity to create and use indicator at local-level so that the policies in place seek to address challenges encountered by each community more precisely.

This study uses microdata from the Aspects of Daily Life (AVQ) Italian survey held during the years 2018 and 2019 (pre-Covid) and 2020 and 2021 (Covid Years).

We recall that AVQ survey is designed to provide accurate estimates at the regional level. Hence, to obtain estimates for poverty at provincial level we can adopt two main strategies. The first consists in increasing the AVQ sample size for the province of interest (oversampling) to ensure the reliability of direct estimates. The second approach requires the adoption of small area estimation (SAE) techniques; see, for example, Rao (2003) and Molina and Rao (2010).

According to the second solution, basic area level and unit level models have been extensively studied in the literature. The availability of auxiliary information at the unit level (e.g. individual or household level) makes it possible to use unit-level small area estimation models developed by Battese et al. (1988) (BHF model). When only area-level data are accessible (e.g. municipality or province level), there is the need to use area-level small area estimation models proposed by Fay and Herriot (1979) (FH model).

In recent years, a few papers on applying small area estimation methods in business statistics have been published, e.g. Hidiroglou and Smith (2005), Krieg et al. (2016), Fabrizi et al. (2016), Zimmermann and Münnich (2018). Furthermore, Marchetti et al. (2015) present a contribution to the use of small area estimation methods combined with big data and social mining aimed at improving the ability to measure, monitor, and predict social performance, well-being, deprivation, poverty, exclusion, and inequality on a fine-grained spatial and temporal scale.

To estimate elementary indicators at province level, we use the Fay–Herriot (FH) small area estimation methodology, which was first presented by Fay and Herriot (1979). We then provide a way to aggregate the FH estimates by using the Adjusted Mazziotta-Pareto Index (see Mazziotta and Pareto (2016, 2018)) and the penalized power mean method of Mariani et al. (2024). In accordance with the methodology described in Pratesi et al. (2021), this approach seeks to generate reliable estimates of multidimensional poverty for the local areas of concern.

As noted by Tzavidis et al. (2018), in recent decades, an increasing number of national statistical institutes and organizations worldwide have recognized the importance of producing small area statistics and their utility in informing policy decisions. The main reason is that National statistical surveys are often insufficient for producing reliable socio-demographic estimates at domain levels when sample sizes are small, primarily due to high costs. Thus, the use of SAE methods allows to provide highly detailed target information even with limited sample sizes (see Arias-Salazar et al. (2023)). In the United Kingdom, the yearly unemployment estimates for unitary authorities and local authority districts by age and gender, as well as the estimates of average income for electoral wards, are noteworthy examples of application of SAE in official national statistics. Case-studies of widespread applications of SAE are discussed in Bedi et al. (2007).

The use of SAE is of particular interest expecially in case of absence of (recent) census data. In this case, it is possible to integrate household level survey data with grid-level geospatial data, typically obtained from satellites, mobile phones, or internet activity (see, among others, Edochie et al. (2024)).

The goal is to improve the understanding of the differences in (multidimensional) poverty at local level in Italy, with a focus on Italian provinces. This knowledge is intended to assist policymakers in directing resources to the areas where the issue is most prevalent.

The construction of a composite indicator of multidimensional poverty involves several steps, such as the selection of (i) the relevant dimensions to represent multidimensional poverty; (ii) a set of indicators for the different domains of poverty; (iii) deprivation cutoffs in each indicator, for estimating the incidence of deprived households in each indicator at provincial level. Finally we aggregate the incidences of deprivation in the elementary indicators using a penalized power mean approach (with adjusted Mazziotta-Pareto index and penalized geometric mean as special cases) to obtain a composite indicator for each dimension of multidimensional poverty.

The empirical analysis reveals that the traditional Italian North vs. South divide becomes less clear when analyzing poverty at provincial level and for the different domains of poverty.

The remainder of the paper is as follows. Sections 2 and 3 describe data and methodologies considered in the analysis. Section 4 is devoted to results of the empirical application. Finally, Sect. 5 draws some conclusions.

2 Data

The data that we consider are from the Aspects of Daily Life ('Aspetti di Vita Quotidiana' - AVQ) survey conducted by the Italian National Institute of Statistics (Istat), focusing on the years between 2018 and 2021. AVQ is an annual multipurpose survey on households conducted by Istat since 1993. It involves yearly interviews with some 20,000 households, asking about their daily life activities, habits and the difficulties they face in everyday life. The data includes useful information for studying the quality of individual life, such as economic situation, employment, education, health status, perceptions of public services, technology use, housing conditions, lifestyle, social engagement and life satisfaction.

The aim of the paper is to estimate, according to a multidimensional approach, the incidence of deprived households in the Italian provinces over the time period of interest.[1]

To assess the multidimensional poverty we consider five domains - health[2], education, economic well-being, neighborhood quality and subjective well-being, each composed of different elementary indicators as described in Table 1.

In order to classify a household as deprived in each of the 10 elementary indicators considered, we first identify the deprivation cut-offs following the approach proposed in De Rosa (2022), which we have slightly modified due to the data availability at provincial level. The deprivation cut-offs, referred to the head of the household, are described in Table 1.

3 Methodology

The methodology implemented is a two-step procedure. We first apply the Fay–Herriot small area estimation model (Fay and Herriot, 1979) to estimate deprivation incidences for each of the 10 elementary indicators at provincial level. Then we aggregate them using non-compensative composite indicators, based on the Adjusted AMPI (Mazziotta & Pareto, 2018) index and the Penalized Geometric Mean approach by Mariani and Ciommi (2022)

[1] We consider 103 Italian provinces, excluding the provinces of Vibo-Valentia, Benevento, Belluno and Sondrio due the very high percentage of missing data.

[2] While we are aware of the potential limitations of the nutrition indicator in capturing nuanced differences over time for the health domain, particularly between the pre-Covid and Covid periods, its inclusion was guided by several considerations. 1) Relevance to health deprivation: the indicator reflects a fundamental aspect of individual well-being that is directly linked to health outcomes. Poor nutrition is a key determinant of both short-term and long-term health risks, which became increasingly relevant during the pandemic as dietary patterns were disrupted by many households. 2) Data availability: at the provincial level, consistent data on potential health-related deprivation indicators were unavailable. For example, the indicator "Self-reported general health" is available only at regional level. 3) Pandemic context: although the indicator may appear elementary, we posit that it provides insight into broader socio-economic disruptions caused by the pandemic, including access to food, economic constraints, and lifestyle changes. Direct links between COVID-19 pandemic and fruit/vegetable consumption have already stressed in literature (see for example Jordan et al. (2021) and Ubiparip Samek et al. (2023).

Table 1 Domains, elementary indicators, deprivation cut-offs

Domain	Elementary indicator	Deprivation cut-off
Health	Nutrition	A person is deprived if s/he consumes less than 3 portions of fruits or vegetables a day
Education	Educational deprivation	A person is deprived if s/he has not completed higher-secondary school
	Cultural deprivation	A person is deprived if in the 12 months before the interview s/he has joined less than 2 of the following activities: 1) at least once to cinema, theater, exhibitions and museums, archaeological sites, monuments, concerts of classical music, opera, concerts of other kind of music; 2) read the newspaper at least once a week; 3) read at least a book
Economic well-being	Material deprivation	A person is deprived if s/he possesses less than 4 out of 6 following items: washing machine, color tv, scooter/moto or car, phone, personal computer
	Housing deprivation	A person is deprived if s/he experiences 3 or more of the following deprivations related to the house: overcrowding; distance from basic services (pharmacy, shops, school); overall poor condition of the floors and/or walls; expenses too high; house not owned)
	Unemployment	A person is deprived if s/he is unemployed
Neighborhood quality	Noise	A person is deprived if the area in which s/he lives is declared to be very noisy; at risk of crime; polluted.
	Crime	
	Pollution	
Subjective well-being	Life satisfaction and future expectations	A person is deprived if s/he experiences 3 or more deprivations related to personal satisfaction (life, economic situation, health, family relationships and friends, leisure and future expectations)

and Mariani et al. (2024), to evaluate multidimensional poverty both domain-specific and overall.

3.1 The Fay–Herriot model

Small area estimation (SAE) allows us to produce estimates in domains or areas that are smaller than those for which the survey was originally planned. SAE combines survey data with auxiliary variables of the population of interest in order to break down regional estimates into sub-regional ones. The auxiliary variables are commonly obtained from population censuses or from administrative registers. If auxiliary information is available at unit-level (e.g., individual or household-level) one can consider unit-level SAE models: see, among others, Battese et al. (1988). When, on the contrary, the auxiliary data are available only at area-level (e.g., district, municipality or provincial level), area-level SAE models can be used.

We follow the latter approach and apply the Fay–Herriot area-level small area estimation model introduced by Fay and Herriot (1979), to obtain reliable estimates of the deprivation elementary indicators at provincial level; see also Molina and Marhuenda (2015) for more details.

Consider a finite population U, partitioned into $d = 1, \ldots, D$ mutually exclusive and exhaustive areas (in our case, provinces); the Fay–Herriot (FH) model is defined in two stages.

Let $\hat{\delta}_d^{DIR}$ be a direct estimator of δ_d, the parameter of inferential interest for area (province) d. In our analysis, parameter δ_d refers to the deprivation incidence in each elementary indicatory for province d. In the first stage, the model assumes that $\hat{\delta}_d^{DIR}$ is an unbiased estimator of δ_d:

$$\hat{\delta}_d^{DIR} = \delta_d + e_d, \qquad e_d \overset{ind}{\sim} N(0, \psi_d), \tag{1}$$

where ψ_d is the sampling variance of the direct estimator $\hat{\delta}_d^{DIR}$ given δ_d, assumed to be known for all $d = 1, \ldots, D$.

Since our target parameter is the proportion of deprived household, we guarantee that the corresponding estimate $\hat{\delta}_d^{DIR}$ will fall within the interval [0, 1] by applying an arc-sin transformation[3] Casas-Cordero Valencia et al. (2016), Schmid et al. (2017), Jiang et al. (2001)), as follows:

$$\hat{\hat{\delta}}_d^{DIR} = \sin^{-1}(\sqrt{\hat{\delta}_d^{DIR}})$$

In the second stage, we assume that the area parameters δ_d are linearly related with a p-vector x_d of area-level auxiliary variables as follows:

$$\delta_d = x_d^T \beta + u_d, \qquad u_d \overset{ind}{\sim} N(0, A). \tag{2}$$

Model (1) is known as a sampling model, as it represents the uncertainty due to the fact that δ_d is unobservable and the direct estimator is based on the sample data, $\hat{\delta}_d^{DIR}$. Model (2) is called linking model, since it relates all areas through the common regression coefficients β, allowing the estimates to borrow strength from all areas.

The model components (1) and (2) can be combined in the following linear mixed model:

$$\hat{\hat{\delta}}_d^{DIR} = x_d^T \beta + u_d + e_d, \tag{3}$$

where u_d is independent of e_d.

An empirical best linear unbiased predictor (EBLUP) is given by the following linear combination of the direct and the regression-synthetic estimators (see Henderson (1975)):

$$\hat{\delta}_d^{EBLUP} = \hat{\gamma}_d \hat{\hat{\delta}}_d^{DIR} + (1 - \hat{\gamma}_d) x_d^T \hat{\beta}, \tag{4}$$

where $\hat{\gamma} = \frac{\hat{A}}{\hat{A} + \hat{\psi}_d}$ represents a shrinkage factor, where $\hat{A}$ and $\hat{\psi}_d$ are consistent estimators of A and ψ_d, respectively. Therefore, if the direct estimates show small variability (estimated with $\hat{\psi}_d$), then the EBLUP estimate will be mainly driven by the direct estimate; on the

[3] The arc-sin transformation reduces the variability of data by compressing the scale of extreme values (near 0 or 1) while expanding intermediate values. This adjustment stabilizes variance across small areas, making the estimates more reliable by reducing the disproportionate influence of extreme values in small sample areas. This, in turn, enhances the robustness of comparisons at provincial level and the overall validity of the findings.

contrary, for areas in which the direct estimates are highly volatile, the EBLUP estimate will mainly rely on the auxiliary variables.

For each of the 10 elementary indicators of deprivation j under analysis and for each Italian province d we obtain an EBLUP estimate, denoted with $\hat{\delta}_{dj}^{EBLUP}$. For sake of simplicity, henceforth we will indicate estimator $\hat{\delta}_{dj}^{EBLUP}$ simply with $\hat{\delta}_{dj}$.

3.2 The proposed aggregation process

To summarize the EBLUP provincial estimates $\hat{\delta}_{dj}$ obtained for each indicator j and for each province d, with $j = 1, \ldots, M$, $d = 1, \ldots, N$ where $M = 10$ and $N = 103$, into a single composite index, we propose two aggregation techniques: the Adjusted Mazziotta-Pareto Index (hereafter, AMPI) (Mazziotta & Pareto, 2018) and the Penalized Geometric Mean (hereafter, PGM) (Mariani & Ciommi, 2022).

We observe that AMPI and PGM are two particular cases of Penalized Power Mean (Mariani et al., 2024) of order 1 and 0, respectively.

First, the provincial estimates are normalized according to the min-max method and scaled in order to set the reference values equal to the mean values in 2018.

More in detail, following Mazziotta and Pareto (2018), we denote by Ref_{δ_j} the reference value for the indicator j and the 'goalposts' $Max(\hat{\delta}_{dj})$ and $Min(\hat{\delta}_{dj})$ are defined as:

$$\begin{cases} Min(\hat{\delta}_{dj}) = Ref_{\delta_j} - \Delta \\ Max(\hat{\delta}_{dj}) = Ref_{\delta_j} + \Delta \end{cases} \tag{5}$$

where $\Delta = \frac{Sup_{\delta_j} - Inf_{\delta_j}}{2}$. Inf_{δ_j} and Sup_{δ_j} are the overall minimum and maximum of the indicator $\hat{\delta}_{dj}$ across all provinces and the years considered. Here, we choose as Ref_{δ_j} the mean of the year 2018.

Hence, the j-th normalized indicator for the province d, r_{dj}, is

$$r_{dj} = \frac{\hat{\delta}_{dj} - Min(\hat{\delta}_{dj})}{Max(\hat{\delta}_{dj}) - Min(\hat{\delta}_{dj})} 60 + 70. \tag{6}$$

and, consequently, r_{dj} will fall approximately in the range (70; 130), where 100 represents the reference value, corresponding to the Italian mean in the year 2018.

Thus, denoting with M_d and S_d, respectively, the mean and standard deviation of the normalized indicators $r_{d1}, r_{d2}, \ldots, r_{dM}$ of province d, the multidimensional poverty index of province d is computed as:

$$\text{AMPI}_d = M_d(1 \pm S_d^2), \tag{7}$$

where the sign $\pm$ depends on the polarity of the indicators. Note that, the term $1 \pm S_d^2$ in (7) is a multiplicative factor which penalizes the indicators with larger standard deviation. Thus AMPI penalizes more the local units showing larger horizontal heterogeneity among the elementary indicators.

Similarly, PGM associated to the province d is defined as:

$$PGM_d = \left(\prod_{j=1}^{M} r_{dj} \right)^{\frac{1}{M}} \cdot \exp\{\pm \tilde{S}_d^2\}, \tag{8}$$

where $M = 10$, $\tilde{S}_d^2$ is the horizontal variance among indicators, after being transformed through the Box-Cox transformation (Box & Cox, 1964) of order 0 (natural logarithm). The term $\tilde{S}_d^2$ is given by:

$$\tilde{S}_d^2 = \frac{1}{M}\sum_{j=1}^{M}\left(\ln(r_{dj}) - \frac{1}{M}\sum_{k=1}^{M}\ln(r_{dj})\right)^2 . \tag{9}$$

and measures the error caused by substituting the vector of indicators $\ln(r_{d1}), \ln(r_{d2}), \ldots, \ln(r_{dM})$ with their arithmetic mean $\frac{1}{M}\sum_{j=1}^{M}\ln(r_{dj})$.

PGM of province d is given by the geometric mean of the indicators multiplied by the penalization factor $\exp(\pm S_d^2)$. Roughly speaking, to compute the penalized factor of PGM, first, we rescale the indicators by their geometric mean. Second, we transform the scaled indicators via the Box-Cox function of order 0 and we compute the sample variance of the transformed scaled indicators. Finally, we obtain the penalization factor anti-transforming the sample mean (see Mariani and Ciommi (2022) for more details).

AMPI and PGM are applied within domain and among domains, first computing a composite indicator at domain level, and then aggregating the 10 elementary indicators into an overall multidimensional poverty index.

4 Empirical results

Results of the empirical application are provided in two sections. Section 4.1 presents the results relatively to the EBLUP estimates, while Sect. 4.2 illustrates the estimates of the composite indicators of multidimensional poverty both domain-specific and overall.

4.1 Provincial deprivation incidences: EBLUP estimates

The direct estimates of the 10 deprivations head-count used for the construction of the overall poverty index and by specific domain for the Italian provinces, are not reliable since the AVQ survey is not planned to produce efficient estimates at the provincial level. For this reason, we first applied the FH model to obtain reliable estimates for each of the 10 elementary indicators before proceeding to the aggregation process.

To compute the FH models, we selected the candidate auxiliary variables to be used as covariates in the model from the ones available through the Istat Population Census 2019 (https://demo.istat.it). For each of the 10 indicators, we selected the best set of covariates using a logistic regression model based on a stepwise procedure. Table 4 in the Appendix reports the list of the auxiliary variables selected for estimating the FH model.

It is expected that model-based estimates lead to gains in efficiency compared to direct estimates (Salvati et al., 2010; Harmening et al., 2023; Tonutti et al., 2022). In Table 2 we report the distribution of the coefficients of variation (CV) for comparing FH model-based estimates and direct estimates, classified according to different values of CV. In Official Statistics an estimate with a CV greater than 33.3% is usually considered unreliable and is not recommended for release, estimates with a CV between 16.6% and 33.3% should be released with caveats due to their high sampling variability, while estimates with a CV of less than 16.6% are of sufficient accuracy to have no release restrictions (Statistics Canada 2016).

Table 2 Number of provinces with coefficient of variation (CV) of direct and FH estimates ≤16.6, between 16.6 and 33.3, and ≥33.3, for year 2021

	Direct			FH		
Elementary indicator	≤16.6	16.6−33.3	≥ 33.3	≤16.6	16.6−33.3	≥ 33.3
Material	44	57	2	103	0	0
Crime	24	63	16	46	44	13
Cultural	91	12	0	103	0	0
Edu. depr	81	21	1	103	0	0
Nutrition	94	9	0	103	0	0
Housing	44	1	58	21	79	3
Noise	7	49	47	16	61	26
Pollution	52	40	11	72	23	8
Life expectation	3	31	69	6	90	7
Unemployment	3	39	61	48	55	0

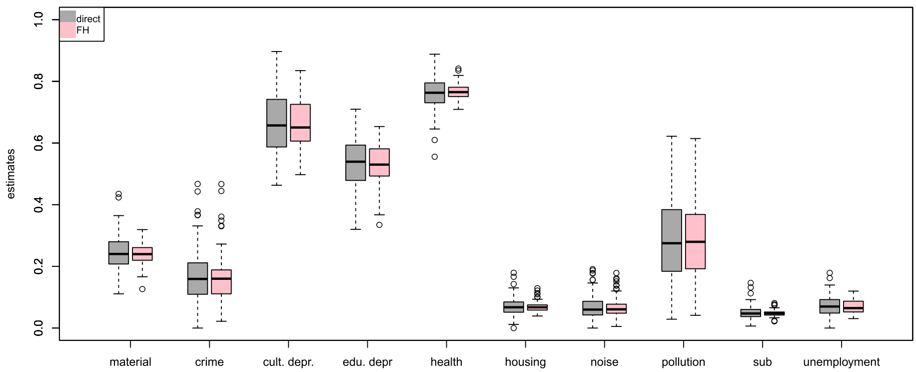


Fig. 1 Boxplot of the provincial estimates for each elementary indicator: direct (grey) vs FH (pink), year 2021

As Table 2 shows, FH model-based estimates provide a very good improvement in terms of estimated efficiency, with almost all CVs smaller than 33.3%.[4]

In Fig. 2, we plot the estimated CV of direct estimates against the CV of small area estimates. In most of the provinces, the small area estimates are more efficient than the direct estimates: the CVs of small area estimates are lower than the CVs of direct estimates associated with almost similar estimate values (see Fig. 1).

Model diagnostics about the distribution of residuals in the three models are shown in Fig. 3. For each of the 10 elementary indicators, a quantile-quantile plot (QQplot) for the sampling errors and for the random effects is shown. The normality assumption can be reasonable for the sampling errors, while it is not for the random effects. However, using the arc-sin transformation, we obtain a better approximation to normality than we would do using a linear FH model. Moreover, the arc-sin transformation has the advantage of stabilizing the variance in those areas where the sample size is very small.

[4] We assessed the reliability of the FH estimates by computing CVs for all the years under analysis: the percentage of provinces with CV greater than 33.3% is 6.21%, 2.62%, 7.57% and 5.53%, respectively for the years 2018, 2019, 2020 and 2021.

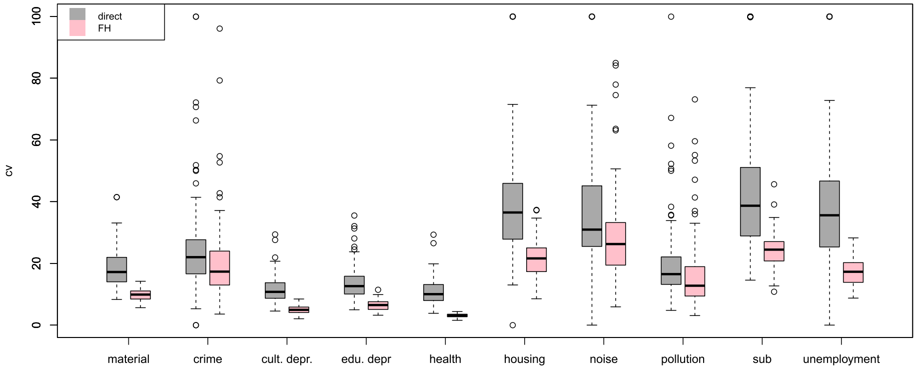


Fig. 2 Boxplot of the provincial coefficient of variation for each elementary indicator: direct (grey) vs FH (pink), year 2021

4.2 Multidimensional poverty composite indicators

We now move on analyze how multidimensional poverty changed over time before and after the outbreak of the Covid-19 pandemic. Here we illustrate the results based on the PGM composite indicator. Figures 4, 5, 6, 7, 8 and 9 in the Appendix depict a geographical representation of how the multidimensional poverty indicators - both domain-specific and overall - are distributed across the Italian provinces over the period 2018–2021. Darker colors in the maps represent higher levels of multidimensional poverty.

Comparing Fig. 4k–n it can be seen how economic poverty clearly divides North from South. In 2021 poverty in the economic dimension decreases in many provinces, since the social protection policies implemented helped the poorest people more. Poverty in the quality of the neighborhood (mainly due to pollution and crime) was higher for the majority of the northern provinces with some exceptions. In 2021 its values decrease in several local territories (Fig. 7a–d).

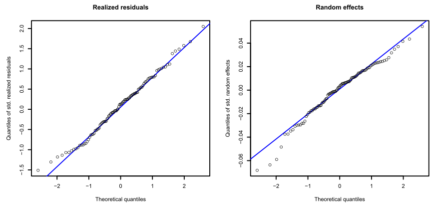
On the contrary, the domains that were mainly affected by the pandemic are health, education and subjective well-being. Figure 6a–d reveals that in the first year of the pandemic, 2020, health poverty increases in most of the country, with the exception of some North-East provinces. Poverty in education and in subjective well-being were also strongly affected by Covid-19 (Figs. 5a–d and 8a–d) mainly associated with a steep increase in the second year of the pandemic, 2021.

If we join all the domains together, the overall multidimensional poverty index, depicted in Fig. 9a–d, seems to have deteriorated mainly during the second year of the pandemic (2021), with its levels remaining higher in the South of Italy.

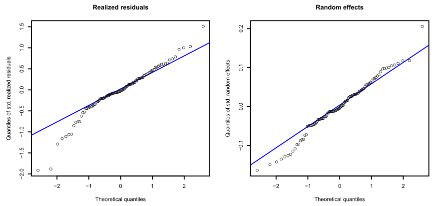
These estimates are summarized in Table 3, where we note that the average levels of deprivation are higher in the South of Italy than in the provinces of Central and Northern Italy for all the years considered. However, deprivations related to the economic dimension and subjective well-being, respectively, decrease and increase in the South due to COVID-19, flattening the mean gap with the North (0.320 vs 0.496 and 0.605 vs 0.602).

We note that some domains of poverty (education and subjective well-being) have worsened in many provinces, but their effects have been compensated by the opposite trend registered for economic well-being and quality of neighborhood.

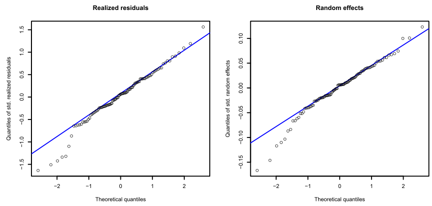
Figure 10 compares provincial rankings based on PGM with the ones based on AMPI composite indicator, revealing that rankings are highly correlated.



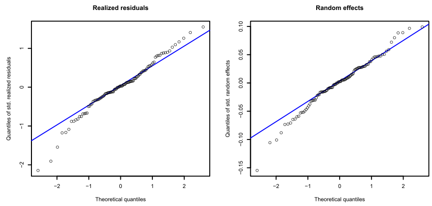
(a) Material



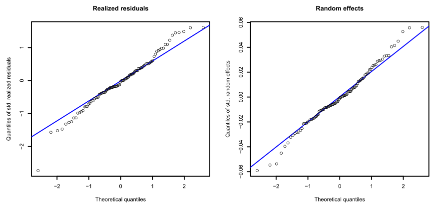
(b) Crime



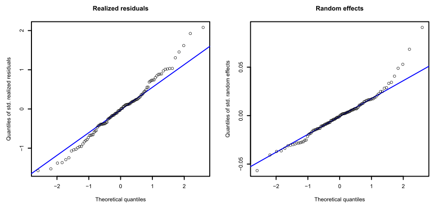
(c) Cultural



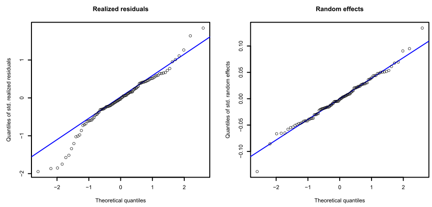
(d) Edu. depr



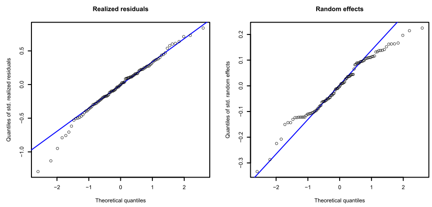
(e) Nutrition



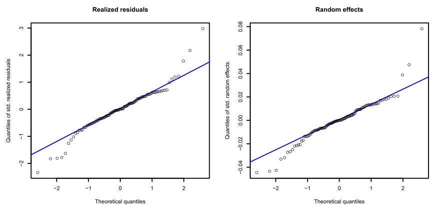
(f) Housing



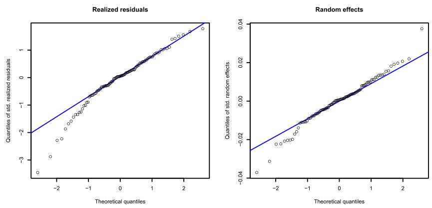
(g) Noise



(h) Pollution

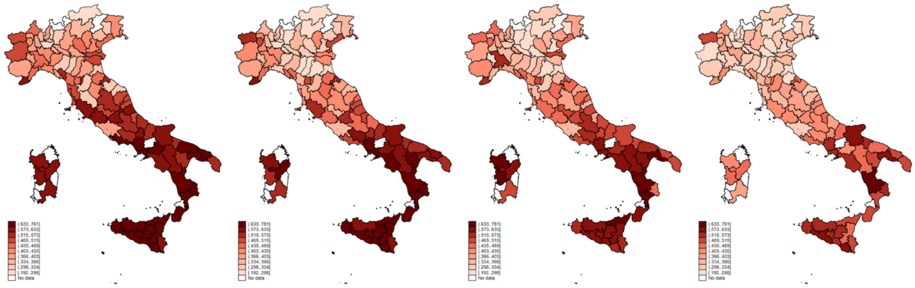


(i) Life expectation



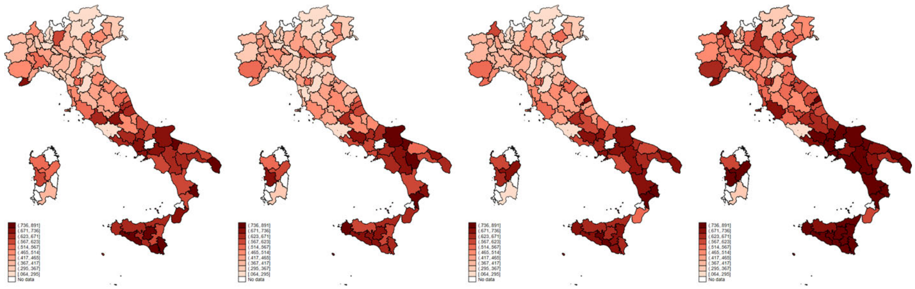
(j) Unemployment

Fig. 3 QQplot for model residuals (sampling errors and random effects) for arc-sin transformed FH models for the deprivation indices



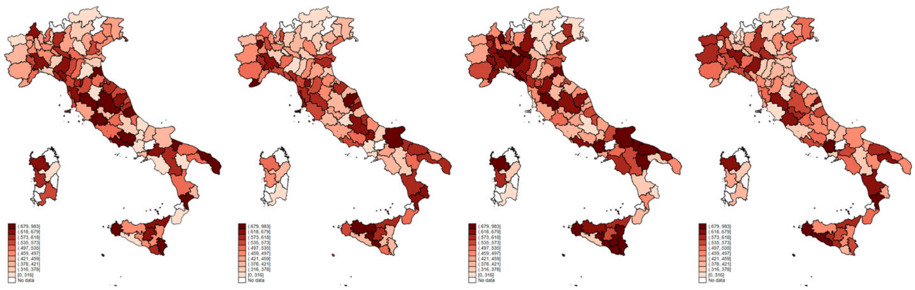
(k) 2018 (l) 2019 (m) 2020 (n) 2021

Fig. 4 Poverty in economics over the years 2018–2021 according to the PGM aggregation technique



(a) 2018 (b) 2019 (c) 2020 (d) 2021

Fig. 5 Poverty in education over the years 2018–2021 according to the PGM aggregation technique

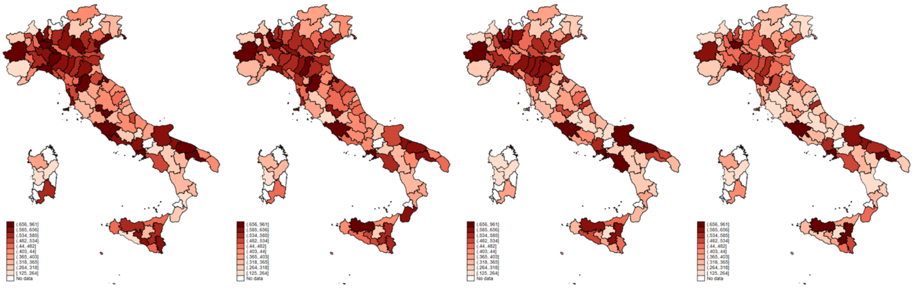


(a) 2018 (b) 2019 (c) 2020 (d) 2021

Fig. 6 Poverty in health over the years 2018–2021 according to the PGM aggregation technique

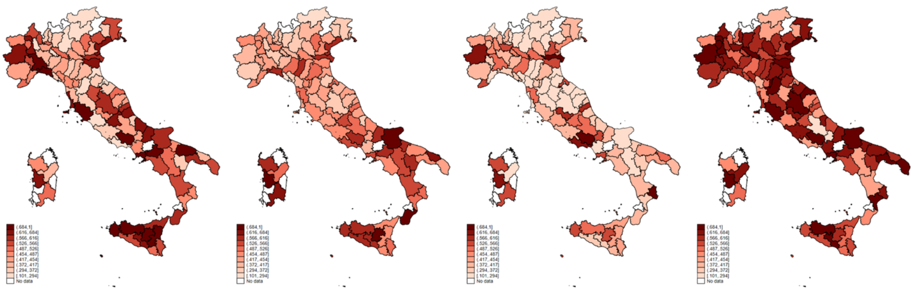
5 Concluding remarks

This study contributes to the understanding of multidimensional poverty dynamics in Italy, offering valuable insights for policymakers in addressing local disparities and focusing on targeted interventions for improved well-being outcomes. A territorial analysis of poverty is, indeed, important in order to detect the geographical areas that are more in difficulty and to better direct the economic resources available.



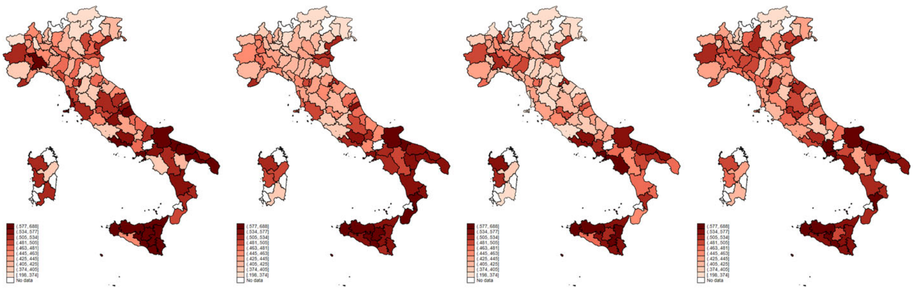
(a) 2018 (b) 2019 (c) 2020 (d) 2021

Fig. 7 Poverty in neighborhood quality over the years 2018–2021 according to the PGM aggregation technique



(a) 2018 (b) 2019 (c) 2020 (d) 2021

Fig. 8 Poverty in subjective well-being over the years 2018–2021 according to the PGM aggregation technique



(a) 2018 (b) 2019 (c) 2020 (d) 2021

Fig. 9 Overall deprivation over the years 2018–2021 according to the PGM aggregation technique

Since survey direct estimates are reliable only at regional (NUTS 2) level, the introduction of small area estimation techniques is of crucial importance to monitor and contrast the phenomenon at a finer geographical level.

The study reveals significant disparities in social and economic well-being between northern and southern provinces, with the northern provinces consistently demonstrating lower levels of multidimensional poverty. Results showed that within the same region there are very

Table 3 Small area estimates of deprivation at province level summarized by Italian partitions

	2018		2019		2020		2021	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Italy								
Economic	0.493	0.485	0.468	0.445	0.446	0.444	0.395	0.392
Education	0.496	0.495	0.477	0.462	0.491	0.483	0.595	0.588
Health	0.500	0.515	0.479	0.486	0.527	0.534	0.480	0.473
Neighbourhood quality	0.492	0.475	0.480	0.471	0.444	0.421	0.413	0.399
Subjective well-being	0.500	0.492	0.475	0.459	0.398	0.399	0.598	0.602
Overall deprivation	0.481	0.468	0.466	0.460	0.446	0.441	0.481	0.473
North								
Economic	0.392	0.395	0.366	0.351	0.359	0.355	0.320	0.311
Education	0.378	0.377	0.366	0.381	0.363	0.377	0.489	0.500
Health	0.464	0.470	0.439	0.452	0.501	0.512	0.445	0.430
Neighbourhood quality	0.532	0.537	0.503	0.519	0.474	0.486	0.425	0.416
Subjective well-being	0.455	0.447	0.430	0.433	0.388	0.398	0.605	0.602
Overall deprivation	0.431	0.442	0.412	0.415	0.404	0.407	0.443	0.445
Centre								
Economic	0.471	0.479	0.436	0.434	0.431	0.441	0.384	0.399
Education	0.483	0.489	0.446	0.461	0.489	0.490	0.583	0.584
Health	0.591	0.585	0.518	0.555	0.507	0.475	0.472	0.485
Neighbourhood quality	0.491	0.440	0.478	0.461	0.419	0.391	0.404	0.360
Subjective well-being	0.461	0.464	0.448	0.452	0.374	0.308	0.579	0.604
Overall deprivation	0.484	0.495	0.456	0.456	0.430	0.428	0.469	0.467
South								
Economic	0.631	0.632	0.615	0.621	0.563	0.570	0.496	0.485
Education	0.652	0.647	0.635	0.647	0.651	0.667	0.736	0.770
Health	0.490	0.514	0.506	0.502	0.570	0.566	0.529	0.511
Neighbourhood quality	0.444	0.418	0.452	0.429	0.422	0.382	0.403	0.354
Subjective well-being	0.581	0.558	0.547	0.549	0.426	0.405	0.602	0.600
Overall deprivation	0.541	0.536	0.539	0.545	0.507	0.517	0.534	0.534

different realities and dynamics in terms of multidimensional poverty. Some provinces have been more affected by the pandemic while others, on the contrary, have improved their poverty level. Some domains of poverty (in particular, subjective well-being, education, health) have worsened in many provinces, while opposite trend was registered for quality of neighborhood. Overall, the multidimensional poverty index seems to have deteriorated mainly during the second year of the pandemic, and poverty levels remain higher in the South of Italy.

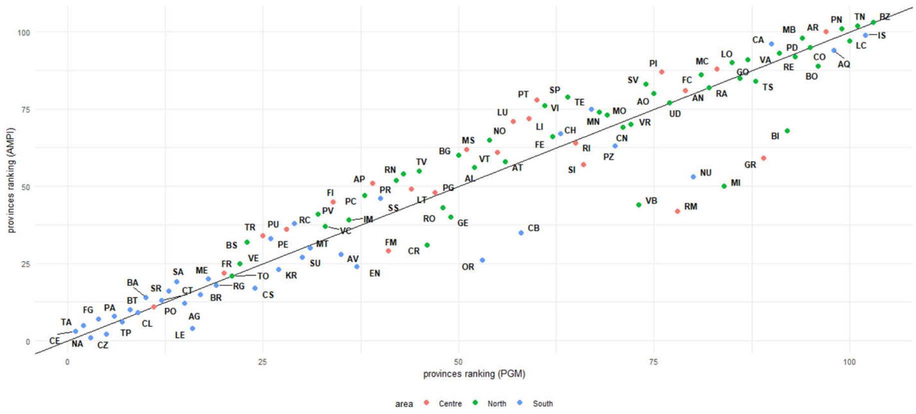


Fig. 10 Rankings of the provinces in the year 2021 according to the AMPI and PGM aggregation techniques. Provinces lying on the straight line do not change their ranking; provinces above (below) the line improve (worsen) their ranking when moving from PGM to the AMPI approach

Appendix A

See Table 4.

Table 4 List of selected auxiliary variables from Population Census 2019 (Istat) for each elementary indicator for the four years considered.

Elementary indicators	Name of covariate variables
Material deprivation	Average annual salary of employees (euro)
Housing deprivation	Average annual salary of employees (euro), Pick-pocketings reported (%), Robberies reported (%), Electrical service irregularities (%)
Unemployment	People aged 4-5, 6-10, 20-29 and 85+in population (%), Female in population (%), Average annual salary of employees (euro)
Cultural deprivation	Average annual salary of employees (euro) , Employed in local units of cultural entreprises (%)
Educational deprivation	Average annual salary of employees (euro)
Nutrition	People aged 30-59 and 85+in population (%), Life expectancy at birth (average number of years), Urban green (%), Electrical service irregularities (%)
Pollution	Life expectancy at birth (average number of years), Urban green (%)
Noise	Robberies reported (%)
Crime	Average annual salary of employees (euro), Robberies reported (%) , Pick-pocketings reported (%)
Subjective well-being	Ratio of people aged 4-5, 15-17, 18-19, 30-59 and 85+in population, PM10 Annual average concentration (micrograms per m^3), Robberies reported (%)

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Data Availibility Statement The data used in this paper are from Istat's Aspects of Daily Life ('Aspetti di vita quotidiana') survey. The elaborations were carried out at Istat's ADELE ('Analisi dei Dati ELEmentari') laboratory and in compliance with the legislation on protection of statistical confidentiality and personal data. The responsibility for results and opinions expressed in the paper rests solely with the authors. The analyses have been carried out without sampling weights.

Declarations

Conflict of interest The authors declare that they have no Conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent Not applicable.

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