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INCOME INEQUALITY AND INNER AREAS. A STUDY ON THE ITALIAN CASE

Graziella Bonanno

University of Salerno, Department of Economics and Statistics

(e-mail: gbonanno@unisa.it)

Filippo Domma

University of Calabria, Department of Economics, Statistics and Finance "Giovanni Anania" – DESF

(e-mail: filippo.domma@unical.it)

Lucia Errico

University of Calabria, Department of Economics, Statistics and Finance "Giovanni Anania" – DESF

(e-mail: lucia.errico@unical.it)

Info
Via Pietro Bucci, Cubo **0/C**
87036 Rende (Cs) - Italia
tel. (+39) 0984 492434 / 492422

http://www.unical.it/desf

Income inequality and inner areas. A study on the Italian case

Graziella Bonanno[a], Filippo Domma[b], Lucia Errico[b]

[a] *Department of Economics and Statistics, University of Salerno, Fisciano (Italy)*
gbonanno@unisa.it

[b] *Department of Economics, Statistics and Finance 'Giovanni Anania', University of Calabria, Rende (Italy)*
filippo.domma@unical.it ; lucia.errico@unical.it

Abstract

This paper investigates the impact of 'inner areas' on income inequality of the Italian municipalities during the period 2012-2018. In doing so, we employ the Beta GLMM approach to overcome the limits arising from the use of the Gaussian distribution in the analysis of income, as suggested by the existing empirical literature. Our main results show that inner areas of Southern Italy seem to have a higher concentration index than the internal areas located in the North. However, in the South, the odds ratio of the average concentration of inner areas appears to be lower than that in central zones. This finding seems to be driven by the peripheral and ultra-peripheral municipalities, highlighting the importance of analysing the phenomenon under scrutiny at a more disaggregated level.

Keywords: Inequality, Inner areas, Italy, Beta GLMM

JEL codes: I30, O15, R10

1. INTRODUCTION

The economic crisis originated by the Covid-19 pandemic has further exacerbated the issue of income distribution and economic inequalities, already at the heart of the political debate both at national and Community levels. Recent contributions provide extensive empirical evidence on income inequality between and within countries and potential factors influencing this disparity (Furceri and Ostry, 2019; OECD, 2021).

However, at least two critical elements are recognisable in the existing literature. The first aspect regards the focus of empirical analyses, which often focuses only on some determinants of the income distribution, neglecting others. In particular, different works tend to consider a broad geographic scope by using data on the entire national territory, leaving out relevant local characteristics, which are fundamental in explaining the wealth and inequalities of income (Atkinson and Brandolini, 2009; Förster and Tóth, 2015; Furceri and Ostry, 2019; Nolan et al., 2019; Viesti, 2021). In other words, the territorial dimension appears to be very important in defining inequalities and, above all, in the opportunities that can be seized to reduce them. The second concern is the methodology adopted, which often does not adequately capture the characteristics of the outcome variable most commonly used in the literature – the income concentration index or Gini index. Indeed, although the latter is included in the continuous interval (0,1), several contributions present empirical analyses involving the estimation of the impact of various explanatory variables on the Gini index by using linear models.

Moving from these considerations, this paper aims to fill the gaps in the existing literature. On the one hand, we analyse the impact of 'inner areas' on the income inequality of Italian municipalities from 2012 to 2018. In particular, this time span allows us to observe for a long period the characteristics of each local government in terms of opportunities and economic trends. Regarding the territorial aspect, the municipalities are considered internal or centre by following the National Strategy for Inner Areas (SNAI) classification in 2014.

More in detail, based on service provision criterion, SNAI identifies six categories of municipalities: 'poles', 'inter-municipality poles', 'outlying', 'intermediate', 'peripheral' and 'ultra-peripheral areas'. These last three classes then constitute the so-called Internal Areas, defined as the part of the Italian territory that is to a considerable distance from the centres of supply of essential services (Carlucci et al., 2012; Barca et al., 2014). Intuitively, the remaining categories flow to the general definition of Centres, which offer an extensive range of essential services (i.e. school, health and rail transport services).[1] The periphery of the territories (in a spatial sense) may represent a handicap under certain conditions and, as a result, influence citizens' quality of life and their level of social inclusion. However, their remoteness can turn a principal value from an environmental point of view that can be exploited for economic purposes.

To the best of our knowledge, the impact of being an 'inner areas' municipality seen as a potential driver of income distribution and, mainly, the role played by the most extreme internal zones has been so far neglected in the literature. Indeed, only Gallo and Pagliacci (2020) and Mastronardi and Cavallo (2020) have addressed such an issue at the municipality level, focusing on the relationship between territoriality and income inequality through the SNAI classification.

On the other hand, employing the Gini index as a measure of inequality and exploiting the panel nature of our data, we use Beta GLMM models – suitable for longitudinal and multilevel structure data – to overcome the statistical limits highlighted by adopting Gaussian regression models in this context.

Our main results of the econometric analysis suggest that the territorial differences are evident between two areas of the country. In detail, the inner areas of Southern Italy appear to

[1] Refer to Barca et al. (2014) for a more precise description of territorial Inner Areas identification and organisation criteria.

have a higher inequality than those located in the North. However, in the *Mezzogiorno*, internal areas seem to decrease income concentration regarding to non-inner municipalities. Moreover, when we look at the disaggregation of the inner areas in the following categories "intermediate", "peripheral", and "ultra-peripheral" municipalities, we find more heterogeneous evidence. In particular, the overall results discussed above appear to be driven by the municipalities classified as peripheral and ultra-peripheral areas, for which we estimate very significant parameters.

The remainder of this work is organised as follows. The next section offers a review of the literature. Sections 3 and 4 illustrate the empirical methodology and data used. Section 5 discusses the results obtained. Section 6 concludes.

2. RELATED LITERATURE

Studies on the economic mechanisms underlying the formation of economic-social inequalities and the economic and social impact, in the short and long term, have attracted a considerable variety of scholars from different disciplines since the end of the 18th century and the beginning of the XIX.

After the demographic growth and the Industrial Revolution, scholars posed the problem of the possible consequences of these events on the wealth distribution and balance of power between social classes. Scholars such as Malthus, Ricardo and Marx analysed economic and social transformations from different points of view and various conceptual tools. In a nutshell, they shared relatively pessimistic conclusions about the long-term wealth distribution process.

Kuznets (1955) gave a decisive turn to the pessimistic views of 19th-century scholars. According to his theory, income inequalities were destined, in the advanced phase of capitalist development, to spontaneously decrease regardless of the policies followed or the country's characteristics until they stabilised at an acceptable level. The optimism placed by Kuznets in the natural force of economic development caused a certain lack of interest in the study and analysis of economic and social inequalities.

The growing availability of datasets on the income and wealth of populations, the development of specific indicators and increasingly reliable statistical models have allowed numerous studies on the dynamics of inequalities, highlighting a considerable increase in the last decades. For instance, Piketty's research from 1998 to 2013 on the historical dynamics of incomes and assets provided strong empirical evidence on the failure to realise Kuznets' optimistic forecasts starting in the 1970s.

Overall, two strands of literature study the impact of several determinants on income inequality. The first one is related to macroeconomic determinants, and the second bunch of papers refers to the analysis of the income concentration at a micro-level (i.e. municipalities, provinces). Our work relates to the second part of mentioned literature.[2]

The empirical literature considers different groups of determinants to consider the theoretical aspects of the income distribution. Specifically, demographic and gender factors represent two essential drivers for income inequality. An approach commonly adopted in empirical contributions is evaluating demographic phenomena using the share of the inactive population (persons under the age of 15 and persons over the age of 65) in the total population (Burtless, 2009). However, the contributions that have dealt with testing the effect of gender on income distribution are very recent and continue to leave many aspects unexplored (Dang and Nguyen, 2021). Furthermore, the explanatory components relating to education and training levels deserve particular attention in studying income distribution (Gregorio and Lee, 2002; Bergh and Fink, 2008; Abdullah et al., 2015). Finally, other fundamental variables and indicators that potentially influence economic inequalities are also accounted for, such as local development indicators (Rajan and Zingales, 2003; Law et al. 2014; Acciari and Mocetti, 2013;

[2] For detailed reviews see Atkinson and Brandolini (2009), Förster and Tóth (2015), and Nolan et al. (2019).

Furceri and Ostry, 2019; Ostry et al., 2021), technological improvements (Dao et al., 2017), and internationalisation (Helpman, 2016; Furceri and Loungani, 2018).

In recent decades, empirical studies on income inequality have highlighted profound geographical differences, especially in Italy, where the highest levels above the European average are recorded. In particular, it was highlighted that the average level of the Gini index, in reality, hides a strong heterogeneity between the geographic macro-areas of the country, between regions and between Italian provinces. The study by Acciari and Mocetti (2013), using data on tax returns from the Ministry of Economy and Finance (MEF), shows that, in 2011, the Gini index in the South was three percentage points higher than that related to Central and Northern regions. However, the authors believe that this gap does not explain all the heterogeneity of inequality at the territorial level. The territorial differentials within the two geographical macro-areas are wide. In this direction, Mauro et al. (2018) provide a set of statistical methods suitable for measuring and comparing family incomes inequality between different regions of Italy and within each area, also to assess how much these inequalities contribute to overall inequality at the national level.

According to a very recent economic literature (Gallo and Pagliacci, 2020; Viesti 2021), in the spatial analysis of the study of differences in inequalities in income between institutional geographical units (regions, provinces and cities), the effect of the centres and suburbs, as defined by the SNAI, should also be taken into account. Indeed, the latter represents a direct action to support sustainable territorial competitiveness and oppose, in the medium term, the demographic decline that characterises the internal areas of the country. In this regard, Gallo and Pagliacci (2020) analyse the impact of territoriality on income inequality using data on the Italian municipalities in 2015. They find a positive effect of being peripheral and ultra-peripheral on the Gini index with respect to cities classified as poles. In this case, the differences between the inner areas and the other categories (inter-pole and belt municipalities) are not estimated. Finally, by using data for the Italian cities in 2015, Mastronardi and Cavallo (2020) use a binary variable to test the differences between poles and other local development groups. Their findings are in line with the idea urban centres present an greater inequality as the characterising social and economic context allows for more job opportunities, especially in the tertiary industry, and high levels of income.

In the light of the existing literature, we study the role of inner areas on inequality compared to all centres typologies (i.e. poles, inter-poles, outlying cities). In doing so, first, we use a dichotomous variable for inner areas towns. Second, disaggregating the internal zones into the simple categories defined by SNAI, we evaluate the effect of intermediate, peripheral and ultra-peripheral municipalities on income concentration by considering three different binary variables. This strategy allows us to exploit the heterogeneity, finding that some critical evidence is driven by the extreme categories comprised in the definition of Inner areas.

3. DATA

Several sources have been used to retrieve our data. The fiscal declarations on a municipal basis for 2012-2018 are drawn from the Ministry of Economy and Finance (MEF – Department of Finance) website.[3] Information on Italian Inner areas, based on the National Strategy for Inner Areas (SNAI) classification in 2014, comes from the National Agency for Territorial Cohesion website.[4]

Data on municipalities' personnel indicators, demographic characteristics and other local features are obtained from ISTAT (Italian National Institute of Statistics).[5] Moreover, we have consulted the Bureau van Dijk's Aida PA to get financial data on the local authorities.[6] Lastly,

[3] https://www1.finanze.gov.it/finanze3/pagina_dichiarazioni/dichiarazioni.php.
[4] https://www.agenziacoesione.gov.it/strategia-nazionale-aree-interne/.
[5] https://www.istat.it/.
[6] https://www.bvdinfo.com/en-gb/our-products/data/national/aida-pa.

information on municipal administrators comes from the Italian Ministry of the Interior website.[7]

The Department of Finance provides tax data of all the municipalities, including the stock of taxpayers and the amount of total income declared by each of them, for seven income intervals. To allow comparability, the latter does not change over time and across municipalities and, in particular, is divided as follows: (i) 0–10,000; (ii) 10,000–15,000; (iii) 15,000–26,000; (iv) 26,000–55,000; (v) 55,000–75,000; (vi) 75,000–120,000; and (vii) greater than 120,000. As a result, seven mean incomes by municipality can be obtained and, hence, exploited to calculate the Gini Index.[8]

According to SNAI classification, municipalities are classified as 'poles', 'inter-municipality poles', 'outlying'; 'intermediate'; 'peripheral' and 'ultra-peripheral' areas (for further details, see Barca et al. 2014).

4. EMPIRICAL STRATEGY: METHODOLOGY, MODEL AND VARIABLES

In this paper, we provide a more appropriate specification of the model that allows to explain the measure of economic inequality (in our casa, the Gini index) with a set of predictors, taking into account both the hierarchical structure and panel nature of the data available. Given that the Gini index can be consider a random variable in the continuous interval $(0,1)$, one of the possible distributions that can be used to interpret this variable with limited support is the Beta distribution. Indicated with G the Gini index, the Beta probability density function (*pdf*) parametrized in terms of mean and precision parameters is given by

$$f(G;\mu,\phi)=\frac{1}{B(\mu\phi,\ (1-\mu)\phi)}\,G^{\mu\phi-1}(1-G)^{(1-\mu)\phi-1}$$

[7] https://dait.interno.gov.it/elezioni/open-data.

[8] This analysis does not consider municipalities created after 31st December 2018.

with $0 < G < 1, 0 < \mu < 1$ and $\phi > 0$, where $B(.,.)$ is the Beta function. It is known that the mean is $E(G) = \mu$ and the variance is $V(G) = \frac{\mu(1-\mu)}{1+\phi}$; the parameter ϕ is a precision parameter because the greater its value, the smaller the variance of G. Indicated by $\{G_1, G_2, \dots, G_n\}$ the value of the Gini index observed for the n municipalities, the Beta regression model requires that the mean and the precision parameter are linked to linear predictor as follows

$$g_1(\mu_i) = \boldsymbol{x}_i'\boldsymbol{\beta}$$

$$g_2(\phi_i) = \boldsymbol{w}_i'\boldsymbol{\gamma}$$

where $\boldsymbol{x}_i'$ and $\boldsymbol{w}_i'$ are vectors of covariates observed along with G_i for $i = 1, \dots, n$, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of unknown regression coefficients (Ferrari and Cribari-Neto, 2004). The functions $g_1(.)$ and $g_2(.)$ are appropriate monotonic link functions; in particular, the function $g_1(.)$ must be such that its inverse function, as the linear predictor $\boldsymbol{x}_i'\boldsymbol{\beta}$ varies, takes value in (0,1), in order to satisfy the constraint $\mu_i \in (0,1)$, instead, the inverse of the function $g_2(.)$ must guarantee the positivity of ϕ_i, as the linear predictor $\boldsymbol{w}_i'\boldsymbol{\gamma}$ varies. In literature, the link logit is usually used for the $g_1(.)$ function, *i.e.* $g_1(\mu_i) = logit(\mu_i) = log\frac{\mu_i}{1-\mu_i}$, while for the precision parameter it is usual to choose a log-linear link, *i.e.* $g_1(\phi_i) = \log(\phi_i)$. In this first version of the paper, we assume that the precision parameter is constant.

Considering the nature of our data, this paper adopts an extended version of the Beta regression model, indicated in the literature with the term of Beta Mixed Model or generalized Beta model with mixed effects (Beta GLMM).[9] This latter, in a nutshell, consists of accounting for random

[9] One of the advantages of using Generalized Linear Mixed Models (GLMM), as in Generalized Linear Models (GLM), is to expand mixed linear models to response variables that cannot be modelled with the Gaussian distribution. Moreover, extending GLMs' assumptions, GLMMs allow contemplating among predictors random effects in addition to the usual fixed effects. Yet, the hypotheses of independence of the sample units and homogeneity are violated. Refer to Lovison et al. 2011 for further details.

effects in a classical Beta regression model, overcoming the problem of dependence within clusters. Indeed, in studies collecting repeated measures on each subject or when subjects are clustered in groups, observations associated with the same statistical unit are usually correlated, implying the not satisfaction of the assumption proper of regression models (Bonat et al., 2015). Consequently, this class of models is suitable for analysing longitudinal and multilevel hierarchical structure data. In this context, denote with G_{it} the Gini index observed in the *i-th* municipalities in the year *t*. Let b_i a vector of random effects and assume that the responses G_{it} are conditionally independent with density

$$f_i(G_{it} \mid b_i, \beta, \phi) = \frac{1}{B(\mu_{it}\,\phi,\ (1-\mu_{it})\phi)}\ {G_{it}}^{\mu_{it}\phi-1}(1-G_{it})^{(1-\mu_{it})\phi-1}$$

The model for the mean becomes:

$$g_1(\mu_{it}) = x'_{it}\beta + z'_{it}b_i$$

where z'_{it} is a vectors of covariates. To complete the specification, we assume Gaussian random effects, *i.e.* $b_i \sim N(0, \Sigma)$.

In the specific case of this work, we estimate the following equation:

$$logit(\mu_{it}) = \beta_0 + \beta_1 INNER\ AREA_i + \beta_2 SOUTH_i + \beta_3\ CENTRE_i + \beta_4 INNER\ AREA_i * SOUTH_i + \beta_5 INNER\ AREA_i * CENTRE_i + \textstyle\sum_k \beta_k X_{kit} + \sum_t \beta_t\, YEAR_t \qquad (1)$$

where the dependent variable (GINI) is the Gini Index of the *i-th* Italian municipality at a given year (*t*); we highlight that the linear predictor includes the key variable of our analysis – INNER AREA – a dummy variable taking value one if the municipal has the characteristic of an internal area with respect to the centres; SOUTH and CENTRE dummies to control for the Italian regional gap; the interaction term between INNER AREA and SOUTH/CENTRE to test how the effect of INNER AREA on income inequality changes among Italian macro-areas.

Furthermore, following the literature investigating the determinants of income inequality, we consider different groups of determinants (X_{kit}) (Furceri and Ostry, 2019; Nolan et al., 2019). Specifically, to consider the institutional context, the mayor characteristics (MAYOR AGE, MAYOR SEX, MAYOR SEX) and TAX AUTONOMY are included in our specifications. We introduce the FEMINISATION RATE as a proxy of gender measure and two regressors for capturing the level of education in each municipality (EMPLO EDUCATION and UNIVERSITY). Finally, YEAR is a set of time fixed effects.

As a robustness check, we estimate the model by including demographic factors and, also, we account for the economic development by using the regional GDP.

Moreover, to a greater degree of disaggregation, the intermediate municipalities are differentiated from the peripheral and ultra-peripheral ones. As a result, we replicate the analysis by substituting our main variable INNER AREA with INTERMEDIATE, PERIPHERAL and ULTRAPERIPHERAL.[10] It is worth to recall that, in our analysis, both INNER AREA dummy and simply classes (INTERMEDIATE, PERIPHERAL and ULTRAPERIPHERAL) are defined in such a way to carry out the comparison with all centre zones categories (i.e. poles, inter-poles, outlying cities).

A description of the variables employed in the estimations and some main summary statistics are reported in table 1.

[TABLE 1]

[10] All estimations are obtained using the glmmTMB package, proposed by Brooks et al. (2017), in the R statistical software. The glmmTMB command allows estimating GLMM models by discriminating among several distribution families, including the Beta one. The corresponding link is the logistic function (Magnusson et al., 2017).

5. ESTIMATION RESULTS

Since our data structure – clustered in the municipality, observed over time – and the outcome variable nature, assumed to be distributed according to a Beta distribution, we estimate a *Beta Regression model with random effects*. In doing so, we insert only a random group intercept in the model, resulting in a comparison that focuses on the conditional model, namely fixed effects. In this respect, the glmmTMB package allows for the confrontation and selection of different models based on several information criteria, including the Akaike Information Criterion (AIC). Following this latter, Column 1 of Table 2 reports the results of the benchmark model, which performs the lowest AIC.

[TABLE 2]

Focusing on our key variable, *INNER AREA*, we find different influence on income inequality on the basis of geographical localization. In detail, if we consider the municipalities localized in the Southern Italy, the log-odds ratio of the average concentration to be an inner area is equal to -0.015. This means that the odds of the average concentration to be an inner area is about 98% ($e^{-0.002-0.015} = 0.983$) of the odds ratio to be a non-inner area in the South of the country.[11]

We do not find any difference between inner and not-inner areas in Central regions and in the North of the country, as we can see from the lack of statistical significance of estimated coefficients on the interaction term *INNER AREA*CENTRE* and *INNER AREA*, respectively.

As Inner areas seem to influence income inequality when considering different geographical positions in the country, a more detailed inspection of the phenomenon is justified. Stated

[11] In the Beta regression, the interpretation of the estimated parameters (β) on binary variables is the logarithm of the odds-ratio. While, e^{β} represents the following odds-ratio: $\frac{\mu(Gini|DUMMY=1)}{1-\mu(Gini|DUMMY=1)} / \frac{\mu(Gini|DUMMY=0)}{1-\mu(Gini|DUMMY=0)}$. From an economic point of view, the latter can be read as the odds of the average concentration when $DUMMY=1$ is (e^{β})% of the odds of the average concentration when $DUMMY=0$.

differently, we choose to even shed light on the subject under scrutiny by analysing whether there exists some difference, in influencing inequality, between South/Centre and North among internal areas municipalities.

According to Column 1 of Table 2, indeed, the log-odds ratio of the average concentration to be located in the South with respect to the municipalities located in the North is different depending on the value of the binary variable *INNER AREA*. In detail, when considering inner areas, the odds ratio of the average income concentration to be located in the South is about 9% ($e^{0.102-0.015} = e^{0.087} = 1.09$) greater than that of municipalities located in the North.

As for as non-inner areas are considered, the log-odds ratios of the average concentration to be located in both SOUTH and CENTRE are always positive and statistically significant - 0.102 and 0.031, respectively. This means that the odds of the average concentration to be located in Mezzogiorno is about 10% ($e^{0.102} = 1.10$) greater than the odds of the average concentration to be located in the North. A similar situation emerges for Central regions but with a lower percentage (3% given that $e^{0.031} = 1.03$).

These results show that the importance of inner areas emerges in a heterogeneous way in our country. First, in line with the literature, the gap between the Southern and Northern regions in terms of inequalities is confirmed – for both inland and non-inland areas. Instead, this gap is less marked or absent when we compare the centre with the north. Moreover, the findings imply a relevance of inner areas in bridging the income inequality gap in marginalized regions of the country. In other words, even where the number of municipalities classified as an internal area is greater as in Southern Italy, and their socio-economic woven is not fully developed and exploited, more remarkable benefits emerge in reducing income disparities in these regions. Encouraging policies - such as SNAI - favouring internal municipalities development could potentially help them to exit the loop of disparities.

Looking at the battery of robustness checks displayed in columns from 2 to 4, the findings obtained by amending our benchmark equation are in line with those discussed above.

Briefly considering the control variables in Table 2, it seems that institutional context characterising municipality does not affect income distribution, except when considering the Mayor age, which positively influences the logit of inequality. Similarly, in the presence of higher levels of education, the logit of income concentration increases. By contrast, FEMINIZATION RATE, accounting for female permanent employees, appears to reduce the logit of inequality in terms of income. Also, SENIOR INDEX and MERGED MUNICIPALITY seem to have a negative impact on the logit of income inequality, while this latter appears to rise with the rate of family growth in the municipality. Finally, our estimations seem to confirm the Kuznets' curve on economic development. Indeed, RGDP – measured as the regional GDP – and its square appears to have a quadratic influence on the dependent variable. In other words, the effect is positive at a lower level of economic development, while a higher level of gross domestic product in the region negatively affects the logit of income inequality.

[TABLE 3]

Table 3 presents results when we deepen the analysis disaggregating the inner area dummy. In this case, variables of our interest are INTERMEDIATE, PERIPHERAL and ULTRA-PERIPHERAL. According to column 1, we evidence a noteworthy difference from the above results. Indeed, in the South (SOUTH = 1), the log-odds ratios of the average concentration to be located in PERIPHERAL is negative and statistically significant (-0.024). This implies that the odds ratio of the average concentration to be located in PERIPHERAL is 97% ($e^{-0.005-0.024} = 0.97$) of the odds ratio of the average concentration to be located in non-inner area group. Also, the log-odds ratios of the average concentration to be located in ULTRA-

PERIPHERAL is positive and statistically significant (0.021-0.055). This implies that the odds ratio of the average concentration to be located in ULTRA-PERIPHERAL is 96% ($e^{-0.021-0.055} = 0.96$) of the odds ratio of the average concentration to be located in non-inner area group.

We do not find any difference between INTERMEDIATE, PERIPEHERAL and ULTRA-PERIPHERAL *vs* non-inner areas in the Central regions of the country.

Finally, for the municipalities located in the North, the log-odds ratio of the average concentration in ULTRA-PERIPHERAL is equal to 0.021, meaning that the odds ratio of the average concentration in ULTRA-PERIPHERAL is about 2% ($e^{0.021} = 1.02$) greater than the odds ratio of the average concentration in non-inner areas.

With regard to disparities between the different parts of the countries when considering the value of our key variable equal to one, as shown in Column 1 of Table 3, the log-odds ratio of the average concentration to be located in the South with respect to the municipalities located in the North is different depending on *PERIPEHERAL* and *ULTRA-PERIPHERAL* values. Indeed, when considering peripheral zones, the odds ratio of the average income concentration to be located in the South is about 9% ($e^{0.106-0.024} = e^{0.087} = 1.09$) greater than that of peripheral municipalities located in the North. Also, for ultra-peripheral areas, the odds ratio of the average income concentration in the South is about 5% greater than in the North ($e^{0.106-0.055} = e^{0.051} = 1.05$).

This finding suggests the importance of analysing the phenomenon under scrutiny at a more disaggregated level. In particular, it seems that peripheral and ultra-peripheral areas drive the gap between Southern and Northern in terms of income disparity. Also, a high heterogeneity is confirmed for the Mezzogiorno: in peripheral and ultra-peripheral areas, furthest away from the essential services than central zones, income inequalities appears reduced, probably due to greater flexibility and propensity to seize the opportunities deriving from government interventions. Therefore, what emerges is that further economic policy efforts should be necessary to promote socio-economic inclusion in more remote country areas.

To conclude, our findings are confirmed even when we change model specification, as above illustrated.

6. CONCLUDING REMARKS

This paper investigates whether internal areas influence the income inequality of Italian municipalities. The importance of this topic emerges both concerning the growing income disparities that have occurred in recent decades and to recent empirical contributions that highlight how territorial aspects could influence income inequality.

In general, identifying the inner regions and the consequent importance for analysing the concentration of income derives from the Italian territory composition, characterised by a polycentric network of urban centres, whose around areas with different levels of spatial periphery gravitate (Carlucci et al., 2012; Barca et al., 2014).

Following the SNAI classification, we consider both the rural-urban divide and each rural and remote class. Moreover, we measure income distribution with the Gini Index, an income concentration indicator included in the continuous interval (0,1). To overcome limitations emerging in the existing literature, we use an innovative methodology to analyse the inequalities in income distribution, namely GLMM with a Beta distribution.

The results suggest that inner municipalities play a crucial role in influencing income inequality depending on the geographical distribution. Indeed, internal areas in the Southern Italy suffer from significant disparities in terms of inequality than those located to Northern Italy. Also, the place matters when we consider internal areas of Southern Italy. In particular, evidence shows that being a municipality classified as an internal zone seems to have a lower odds of average concentration index than non-internal zones.

However, a greater degree of disaggregation seems to be necessary for emerging further differences and corroborating our main evidence on the North-South dualism. In this line of inquiry, we find that the overall result for the inner area of Southern Italy compared to those located in the North is confirmed by the disaggregated analysis. Indeed, it is driven by the peripheral and ultra-peripheral municipalities, which show greater odds of average concentration. Lastly, these categories of inner areas seem to register lower inequality compared to central ones located to the South.

Our estimation results on the effects of 'inner area' on income concentration – specifically those showing heterogeneity among the Italian territory – are relevant for developing economic policies at the local and supranational levels. Indeed, as income and wealth inequality has increased enormously in recent decades, various international institutions place the question at the centre of political debate and their agendas to understand their causes, consequences on society and possible solutions.

The policy implications are noticeable. SNAI, together with the EU interventions, aims at promoting rural jobs and economic growth in nonurban areas, maximising the development potential of each territory. Both measures find a strong justification because they are essential to reducing income inequality.

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Table 1: Description and summary statistics of the variables used in the estimations

VARIABLE	DESCRIPTION	Mean	StdD	Min	Max	Obs
GINI INDEX	Gini concentration index	0.38	0.04	0.16	0.76	55,314
INNER AREA	Dummy = 1 for Inner Area (D+E+F)	0.52	0.50	0	1	55,314
INTERMEDIATE	Dummy = 1 for intermediate areas (D)	0.29	0.45	0	1	55,314
PERIPHERAL	Dummy = 1 for peripheral areas (E)	0.19	0.39	0	1	55,314
ULTRAPERIPHERAL	Dummy = 1 for ultra-peripheral areas (F)	0.04	0.19	0	1	55,314
SOUTH	Dummy = 1 if a municipality is located in South Italy	0.32	0.47	0	1	55,314
CENTRE	Dummy = 1 if a municipality is located in Centre Italy	0.12	0.33	0	1	55,314
MAYOR AGE	Mayor age (in unit)	52.20	10.52	20	96	54,098
MAYOR SEX	Dummy = 1 if the Mayor is female	0.13	0.34	0	1	54,102
MAYOR EDUCATION	Dummy = 1 if the Mayor has a bachelor degree or a grater education level	0.49	0.50	0	1	54,027
TAX AUTONOMY	Tax revenue over the sum between tax revenue, income from contributions and current transfers, and non-tax revenue	0.63	0.19	0.00	0.97	55,307
FEMINISATION RATE	Permanent and executive female employees over permanent employees and managerial staff	0.47	0.21	0.00	1.00	55,034
EMPLO EDUCATION	Permanent employees and managerial staff with at least a bachelor degree over permanent employees and managerial staff	0.19	0.15	0.00	1.00	55,027
UNIVERSITY	Dummy = 1 if a University is located in the municipality	0.01	0.09	0	1	55,314
SENIOR INDEX	Inhabitants >= 65 over inhabitants <= 14	2.10	1.58	0.27	56.00	55,286
MERGED MUNICUPALITY	Dummy = 1 for municipalities merged between 2012 and 2018	0.01	0.11	0	1	55,314
FAMILY GROWTH RATE	Growth rate of families in a municipality between 2011 and 2018	0.01	0.19	-0.32	4.16	55,118
RGDP	Regional GDP	142499.5	117777.9	4346.261	381555.4	55,314

Table 2: Beta GLMM results

	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Intercept	-0.539^{***}	-0.554^{***}	-0.552^{***}	-0.538^{***}
	(0.004)	(0.006)	(0.006)	(0.004)
INNER AREA	-0.002	-0.002	0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
SOUTH	0.102^{***}	0.111^{***}	0.108^{***}	0.101^{***}
	(0.005)	(0.006)	(0.006)	(0.005)
CENTRE	0.031^{***}	0.035^{***}	0.037^{***}	0.033^{***}
	(0.006)	(0.007)	(0.006)	(0.006)
INNER AREA*SOUTH	-0.015^{***}	-0.015^{***}	-0.013^{***}	-0.013^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
INNER AREA*CENTER	0.008	0.007	0.007	0.009
	(0.005)	(0.006)	(0.006)	(0.006)
MAYOR AGE	0.000^{***}	0.000^{**}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
MAYOR EDUCATION	-0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
TAX AUTONOMY	-0.005	-0.005^{*}	-0.005^{*}	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
MAYOR SEX	-0.001	-0.004^{***}	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
FEMINISATION RATE	-4.024^{***}	-3.179^{***}	-3.043^{***}	-3.073^{***}
	(0.925)	(0.924)	(0.926)	(0.926)
EMPLO EDUCATION	0.014^{***}	0.013^{***}	0.013^{***}	0.013^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
UNIVERSITY	0.196^{***}	0.199^{***}	0.194^{***}	0.194^{***}
	(0.021)	(0.021)	(0.021)	(0.021)
SENIOR INDEX			-0.001^{***}	-0.001^{***}
			(0.000)	(0.000)
MERGED MUNICUPALITY			-0.339^{***}	-0.349^{***}
			(0.029)	(0.029)
FAMILY GROWTH RATE			0.237^{***}	0.241^{***}
			(0.016)	(0.016)
RGDP		0.001^{***}	0.001^{***}	
		(0.000)	(0.000)	
RGDP2		-0.000^{*}	-0.000^{**}	
		(0.000)	(0.000)	
2013	-0.005^{***}	-0.005^{***}	-0.005^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2014	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2015	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2016	0.007^{***}	0.007^{***}	0.008^{***}	0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2017	0.023^{***}	0.023^{***}	0.023^{***}	0.023^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2018	0.028^{***}	0.027^{***}	0.028^{***}	0.028^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
AIC	-299065.929	-299061.600	-298215.225	-298210.999
Log Likelihood	149553.964	149553.800	149133.613	149129.499
Var: municipality (intercept)	0.025	0.025	0.024	0.024
Dispersion parameter	1980	1980	1980	1980
Observations	53706	53706	53525	53525

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The dependent variable is Gini Index.
Results are not expressed as marginal effects. The standard errors are reported in parentheses.

Table 3: Beta GLMM results

	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
Intercept	-0.539^{***}	-0.553^{***}	-0.550^{***}	-0.538^{***}
	(0.004)	(0.006)	(0.006)	(0.004)
INTERMEDIATE	-0.002	-0.003	-0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
PERIPHERAL	-0.005	-0.006	-0.003	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
ULTRAPERIPHERAL	0.021^{**}	0.023^{**}	0.019^{**}	0.020^{**}
	(0.009)	(0.009)	(0.009)	(0.009)
SOUTH	0.106^{***}	0.114^{***}	0.109^{***}	0.104^{***}
	(0.005)	(0.006)	(0.006)	(0.005)
CENTRE	0.030^{***}	0.034^{***}	0.034^{***}	0.033^{***}
	(0.006)	(0.007)	(0.006)	(0.006)
INTERMEDIATE*SOUTH	-0.009^{*}	-0.009^{*}	-0.007	-0.007
	(0.005)	(0.005)	(0.005)	(0.005)
PERIPHERAL*SOUTH	-0.024^{***}	-0.026^{***}	-0.021^{***}	-0.021^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
ULTRAPERIPHERAL*SOUTH	-0.055^{***}	-0.053^{***}	-0.048^{***}	-0.048^{***}
	(0.011)	(0.011)	(0.011)	(0.011)
INTERMEDIATE*CENTRE	0.007	0.005	0.007	0.007
	(0.006)	(0.006)	(0.006)	(0.006)
PERIPHERAL*CENTRE	0.016^{*}	0.015^{*}	0.015^{*}	0.017^{*}
	(0.009)	(0.009)	(0.009)	(0.009)
ULTRAPERIPHERAL*CENTRE	0.006	0.005	0.010	0.009
	(0.015)	(0.015)	(0.015)	(0.015)
MAYOR AGE	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
MAYOR EDUCATION	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
TAX AUTONOMY	-0.005^{*}	-0.006^{**}	-0.005^{*}	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)
MAYOR SEX	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
FEMINISATION RATE	-3.954^{***}	-3.592^{***}	-3.022^{***}	-2.995^{***}
	(0.925)	(0.924)	(0.927)	(0.926)
EMPLO EDUCATION	0.014^{***}	0.013^{***}	0.013^{***}	0.013^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
UNIVERSITY	0.194^{***}	0.194^{***}	0.194^{***}	0.191^{***}
	(0.021)	(0.021)	(0.021)	(0.021)
SENIOR INDEX			-0.001^{***}	-0.001^{***}
			(0.000)	(0.000)
MERGED MUNICIPALITY			-0.342^{***}	-0.338^{***}
			(0.029)	(0.029)
FAMILY GROWTH RATE			0.239^{***}	0.235^{***}
			(0.016)	(0.016)
RGDP		0.001^{**}	0.001^{**}	
		(0.000)	(0.000)	
RGDP2		-0.000^{*}	-0.000^{*}	
		(0.000)	(0.000)	
2013	-0.005^{***}	-0.004^{***}	-0.005^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2014	-0.003^{***}	-0.002^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2015	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2016	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2017	0.023^{***}	0.023^{***}	0.023^{***}	0.023^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
2018	0.028	0.028^{***}	0.028^{***}	0.028^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
AIC	-299095.326	-299095.428	-298237.472	-298235.289
Log Likelihood	149574.663	149576.714	149150.736	149147.644
Var: municipality (intercept)	0.025	0.024	0.024	0.024
Dispersion parameter	1,980	1,980	1,980	1,980
Observations	53706	53706	53525	53525

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The dependent variable is Gini Index.
Results are not expressed as marginal effects. The standard errors are reported in parentheses.