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RESEARCH PAPER

The Geography of the Italian Citizenship Income: The Role of Poverty and Inequality in Determining Spatial Heterogeneity Across the Italian Municipalities

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Abstract

This paper evaluates the influence of poverty and inequality on the distribution of the Italian Citizenship Income Policy aimed at supporting poor and in-need Italian households. We implement a variety of spatial econometric models that relate the number of households benefiting from income support interventions with local well-being indicators, including the average per capita income, the share of poverty, and the Gini index. These models account for the strong spatial heterogeneity exhibited by the recipient households by grouping municipal units into homogeneous and spatially contiguous groups and estimating local relationships. In this way, we evaluate how geographical and local factors have influenced the coverage of the policy. The results show that both poverty and inequality were relevant drivers of the geographical distribution of participation in income support. However, the sign and magnitude of the estimates depend on local structural characteristics. We estimate positive and statistically significant correlations with respect to per capita income and the share of municipal poverty, with particular interest in areas in which both high socioeconomic weakness and low-income levels persist. Conversely, we observe that where both average per capita income and income inequality were high, the policy was unable to reach potential household targets, while in areas characterized by low income but with

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lower income inequality, the income support reached a high number of households. We also noted the complexity of the socioeconomic situation in Italy, marked by a growing spatial heterogeneity throughout the period of interest, probably enforced by the outbreak of the COVID-19 pandemic.

Keywords Guaranteed minimum income · Municipal income inequality · Spatially clustered regression · Policy evaluation · Spatial heterogeneity and complexity

JEL Classification H53 · I38 · R12 · C21

1 Introduction

In recent decades, due to the recessive effects of several economic crises generated on a global scale, there has been a rapid increase in poverty and inequalities, affecting the socioeconomic sphere and the well-being of citizens (Lambert 1992; Jenkins et al. 2012; Stiglitz 2012; Piketty and Saez 2014; Rodríguez-Pose and Hardy 2015; Aaberge and Brandolini 2015; Fadda and Tridico 2017; Liberati et al. 2023).

The accelerated growth of these phenomena, as shown in a large number of studies, could depend on multiple interconnected factors and variables, such as the automation of production processes with the transition from human labor to technology (Acemoglu and Restrepo 2018, 2022; Gregory et al. 2022; Moll et al. 2022), globalization (Milanovic 2016; Ravallion 2018; Nolan et al. 2019), unequal redistribution of wealth between classes (Collins 2012), the flexibilization of the labor market (Tridico 2018), and differentiated access to educational and professional systems (Bonacini et al. 2021, 2024).

The growth of economic inequality may also depend on specific changes in tax policies, such as the reduction of the highest marginal tax rates, and on the progressive loss of power of unions of workers. In particular, many studies highlight how the reduction of marginal tax rates for top earners has contributed to an increase in inequality. Roine et al. (2009) show, for example, that lower rates and less progressivity in taxation are associated with an increase in the income shares of the richest citizens. Piketty et al. (2014) confirm that tax cuts are correlated with an increase in the share of the richest 1%, without generating real economic growth. Furthermore, Piketty and Saez (2006) document how the progressive reduction in tax rates has determined an increase in the concentration of income from capital compared to that from work. Recent studies also suggest that while tax systems may be only slightly progressive for middle- and upper-income earners, they tend to become regressive for the richer classes, further accentuating inequality (Guzzardi et al. 2024). In parallel, numerous studies have highlighted that the weakening of unions has reduced workers' bargaining power, contributing to the increase in economic inequality. Farber et al. (2021) document how, historically, unions have played a fundamental role in reducing income inequality. Similarly, Layard (2005) observes that the decline in the bargaining power of workers has led to a reduction in the share of income of the labor force. In this sense, Jaumotte and Osorio Buitron (2020), show that the relationship between the decline in union density and the increase in the income shares of the top earners is causal in several advanced economies. Furthermore, Card (2001) and Lemieux et al. (2009) confirm that the decline in unionization has had a significant impact on the increase in wage inequality, with particularly marked effects on low-skilled and low-specialization groups.

Today, the income gap between different segments of the world population is increasingly marked, especially if we look at specific and distinct territorial contexts (Rodríguez-Pose and Hardy 2015). From an empirical perspective, a substantial amount of scientific studies, such as the works of Krugman (1991), Alesina et al. (2004), Sicular et al. (2007), Checchi and Peragine (2010), Iammarino et al. (2019), Chancel and Piketty (2021), Liberati and Resce (2022), Albanese et al. (2023), have highlighted the decisive and central role of spatial heterogeneity and geographical distance in explaining income differentials.

In spatial terms, inequality can be classified along two different dimensions depending on how it interacts with space: a “within" dimension concerning disparities within the same country or community, and a “between” dimension which refers, instead, to the differences between different states, regions, and territories (Bourguignon and Morrisson 2002; Liberati 2015; Chancel and Piketty 2021). From this classification, we can observe a higher concentration of inequality in highly urbanized areas, with a growing dualism between suburbs, characterized by greater social and material vulnerability, and centers (Lelo et al. 2019; Nijman and Wei 2020). In contrast, in less densely populated areas, such as rural villages and remote communities, fewer internal disparities are observed, due to lower and more homogeneous income levels on average, determined by limited job opportunities, which are mainly concentrated in economic sectors with low added value and with limited degrees of technical innovation, such as agriculture and small local and family businesses (Rodríguez-Pose and Hardy 2015). However, if we observe the distance between areas (inequality between) one can find that lower rurality leads to lower income inequalities (Zhong et al. 2022). Poverty also appears to follow spatial patterns similar to those of socioeconomic disparities, with a higher concentration of situations of social exclusion and vulnerability in the most remote areas and places or in the extreme outskirts of cities with a high population density (Rodríguez-Pose and Hardy 2015; Zhong et al. 2022).

To try to limit the prevalence of these phenomena, political decision makers at all levels are increasingly committing important public resources to the organization of coherent welfare programs and interventions, aimed at supporting citizens in difficult situations (Atkinson and Bourguignon 2014; Atkinson 2015; Blanchard and Rodrik 2023). In fact, over the years, many international institutions, and in particular the European Union, national states, and regions, have oriented their policies towards the activation of social protection schemes against poverty and inequalities. Today, political attention aimed at mitigation has been further accentuated by the COVID-19 pandemic, which has widened the disparity between citizens, worsening pre-existing situations of poverty and inequality (Palomino et al. 2020; Cerqua and Letta 2022; Gallo and Raitano 2023). To a large extent, these programs have been organized in the form of subsidies and direct transfers or through structured guaranteed minimum income schemes, based on specific conditions (for example, the level of family or individual income) (Immervoll and Scarpetta 2012).

However, despite the increased institutional attention focused on these issues, the effectiveness of the measures adopted by governments to support income is still much debated at the level of scientific literature and there is no univocal consensus, especially if we look at the distribution of the take-up rate[1] of minimum income schemes (Bramley et al. 2000; Bargain et al. 2012; Bhargava and Manoli 2015; Aprea et al. 2024; Boscolo and Gallo 2024).

1.1 Our Contribution

This article investigates the influence of income inequality and poverty on a specific Italian public policy of guaranteed minimum income, intended for families and individuals in difficulty, namely the *Reddito di Cittadinanza* (in English, *Citizenship Income*, hereinafter referred to as Guaranteed Minimum Income or GMI), approved in 2019 and implemented until 2023.[2] The main goal of the GMI policy was to support the income of Italian families living below the poverty threshold, through the provision of a guaranteed minimum income, conditional on specific eligibility criteria.

Throughout its implementation phase, the GMI has been the subject of multiple public and political criticisms and discussions, with reference to cases of the fraudulent obtaining of the benefit, the possible employability of beneficiaries, and the coverage of eligible target units (Busilacchi and Fabbri 2023; Tonutti et al. 2022; Maitino et al. 2024). To address these criticisms, this study implements a spatial analysis to investigate how the geographical distribution of income and poverty influences access to support measures. In fact, previous studies have suggested that income inequality can significantly influence the effectiveness of income support policies, with results varying depending on the local context (Acemoglu and Robinson 2013; Pickett and Wilkinson 2015; Brown and Long 2018). Our study builds on this literature by specifically examining the influence of income inequalities in Italian municipalities, a less explored but critical area of research for understanding policy dynamics at the micro-territorial level. We do this through a detailed exploration of spatial variability; our work aims to identify how the GMI has operated in specific territorial areas, in order to provide pointers towards a more targeted and effective policy implementation. In particular, this analysis uses an innovative spatial methodology to highlight how territorial heterogeneity influences the effectiveness of the GMI, demonstrating that areas with marked inequality may experience divergent participation dynamics. The results suggest the need for more targeted and flexible policies that take into account territorial specificities, thus guiding a more precise targeting and timely resource allocation,

[1] In economics, take-up refers to the rate of enrollment in a social program or benefit, such as subsidies or direct transfers against poverty. It measures the percentage of eligible people who actually apply for or receive the benefit. In other words, it represents the share of individuals eligible to benefit from a given policy who succeed in obtaining it. A low take-up rate can be caused by several factors, such as inadequate information or communication, technical bureaucratic obstacles, or social barriers related to the condition of the applicants.

[2] The Citizenship Income was introduced with Legislative Decree no. 4 of 28 January 2019, converted with Law no. 26 of 28 March 2019. The provision was abolished from 1 January 2024, by Law No. 197 on 29th December 2022.

providing distinct insights that can help decision makers optimize the effectiveness of income support policies.

In general, the economic literature, as described in Sect. 2, shows that income support measures generate heterogeneous results, mainly deriving from the nature of the measures themselves and their access conditions (e.g., families can apply for support only if below a specific income), as well as from the timeframe and territorial characteristics in which they operate (Almeida et al. 2022; Guimarães and Lourenço 2024). Motivated by such a general uncertainty on the effectiveness of the programs, as well as by the high amount of public resources invested in the period of operation of the GMI measure, that is, around 23 billion Euros between 2019 and 2022 (INPS 2022a, b), we stress the importance of analyzing the socioeconomic determinants of the geographical heterogeneity in the rate of access of Italian families to the GMI program.

In particular, our study aims to explore the distribution of the number of recipient families across the Italian municipalities in relation to two pillars:

1. The role of poverty, wealth and inequality in determining the GMI participation;
2. Geography and spatial heterogeneity.

Following the *take-up* framework on minimum income measures (Bargain et al. 2012; Bhargava and Manoli 2015; Aprea et al. 2024; Boscolo and Gallo 2024) and the copious literature on the *participation rates* in the policy programs (McGarry 1996; Hernandez et al. 2007; Åslund and Fredriksson 2009; Chetty et al. 2013; Markussen and Røed 2015; Bauer and Dang 2016; Grossman and Khalil 2020), we are interested in studying how the Italian income support program (i.e., the share of families requiring the GMI in a certain year) varied across the Italian municipalities according to local socioeconomic and well-being determinants, that is, the average per capita income, the municipal share of poverty, and the index on the declared income (these indicators are illustrated in Sect. 3).

Regarding the geographical pillar, many social and economic statistics at the territorial level show that Italy is strongly characterized by heterogeneity across spatial units and areas (i.e., there exists an apparent spatial heterogeneity as defined by the Second Law of Geography Zhu and Turner 2022). In fact, within the Western bloc, and, in particular when compared to other European countries, Italy presents high levels of socioeconomic and income inequalities with considerable heterogeneity within the country (Simonazzi et al. 2013; Salvati and Carlucci 2014; Celi et al. 2017; Tridico 2018). This internal heterogeneity, clearly illustrated in Fig. 2, derives from the historical divergence in growth and economic development between the rich regions of the north and the poorer regions of the south, which, today, are becoming increasingly marked (Checchi and Peragine 2010; Lagravinese 2015; Felice 2018; Cerqua and Pellegrini 2018; Mussida and Parisi 2019; Chelli et al. 2023; Guzzardi et al. 2024). Such a marked spatial heterogeneity weakens the implementation and the efficiency of public policies, in particular, those related to social assistance and protection measures (Albanese et al. 2023) in the Italian context. Looking at the municipal-level data represented in Fig. 1, the distribution of the GMI was also influenced by the typical Italian dualism. In fact, a much higher concentration of households was recorded in the southern regions compared to the central and northern regions, during the entire period of execution of the measure (Busilacchi and Fabbri 2023; Maitino et al. 2024; Monturano et al. 2025). We address this issue adopting a spatial econometric methodology, namely the Spatially-Clustered Regression (SCR) approach by Sugasawa and Murakami (2021), which breaks up the whole national territory by clustering municipal units into homogeneous and spatially contiguous groups while estimating local relationships via regression. In particular, the method is used to obtain global and local estimates of the influence of several socioeconomic and administrative factors, including poverty and inequality, on the number of households requiring and obtaining the GMI income support measure at the most granular level possible for Italy. Furthermore, to investigate the temporal dynamics of the relationship between inequality, poverty, and participation in income support, the spatial regression algorithm is replicated for municipal data from 2019 to 2022, thus fully including the peak period of the COVID-19 pandemic. This provides several policy implications, including whether and how the relationships have changed during the political period and whether these changes affected the entire country or only some areas.

To the best of our knowledge, this work represents the first attempt, conducted at a local granular level, to investigate the influence of socioeconomic disparities on the GMI, jointly exploiting variables that change across space and time. We stress that we do not seek to estimate a causal relationship among socioeconomic variables and the coverage (in terms of reached families) of GMI policy. Our primary goal is to identify statistically significant relationships among the above-mentioned variables, expected to be non-constant across space and time due to the spatial heterogeneity and the temporal dynamic. Specifically, we are interested in evaluating how these relationships varied across the Italian areas, and how the role of poverty and inequality changed according to different geographical and administrative partitions of Italy.

Our results show a strong spatial correlation between the effectiveness of the GMI and the distribution of per capita income, as well as the share of municipal poverty, confirming that the program responds effectively to situations of social exclusion. However, we observed an uneven, yet increasing, relationship between levels of income inequality and household participation in the measure during the period of policy implementation. In particular, in many areas with a high degree of inequality, a higher average income tends to reduce the effectiveness of the GMI. Households just above the poverty line are often unsuccessful in their attempts to benefit from welfare measures due to failing to meet the eligibility criteria, which are based on declared income or ISEE (as detailed in Sect. 2.1). These criteria do not adequately reflect local inequalities or the real economic difficulties of households. This limitation of the eligibility criteria has prevented the GMI from reaching some potential beneficiaries who, despite appearances, face serious economic difficulties.

Therefore, our analysis suggests that income support policies can benefit from a differentiated approach, which takes into account, not only income, but also wealth distribution and internal socioeconomic disparities within communities. In general, these findings underline the importance of organizing and adapting minimum income policies according to local specificities and characteristics, in order to ensure that cash transfers effectively reach deserving recipient households.

The remainder of the paper is structured as follows. Section 2 presents a review of the literature on guaranteed minimum income and the description of the Italian GMI, including the available data at the municipal level. Section 3 describes socioeconomic data for the empirical analysis, mainly focusing on the three key determinants identified, namely, average per capita income, the municipal share of poverty, and the index of the declared income. Section 4 describes the spatially clustered regression methodology used to estimate the global and local effect of socioeconomic weaknesses on GMI participation. Section 5 presents the empirical strategy used for the estimates. In particular, we provide the econometric specifications used in the analysis and the rationale for the empirical choices. Section 6 contains and discusses the main findings obtained. Policy implications are also discussed. Finally, in Sect. 7, we synthesize the paper's contents and provide conclusive remarks.

2 Guaranteed Minimum Income Policies: Theoretical Frameworks and the Italian Application

Although protection measures developed through guaranteed minimum income schemes have a consolidated history in relation to the fight against poverty and the mitigation of the effects of unemployment (Marx and Nelson 2013; Baldini et al. 2018a; Natili 2020; Busilacchi and Fabbri 2023), only recently, due to the increase in economic disparities, have they acquired an important value on an international scale as effective measures to combat socioeconomic inequalities (Baldini et al. 2018b; Gallo 2021). Historically, in fact, minimum income policies have evolved considerably compared to current formulations. As highlighted in various works, such as Marx and Nelson (2013), Baldini et al. (2018a), Natili (2020), these policies have evolved through different phases of transformation, driven mainly by political and institutional concerns related to the efficiency of benefits regarding their capacity to promote active inclusion. Initially, in fact until the 1980s, they were conceived as protection tools, to prevent situations of vulnerability, providing financial support to individuals in conditions of serious poverty (Marx and Nelson 2013; Natili 2020; Busilacchi and Fabbri 2023). Subsequently, in an attempt to avoid the risk of a so-called "welfare trap", i.e. the situation in which beneficiaries become dependent on state assistance, distancing themselves from the labor market (Immervoll et al. 2015), minimum income policies have embraced the paradigm of work activation (Hemerijck 2017; Natili 2020), and the concept of workfare (Xu and Carraro 2017; Groot et al. 2019; Spies-Butcher 2020). These developments have profoundly transformed the initial objectives of these policies, which have evolved from simple passive income support mechanisms into dynamic tools aimed at encouraging their beneficiaries to seek work and become socially integrated. Currently, the principles of activation and workfare are moving these objectives even further away from a universalistic perspective of the benefit (Van Parijs and Vanderborght 2017; Groot et al. 2019; Spies-Butcher 2020). In many countries, especially on a micro-territorial scale, forms of universal minimum income (UBI) (Groot et al. 2019; Feinberg and Kuehn 2020; Banerjee et al. 2023) are being tested, focused solely on residence in a specific place without a requirement to provide proof of income. Yet, in this framework of change, which expresses the political will to make minimum income schemes more efficient and standardized, observation of the various measures approved on an international scale reveals a still very fragmented and heterogeneous picture, in terms of structure, implementation, and effectiveness (Natili 2020; Aprea et al. 2022).

At the scientific literature level, following Immervoll and Scarpetta (2012), we can identify the *guaranteed minimum income* as a plurality of welfare and social assistance interventions usually aimed at families in poverty, connected to the verification of economic means. Interventions aimed at integrating income from work or pension, education, housing emergency, employment, disability etc. therefore, can also be considered forms of minimum income.

In practical terms, these measures represent direct monetary transfers or services useful to supplement the incomes of low-income families.

Generally, especially in European countries, they are organized on a principle of selective universalism, which allows for: (1) examining family incomes globally, without considering specific groups of individuals or social classes; (2) presenting specific eligibility criteria and conditions (Natili 2020).

Frazer and Marlier (2016), Curci et al. (2020) and Aprea et al. (2022) highlight how the thresholds for access to minimum income schemes are often represented by multiple socioeconomic and/or well-being indicators, such as a specific poverty threshold, or from the minimum wage level or unemployment benefits. In this regard, the European Union anchors the eligibility for obtaining these measures at a specific relative poverty threshold, defined as AROPE,[3] below which one is considered poor in the EU. This threshold value represents 60% of the national median equivalent disposable income (Atkinson et al. 2015). Despite this, minimum income schemes are often subordinated, not only to a calculated level of deprivation or vulnerability, but also to other factors, such as citizenship and/or long-term residence requirements, family size and structure, as well as other regulations related to wealth levels and participation in inclusion and training programs. These differences contribute to increasing the heterogeneity between the various regulatory systems governing these policies.

At the community level, the European institutions have repeatedly asked for the introduction of specific guaranteed minimum income schemes in all member states (Natili 2020). Today, minimum income schemes are present in all countries of the Union. Even with differences in terms of time extension, amounts payable, and the number of eligible people, they present many similarities with respect to the conditions for accessing the benefit.

However, until 2017, Italy and Greece, the European countries most marked by internal disparities and among the most impacted by the increase in inequalities and large-scale social exclusion, were the only two EU member states not to have a national program including income support (Gallo 2021; Busilacchi and Fabbri 2023; Maitino et al. 2024).

It is only as recently as 2018 that Italy adopted a national measure for income support with the introduction of Inclusion Income (ReI).[4] However, minor protection

[3] Eurostat defines the AROPE rate (“at risk of poverty or social exclusion’) as the sum of people who are at risk of poverty, or who are seriously deprived materially and socially or who live in a family with a very low work intensity.

[4] The Inclusion Income ReI, Law 15 March 2017, n. 33, is a universal measure to combat poverty, conditioned on the evaluation of the economic condition. It was abolished in 2019 and replaced with Citizenship Income, GMI.

schemes lacking universality in treatment, were already present at a national level[5] and in various regions; for a review of these measures see Gallo (2021) and Busilacchi and Fabbri (2023). The Inclusion Income scheme only lasted for a very short time since, just over a year after its activation, it was replaced by the Italian Citizenship Income (GMI); this was a more structured guaranteed minimum income policy, to which three times more public resources were allocated (see the section below, Sect. 2.1, for a detailed overview of the measure).

At a general level, although guaranteed minimum income measures have a consolidated history, the effects of mitigating poverty and inequalities are not yet entirely clear (Marx and Nelson 2013). In fact, we can observe differentiated impacts in terms of direction and intensity, both in advanced countries and in poorer states. For example, in China (Yu and Li 2021) and other Asian states (Wagle 2017), despite the pronounced regional differences, a positive and lasting correlation is found between social security spending and urban-rural income disparity, particularly in Asian states with lower income. Within the African continent, government transfers appear to be more correlated with income growth and long-term economic expansion and employment (Maket et al. 2023). In fact, Banerjee et al. (2023) presents an extensive empirical investigation, conducted with data obtained in the field in remote villages of Kenya, and highlights how the provision of a universalistic minimum income and other forms of income support, aimed at poor local populations, have led to changes in occupational choices, with the transition from employment to entrepreneurship, as well as significant economic expansion, with important implications for saving, access to credit, and investment behavior. Differently, in Western countries which allocate larger shares of GDP to assistance, these programs seem to have a more nuanced impact (Almeida et al. 2022; Rauh and Santos 2022; Gallo and Raitano 2023; Guimarães and Lourenço 2024), if not potentially negative in terms of macroeconomic evaluations (Conesa et al. 2023; Connolly et al. 2024; Daruich and Fernández 2024). Despite this, even in these richer countries, there are positive effects of these measures on income levels and poverty, with specific attention being paid to homeless citizens (Gubits et al. 2018; Locks and Thuilliez 2023), to unemployment (Terracol 2009; Card et al. 2015, 2018; Calnitsky 2020), and to wage inequality (Calnitsky 2020; Cantillon et al. 2020).

In the Italian context, despite great initial expectations, the GMI has been accompanied, throughout its period of activity, by numerous critical issues and discussions. These criticisms have been mainly linked to cases of fraud in obtaining the benefit (Monturano 2023). Other debated issues have concerned the effectiveness of the GMI in making recipients active and employable (Busilacchi and Fabbri 2023; Maitino et al. 2024), the take-up rates connected to the income criteria of the measure (Ansaloni et al. 2024; Boscolo and Gallo 2024), as well as the targeting capacity of the GMI, considered a sort of generalized subsidy for the southern regions (Monturano et al. 2023). Some studies have specifically focused on assessing the impacts of the GMI on poverty (Tonutti et al. 2022, with quantitative estimates on small areas) and inequalities (Gallo 2021, through fiscal microsimulation estimates), with divergent results.

[5] The Inclusion Income (ReI) abolished the Support for Active Inclusion (SIA) and the Unemployment Allowance (ASDI).

Within this literature, at least to our knowledge, no work has so far studied the influence of income inequality and poverty on the measures of the Italian minimum income whilst also considering the spatial component. In this sense, given the spatial heterogeneity present in Italy, the Italian Citizenship Income emerges as a unique experiment to study the effectiveness of these policies.

2.1 The Italian GMI: Characteristics and Prerequisites

The GMI represented the most structured guaranteed minimum income policy approved in Italy. It was aimed at families and individuals with the objective of combating poverty and inequalities. Despite the name, which refers to universal basic income schemes, this income support was structured as a guaranteed minimum income, focused on monetary transfers to low-income families. The measure also included active employment policies, aimed at encouraging employment and social inclusion, with a view to workfare.

The program was structured according to the principle of selective universality, conditional on the verification of economic resources as gauged by the Equivalent Economic Situation Indicator (ISEE)[6]. Along with the income requirement, the benefit was subject to a number of other criteria, such as possession of Italian citizenship, or continuous residence for at least ten years, defined family structures and specific sizes, certain real estate and financial assets, etc. In this sense, access to the benefit was not guaranteed simply by meeting one specific criterion, because access to the program necessitated simultaneously satisfying all the eligibility criteria (see Table 2 for the complete details of the access requirements to the GMI). The benefit had a renewable duration of 18 months. The amount varied from 780 to 1716 euros per month, depending on the family composition and any rent costs.

Throughout the paper, we consider as a phenomenon of interest the number of households (or families) as beneficiaries of the GMI policy over the total number of resident families. GMA data at the municipal level were provided by the Italian National Institute of Social Security (INPS). Available data refer to the years between 2019 and 2022, that is, the entire time interval during which the policy operated without any regulatory changes in the eligible population.

As reported in Table 3, during its implementation phase, the GMI reached a very large number of families. Before the outbreak of the COVID-19 pandemic, the measure had already reached in excess of 1 million families. These figures grew dramatically during the two-year period 2020–2021, the one most affected by the lockdown measures (INPS 2023a, b). In the last year of activation, that is 2023, the number of beneficiaries decreased, due to the change in the GMI regulations, which reduced the number of eligible people. These numbers reflect the importance that the GMI had assumed throughout the health emergency in limiting the spread of poverty and inequalities among Italian families (INPS 2022a, b; Gallo and Raitano 2023). Conversely, the temporal dynamic of the average monthly amount of support provided to the families on a regional basis showed an ever-increasing trend throughout the entire

[6] The Equivalent Economic Situation Indicator (ISEE) for obtaining the GMI referred to the year preceding the request.

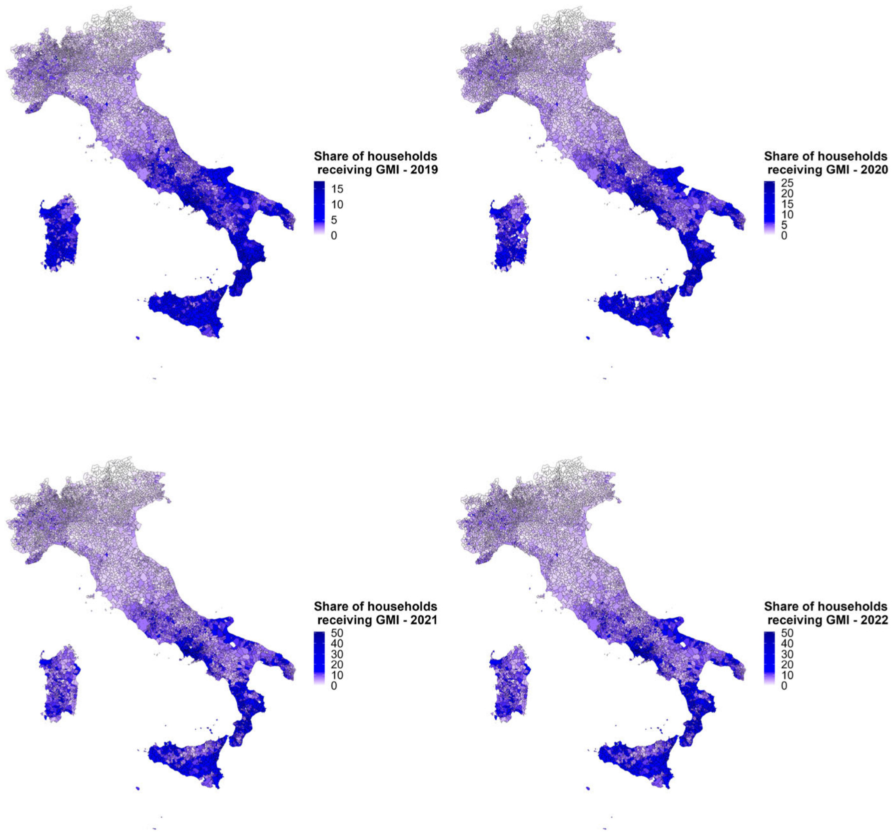

Fig. 1 Spatial distribution of the average municipal share of total households receiving the GMI across the period 2019–2022. . *Source* Author's processing of INPS data

period of activity of the measure, rising from 492.17 euros in 2019 to 562.81 euros in 2023[7].

Figure 1 shows the spatial distribution across the country of the share of households receiving the GMI at the municipal level (notice that Table 3 instead contains the aggregate values on a regional and macro-regional scale). The share is computed as the ratio of the number of beneficiary households to the total number of households living in the municipality. In terms of the number of households receiving GMI, we can detect a high average municipal difference between the north and the south. On average, in the municipalities of the North-East, approximately seventy families have benefited from the GMI in the years of implementation of the policy. Differently in the southern and island regions much higher values are recorded, above the three hundred units at the average municipal level.

The empirical analysis presented in the following sections will reveal a close link between applications for state assistance and places where socioeconomic indicators

[7] The data is present in the INPS Report on GMI, at this link: https://www.inps.it/it/it/dati-e-bilanci/osservatori-statistici-e-altre-statistiche/dati-cartacei—rdc.html.

reflect lower levels of well-being in terms of poverty and social exclusion. In particular, these trends would seem to indicate that the GMI scheme has played a crucial role in supporting the needs of families in difficulty, especially in more economically and socially disadvantaged areas, but less in terms of addressing income inequalities. However, in order to fully understand the nature and influence of these relationships and their implications for public income support policies, and, in particular, for the evaluation of the GMI, it is necessary to conduct an in-depth analysis that also takes into account other different socioeconomic, geo-demographic, political-institutional and labor market variables. In this sense, spatial econometric analysis becomes useful for understanding the basic relationships between these phenomena.

3 Further Socioeconomic Data

Starting from studies conducted on micro-territorial data, for example, Antulov-Fantulin et al. (2021), Resce (2022), Monturano et al. (2025), we build a rich panel dataset on municipal variables, collected from multiple national statistical sources. The panel includes municipal data from 2018 to 2022, starting from the year prior to the GMI implementation, as lagged variables. Specifically, we considered the following information:

- Citizenship Income beneficiaries (i.e., number of recipient families by municipality) from the Italian National Institute of Social Security (INPS) as described in the previous Sect. 2.1;
- Income data derived from the database on municipal incomes of the Italian Ministry of Economy and Finance (MEF);
- Social, demographic, and environmental variables sourced from the Italian National Statistics Office (ISTAT) and the Ministry of the Interior (i.e., characteristics of local administrators).

The available data are capable of identifying economic, social, demographic, geographical, environmental, and administrative-institutional circumstances that could have influenced the choices of households regarding participation in the GMI program. Table 1 reports the main descriptive statistics on the available variables aggregated on a macro-regional territorial scale (macro-regions are defined according to the NUTS-1 classification of Eurostat 2023). This subdivision allows us to observe, on the large-scale, the clear spatial heterogeneity characterizing the GMI phenomenon during the operation period, providing a solid comparison between the areas of the country.

3.1 Main Socio-economic Drivers

Following ISTAT (2024), we consider the other three socioeconomic variables as relevant and predominant and capable of identifying social and economic well-being at the local level. The three socioeconomic determinants are calculated starting from the income data provided by the MEF and are defined as follows:

- *Income inequality*: following Antulov-Fantulin et al. (2021) and Resce (2022) we computed the index for every municipality based on the declared income by aggre-

Table 1 Descriptive statistics on socio-economic variables

	Years	North-East	North-West	Center	South	Islands
Economic						
Per capite income	2018–2021	19,834.44 (2430.76)	19,893.38 (3126.37)	17,575.90 (2337.60)	14,108.64 (2151.76)	14,062.89 (2069.21)
Share of poverty	2018–2021	24.55 (4.79)	24.67 (5.94)	29.81 (5.18)	42.04 (6.67)	40.84 (5.89)
Number of taxpayers	2018–2021	6390.86 (16,645.69)	3933.43 (24,256.14)	8696.04 (63,885.52)	4730.59 (15,285.53)	5120.31 (16,903.31)
Social						
GMI's number of households	2019–2022	71.41 (319.59)	73.79 (875.02)	221.59 (2192.98)	311.27 (1931.18)	402.68 (2117.39)
Local units	2018–2021	729.53 (2264.56)	469.51 (4321.81)	1072.43 (9261.02)	528.28 (2200.39)	535.33 (2054.45)
Employees of local units	2018–2021	2997.74 (9139.23)	1880.05 (18797.93)	3730.31 (34266.97)	1589.83 (7452.67)	1521.40 (6753.87)
Employment rate 20–64 years	2019	72.94 (3.98)	70.34 (5.21)	65.24 (6.05)	53.89 (5.83)	51.96 (5.64)
Distance to essential services	2019	29.20 (18.35)	25.78 (14.51)	30.85 (15.61)	36.78 (18.80)	42.29 (23.73)
Demographic						
Resident population	2019–2022	8383.46 (21,859.15)	5331.30 (32,777.14)	12,216.63 (91,763.44)	7623.43 (27,184.59)	8416.15 (29,656.03)
Share of immigration	2019–2022	7.92 (3.89)	7.72 (4.35)	8.74 (3.86)	4.37 (3.01)	2.85 (2.61)
Register for foreigners	2019–2022	33.21 (89.04)	19.68 (122.36)	38.45 (210.85)	20.26 (59.22)	24.87 (77.04)
Population growth rate	2019–2022	9.59 (42.55)	6.36 (52.28)	− 2.85 (42.94)	− 28.01 (48.35)	− 25.46 (42.01)
Population dependency index	2019–2022	72.13 (9.16)	73.97 (10.35)	73.20 (8.73)	71.11 (10.72)	71.45 (8.58)
Population density	2019–2022	1.87 (3.52)	2.58 (7.69)	2.23 (3.36)	2.06 (2.81)	2.51 (2.89)
Population 25–64 with low school	2019	35.13 (6.53)	39.40 (7.31)	37.04 (6.30)	41.33 (7.85)	50.12 (8.31)

Table 1 continued

	Years	North-East	North-West	Center	South	Islands
Geographic						
Level of urbanisation	2019–2022	2.60 (0.52)	2.56 (0.57)	2.68 (0.50)	2.60 (0.59)	2.66 (0.50)
Territorial surface	2019–2022	44.73 (47.04)	19.35 (22.58)	59.94 (73.62)	41.30 (49.93)	65.17 (72.01)
Altitude of the center	2019–2022	305.24 (368.43)	346.85 (289.60)	355.56 (222.74)	411.59 (284.07)	336.35 (259.51)
Environmental						
Protected natural areas	2019	14.27 (22.30)	11.22 (21.11)	18.79 (25.33)	24.88 (31.79)	17.19 (24.26)
Landslide hazard zones	2019	6.19 (11.24)	7.46 (15.08)	9.76 (10.74)	12.33 (16.63)	4.81 (7.75)
Land consumption	2019	10.56 (8.22)	11.87 (11.49)	7.25 (6.32)	9.19 (11.02)	6.51 (7.58)
High emission motor rate	2019	18.95 (4.91)	19.95 (6.25)	26.37 (7.21)	31.77 (7.52)	33.46 (8.13)
Undifferentiated urban waste	2019	135.69 (105.91)	172.89 (128.89)	191.01 (138.98)	163.20 (104.56)	132.88 (95.08)
Administrative						
Age of mayor	2019–2022	56.51 (9.12)	58.64 (10.44)	56.95 (9.79)	56.79 (8.98)	56.31 (9.52)
Average age of councilors	2019–2022	51.36 (4.29)	52.96 (5.19)	51.67 (4.46)	50.34 (4.39)	48.87 (4.41)

Source Author's calculations based on INPS, Ministry of Economy, ISTAT and Ministry of the Interior data

The values for the 2022 year relating to the "Number of Taxpayers", "Local Units" and "Employees of Local Units" are obtained as the average of the previous years due to the lack of available data. The index is not present because it was calculated only at municipal level for econometric estimates gating data from different municipal income brackets/classes. Let us assume that the overall population of a municipality and the corresponding declared incomes can be divided into $j = 1, 2, \ldots, k$ ordered classes.[8] The grouped-data Gini index can be computed as follows:

$$G = \frac{\sum_{j=1}^{k}(F_j - F_{j-1}) \times (A_j + A_{j-1})}{2 \times N \times \sum_{j=1}^{k} a_j}$$

where $F_j = \sum_{i=1}^{j} f_i$ represents the cumulative frequency of individuals declaring an income up to the j-th ordered income bracket (with f_i being the share of the population over the total associated with the i-th ordered income class); F_{j-1} represents the cumulative frequency of declaring an income up to the previous ordered income bracket; A_j represents the cumulative amount of income declared up to the j-th ordered income bracket (with a_i being the share of total declared income associated with the i-th ordered income class); A_{j-1} represents the cumulative amount of income declared up to the previous income class; $\sum_{j=1}^{k} a_j$ is the total amount of income declared within a given municipality; and N is the total number of taxpayers in the municipality;

- *Average per capita income*: following ISTAT (2024) we computed the ratio of the total amount of income declared in each municipality to the total number of resident taxpayers;
- *Share of poverty*: share of the municipal population declaring an income of 10,000 euros or less (that is, the ratio of the number of individuals who declare an income between 0 and 10,000 euros to the total number of taxpayers in the declaring population of the municipality), see ISTAT (2024) for further details.

We acknowledge that grouped data structure provided by MEF is not the most comprehensive for estimating income inequality as it does not account for individuals who do not submit tax declarations for various reasons. Indeed, as noted by Guzzardi and Morelli (2024), this can introduce limitations in the estimation process, following also the perspective of Piketty et al. (2018), on considering both top-income earners and individuals in poverty, when analyzing inequality dynamics. However, we emphasize that the MEF database remains the only official and publicly available source of declared income at the municipal level in Italy. In the absence of alternative datasets, it serves as the primary basis for empirical analysis in the literature, being widely utilized in several studies (see, for example, Ercolano et al. 2018; Gallo and Pagliacci 2020; Antulov-Fantulin et al. 2021; Cerqua and Letta 2022; Atella et al. 2023; Di Stefano and Resce 2025). Furthermore, as recognized by ISTAT, the MEF database is officially classified as a key source for measuring local economic well-being. These indicators, derived from tax data, such as per capita income and the share of individuals earning below €10,000, are crucial for assessing socioeconomic conditions at the

[8] Specifically, for the MEF data on declared income at the municipal level, the ministry provides information about the number of taxpayers and the total income declared by each class for the following income brackets: 0€declared; from 0 to 10K€; from 10K€to 15K€; from 15K€to 26K€; from 26K€to 55K€; from 55K€to 75K€; from 75K€to 120K€; over 120K€declared.

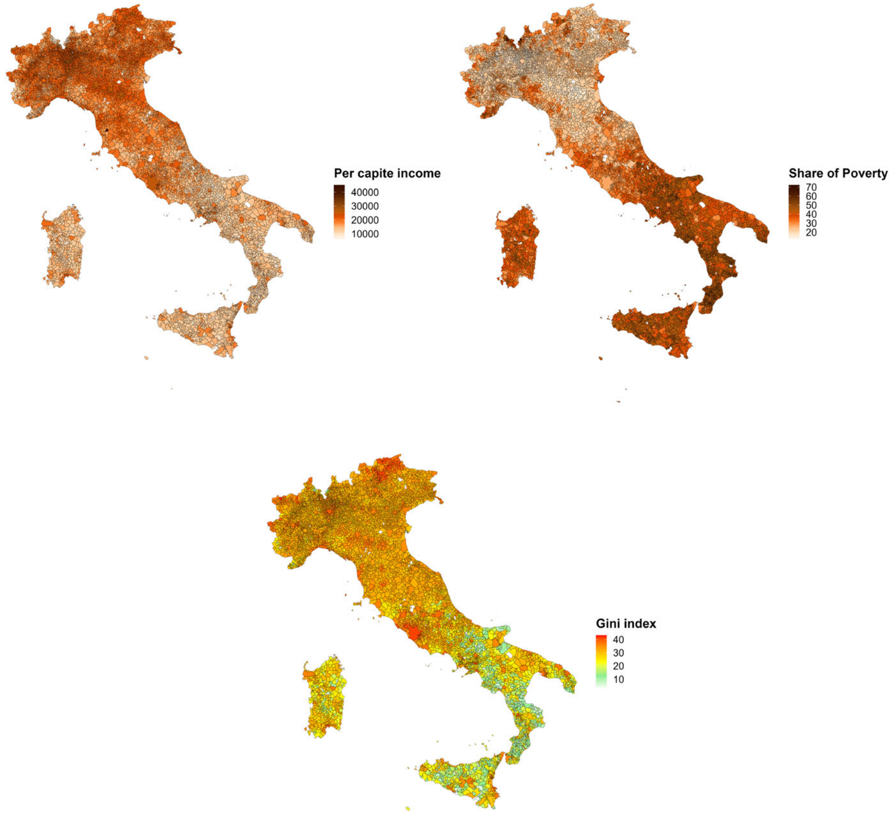

Fig. 2 Municipal spatial distribution of average municipal per capita income, share of poverty and index (average 2018–2021). . *Source* Author's processing of MEF data

municipal level. These indicators are also integrated into national accounting systems for planning, management, and coordination of local institutions.

Figure 2 illustrates the average municipal values of three socioeconomic variables at local level, namely income inequality (calculated using the index), average per capita income, and the share of citizens in poverty, for the years 2018–2021. As a complement, in Table 4 in the Appendix we present descriptive statistics for the available variables at the regional (i.e., NUTS-2) level.

By comparing the spatial distribution of the GMI beneficiaries (i.e., Fig. 1) and the maps related to the three socioeconomic factors (i.e., Fig. 2) we are immediately prompted to infer several insights about the geographical relationship between economic disparities and the number of families who received the GMI. In particular, we can highlight some direct socio-spatial connections between inequalities and poverty and obtaining the monetary benefits of the GMI.

In general, it is observed that the areas characterized by low levels of per capita income, lower inequalities, and higher shares of poverty are those with a greater number of families benefiting from the GMI. In fact, there is a greater concentration of beneficiaries in the regions of Southern Italy and large cities. For example, regions such as Calabria, Campania, and Sicily jointly present a high share of poverty (in the South and the Islands the poverty share is above 40%, see Table 4), a high percentage of families treated (about 15%, relative to the ratio between families receiving GMI and the total number of families in these regions, Table 3), as well as per capita incomes and lower economic inequalities. In contrast, in territorial contexts characterized by higher rates of well-being and a more prosperous economy, such as regions of Northern and Central Italy (Mussida and Parisi 2019), there is less need for welfare interventions. Regions such as Lombardy, Emilia-Romagna, Veneto, and Trentino Alto Adige have lower poverty shares. Therefore, the registered share of families benefiting from GMI is much lower than that of the South (about 2% in the North-East in 2022, see Table 3).

3.2 Other Control Variables

Table 1 shows that socioeconomic disparities on a macro-regional scale can be found in access to essential services and in data on the labor market, with the employment rate in the working age being very marked between the north and the south (around 20 points). Although less spatially heterogeneous in the north–south dichotomy, inequalities are also present in terms of production plants at local level, with the Italian municipalities of the central regions recording the highest number of production sites and employees at municipal level (300 units more local than in the north-east, 500 compared to the municipalities of the south and 600 compared to the north-west), as they are territories characterized by successful experiences in specific sectors of manufacturing and craftsmanship. The differences between the share of the working-age population with a level of elementary education are very marked, with much worse average values in the municipalities of the southern regions and on the islands. At a demographic level, the Population Growth Rate demonstrates the long-term depopulation that afflicts the south, showing very negative municipal average values in these regions. In the north, and also in the municipalities of central Italy, there is, instead, a high growth in the population. In the north-east the average municipal figure is close to 10%. The share of immigrants also follows similar trends, with a distribution of foreign citizens concentrated mainly in the centre-north. We also considered time-invariant variables describing the geographical characteristics or the elementary indicators of fragility at the local level. For instance, the Composite Index of Municipal Fragility (IFC) consists of 12 elementary indicators of a socioeconomic or environmental nature and represents the level of fragility of the municipalities and is used to study territorial risk factors. The geographical and environmental variables highlight values that vary territorially, depending on the nature of the indicator considered, with the southern municipalities which, on average, present greater morphological problems, but fewer environmental problems, with less production of undifferentiated waste, and lower incidence of hydro-geological risk, also connected to lower land consumption. Finally, there are no significant differences between the territorial areas in terms of characteristics of municipal administrators, such as the age of the mayor and the average age of councilors, suggesting a certain stability in local governance.

In general, data reflect the economic disparities present in Italy, underlining the importance of targeted public policies and specific interventions, aimed at reducing inequalities, particularly in the southern and island regions, where critical socioeconomic issues require priority attention (Salvati and Carlucci 2014; Lagravinese 2015; Guzzardi et al. 2024). At the same time, they highlight the need for an accurate evaluation of the protection programs implemented.

4 Estimating Spatially-Varying Relationship via Spatially Clustered Regression

As previously stated, our goal is to investigate the spatial distribution of the families involved in the GMI across the Italian municipalities and its relationship with a set of socioeconomic variables related to local well-being indicators, namely the Gini Index, average per capita income, and the share of poverty (ISTAT 2024). Taking into consideration the strong geographical heterogeneity of Italian macroeconomic and socioeconomic data, we might expect that this relationship would not be uniform throughout the country, but would exhibit complex spatial and temporal patterns. Consequently, we employ a spatial regression technique denoted as Spatially Clustered Regression (henceforth, SCR) that allows us to estimate spatially-varying empirical relationships in which the coefficients linking the response variable and the covariates are grouped into internally homogeneous spatial clusters. This technique was introduced by Sugasawa and Murakami (2021) as an innovative method to integrate statistical clustering of observations within a regression framework under spatial proximity constraints on the data. The method is often opposed to other spatial regression techniques aimed at solving the issue of spatial heterogeneity in regression, also called the Second Law of Geography (Goodchild 2004), such as the well-known Geographically Weighted Regression (GWR) of Brunsdon et al. (1998) and Fotheringham et al. (2022). By spatial heterogeneity (Zhu and Turner 2022), we mean empirical frameworks in which the relationship between variables is not constant over space but evolves according to the geographical context (often, this is denoted as *spatial instability of the regression parameters)*. GWR allows the estimation of spatially-varying regression parameters, which vary for each location in a study area, using spatial subsets of the original data (groups are identified by the spatial distance between observations); such ‘local’ estimation (Yatchew 2003) extends the classical ‘global’ linear regression model, or the spatial econometric models (Elhorst 2014), which instead, estimate a single set of parameters assumed to be constant across the study area (Oshan et al. 2020). However, as pointed out by Sugasawa and Murakami (2021) and Murakami et al. (2019), GWR and its variants, such as Geographically Weighted Regression LASSO (Wheeler 2009) and Geographically-and-Temporally Weighted Regression (Wu et al. 2014), frequently lead to unstable estimates that are sensitive to the size of the dataset being considered and in presence of collinearity of local predictors.

The SCR methodology provides a good compromise between computational efficiency, stability of results, and interpretability. SCR combines linear regression models and spatial clustering (see Kopczewska 2022, for an extended review of spatial clustering algorithms) of cross-sectional units based on the idea that the relationship between covariates and response variable for nearby observations is similar (or even identical), but that this relationship may vary between spatially distant groups of observations (i.e., regression coefficients are spatially-varying). In practice, SCR assumes that (1) units can be divided into a finite number of spatial clusters where units in the same groups share the same regression coefficients; (2) group membership is based on the idea that nearby or neighboring geographic units are likely to belong to the same groups (Potts 1952). Technically, clustering is performed through a penalized version of the iterative K-means algorithm in which spatial proximity between observations is taken into account to form groups, favoring the clustering of neighboring units in space (a similar idea was adopted by Wang et al. (2021), to create non-overlapping spatial partitions of locations in a model validation context). As the SCR treats the spatial dependence by means of a spatial weighting matrix, such dependence can be modeled either by a spatial contiguity matrix or by a distance matrix (see, for instance, Section 4 of Kopczewska 2020).

Let us denote the observed response variable at location s as y_s and denote the $(p \times 1)$ vector of covariates at location s as $\boldsymbol{x}_s$, where $s = 1, \ldots, n$ is the index for the locations and n is the overall number of locations. In the present case, the locations are the $n = 7850$ Italian municipalities.

Sugasawa and Murakami (2021) showed that SCR naturally adapts to the case of Generalized Linear Models (GLMs) (see Section 15 of Fox 2015), enabling the response variable to exhibit a non-Gaussian distribution. In the GLMs framework, such a distribution is a member of an exponential family, such as the Gaussian random variable for continuous data, the Poisson distribution or the Negative Binomial for counts or the Binomial distribution for binary outcomes. Therefore, let us suppose that, conditioning on the p exogenous covariates, the response variable follows a certain conditional distribution

$$f(y_s|\boldsymbol{x}_s; \boldsymbol{\theta}_s) \tag{1}$$

belonging to the exponential family with $\boldsymbol{\theta}_s$ being a vector of unknown parameters to be estimated. In the GLMs framework such an assumption implies that the expected value of the response variable (i.e., $E(y_s) = \mu_s$) and the p covariates are linearly related through a linear link function $\eta_s = g(\mu_s)$ transforming the expectation of the response variable into the linear predictor, that is,

$$\eta_s = \theta_{0s} + \boldsymbol{\theta}_s \boldsymbol{x}_s \quad \forall s = 1, \ldots, n \tag{2}$$

where $\boldsymbol{\theta}_s$ is the vector of p unknown regression parameters and θ_{0s} is the unknown intercept.

Due to the spatial heterogeneity, for each observations s, we might assume that each location s is associated with a location-specific set of regression parameters. However, the model would suffer from an identification problem, making its estimation unfeasible[9] Therefore, we assume that the n locations can be divided into a finite

[9] In other words, the SCR methodology does not allow for a coordinate-specific coefficient, that is, a specific coefficient for each spatial unit. This, on the other hand, is potentially feasible in a GWR-type approach.

number $G < n$ of clusters and that observations within each group $g = 1, \ldots, G$ share the same parameter values. Consequently, Eq. (2) reduces to

$$\eta_{s_g} = \theta_{0g} + \boldsymbol{\theta}_g \boldsymbol{x}_{s_g} \quad \forall g = 1, \ldots, G \tag{3}$$

where $\boldsymbol{\theta}_g$ is the vector of p cluster-specific regression parameters, θ_{0g} is the cluster-specific intercept, $\boldsymbol{x}_{s_g}$ and y_{s_g} represent, respectively, the value of the covariates and response variable for the n_g locations belonging to the g-th cluster, while $\eta_{s_g} = g(\mu_{s_g})$ is the link function for g-th cluster. Notice that we assume different group sizes and group-wise parameters, but a common link function.

SCR are fit via maximum likelihood (ML), which provides both estimates of the regression coefficients and the corresponding asymptotic standard errors. The membership of a unit to a certain group is unknown and must be estimated. In order to have groups consisting of spatially close (or even contiguous) units, following the approach of Potts (1952), the function to be optimized is the model's log-likelihood augmented by a penalty term ϕ that induces neighboring units to clump together, that is,

$$Q(\boldsymbol{\theta}, g) = \sum_{s=1}^{n} f(y_s|\boldsymbol{x}_s; \boldsymbol{\theta}_g) + \phi \sum_{s<s'} w_{s,s'} I(g_s = g_{s'}) \tag{4}$$

where $\boldsymbol{\theta} = [\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_g, \ldots, \boldsymbol{\theta}_G]'$ is the full set of group-specific regression parameters and $w_{s,s'} = w(s, s') \in [0, 1]$ is a spatial weighting function, $I(g_s = g_{s'})$ is an indicator function assuming the value 1 if two observations s and s' are clustered together and 0 otherwise. Also, ϕ is the spatial penalty parameter controlling the strength of spatial correlation among units (i.e., as ϕ increases the weight associated with the spatial penalty increases) which is treated as user-fixed tuning parameter.

Maximum likelihood estimation of the group-wise parameters and membership is established by employing a K-means-like iterative algorithm that iteratively updates the membership and the local regression parameters. At each iteration, for each statistical unit, the algorithm calculates the value of the log-likelihood that would be obtained if it was assigned to each of the potential clusters; thus, the update consists of maximizing the log-likelihood function by assigning units to the cluster such that its individual contribution (i.e., the unit-specific likelihood) is maximum. Computational details of the algorithm are described in Sect. 2 (Algorithm 1) of Sugasawa and Murakami (2021). Intuitively, SCR relaxes the assumption of stability of coefficients in space by dividing the sample into groups, but leaves the other assumptions unchanged. Therefore, being fully part of the ML framework, within each cluster the estimated model retains the same properties as the global regression model (e.g., asymptotic normality of the regression coefficients). As a further remark, recall that both the number of clusters G and the penalty parameter ϕ are, a-priori, fixed by the user. However, as the estimation is performed under a likelihood paradigm, model selection (i.e. to identify the optimal values for the hyperparameters) can be performed using information criteria (Sugasawa and Murakami 2021; Di Mari et al. 2023; Cerqueti et al. 2025b) or likelihood-based hypothesis tests (Fox 2015).

The SCR approach has been expanded recently by Cerqueti et al. (2025b) to encompass Gaussian spatial linear regression models (e.g., spatial autoregressive and spatial error models) to account for potential spatial autocorrelation between observations, with the latter being group-specific. Further extensions involve panel data specifications with fixed-effects (Cerqueti et al. 2025a). However, these models do not admit spatiotemporal specification or random or mixed effects. In the following Sect. 5, we will provide an empirical strategy to overcome this drawback. Also, leveraging on existing extensions of the GLMs, the SCR could be adapted to more complex data structures through Generalized Additive Models (Wood 2020), linear mixed models (Gelman and Hill 2012) and penalized regression (Tay et al. 2023). Notice that, in its current formulation, eventually the SCR formulation does not allow the user to control for the number of units allocated to each cluster. However, group size controls could be straightforwardly embedded in the algorithm by employing size-constrained clustering procedures (Zhu et al. 2010).

5 Empirical Strategy

5.1 Model Specification

Following the methodological design illustrated in Sect. 4, we adopt an empirical strategy that considers as the response variable the number of households benefiting from the GMI at the municipal level for Italy.

The number of families is actually a count variable that takes integer values only. The natural choice of GLM for count data is the Poisson distribution. Specifically, we adopt a Poisson regression approach with a logarithmic link function, which has as its main advantage the ability to interpret the estimated regression coefficients as a percentage change in the response following a unit increase in the covariate. Given the generic covariate x_{js_g} for group g, with $j = 1, \dots, p$ and $g = 1, \dots, G$, and the corresponding coefficient estimate $\hat{\beta}_{jg}$, the value $100 \times \hat{\beta}_{jg}$ represents the estimated local (i.e., for the g-th spatial cluster) percentage variation in the number of GMI-receiving households associated with a unit change in x_{js_g}. Also, the total number of resident families in a given municipality is used as the exposure factor (i.e. the logarithm of the total number of families is the model's offset having a fixed coefficient equal to 1), thus allowing us to model the share of families participating in the GMI program.

As previously stated, we use a large set of municipal-level characteristics from 2018 to 2022, where the main drivers of the analysis are three variables related to local well-being, namely the Gini index, the average municipal per capita income, and the poverty share. By construction, the policy refers to an income condition (ISEE) delayed by one year in relation to the request for subsidy. Therefore, these three indicators are included in the model with a lag of one period compared to the years of policy operation (e.g., one using the GMI for 2021, the per capita income variable refers to the year 2020). Furthermore, to avoid spurious results, we introduce into the regression model a set of socio-demographic, geographical, environmental, and institutional control variables, temporally aligned with the years of activation of the policy. Overall, $q = 21$ control variables were included in the model. These variables are reported in Table 1.

Although it is not explicitly modeled, we take into account the temporal dynamics of the relationships by considering more than one year of municipal data. Specifically, SCR is independently applied to data for the years 2019, 2020, 2021, and 2022.[10] The temporal evolution of the estimated local coefficients, municipal membership, and number of groups will provide insights into how and whether the phenomenon of income support claims has changed or settled.

The empirical specification of the Poisson regression model for the generic cluster g, composed of the units s_g, and the generic year t is described in Eq. (5):

$$\begin{aligned} log[E(y_{s_g t}|\boldsymbol{X}_{s_g t})] = \beta_{0gt} + \beta_{1gt} Gini_{s_g t-1} + \beta_{2gt} PerCapitaIncome_{s_g t-1} + \\ \beta_{3gt} ShareOfPoverty_{s_g t-1} + LogNumFam_{s_g t} + \boldsymbol{\gamma}_{gt} X_{s_g t} \\ \forall t = 2019, \ldots, 2022 \text{ and } \forall g = 1, \ldots, G \end{aligned} \tag{5}$$

where $y_{s_g t} \sim Poisson(\eta_g)$ are the observed number of recipient families for year t in group g, β_{1gt} is the coefficient associated with the income inequality (Gini index) for group g at year $t-1$, β_{2gt} is the coefficient associated with the per capita income for group g at year $t-1$, β_{3gt} is the coefficient associated with the share of poverty for group g at year $t-1$, $LogNumFam_{s_g t}$ represents the logarithm of the number of families living in municipality s at time t (recall that, being an offset, the associated coefficient is fixed to 1), and $\boldsymbol{\gamma}_{gt}$ is the set of $q = 21$ contemporaneous coefficients associated with the cluster-specific control variables. In the following, we will refer to Eq. (5) as *Specification 1*.

The empirical strategy adopted has several merits. First, it allows us to identify the effect of global and local socioeconomic weaknesses on citizens' participation in cash benefits for income support, taking into account other exogenous factors. Second, it allows us to explicitly take into account the spatial heterogeneity and therefore to study any territorial and regional dependencies, in relation to the number of households benefiting from the measure. Third, we are allowed to study the temporal dynamic of the estimated relationships by comparing the four separate models.

5.2 Robustness Analysis

As a robustness analysis, we repeat the estimates with respect to different specifications of the main model in (5). For each robustness specification, we consider a subset of three lagged socioeconomic variables listed above (i.e., we estimate models with only one of three or with pairs of variables) accompanied by the relevant controls. In this way, we obtain a direct comparison useful for determining the weight that each specific income variable has on obtaining the GMI. In general, five empirical specifications are estimated, of which *Specification 1* (i.e., Eq. 5) is used as a benchmark model. For

[10] Notice that, due to abolishments and fusions among municipalities, the yearly number of units varies across the period. In the present study, the number of municipalities for 2019 is 7862, for 2020 is 7829, for 2021 is 7848, and for 2022 is 7895.

the sake of brevity, the equations of specifications 2 to 5 are reported in the Appendix C, and the results in the Supplementary Materials.

A further issue to be considered is the way in which spatial dependence is treated. The spatial dependence in an SCR model is modeled through a spatial contiguity matrix or a distance matrix. Since we are dealing with areal data (lattice), in our case, we prefer to use a contiguity matrix in which the number K nearest neighbors is fixed. Considering the high number of cross-sectional units at our disposal, we test three different specifications of the contiguity matrix: $K = 25$, $K = 50$ or $K = 100$ neighbors.

Finally, only for the Main Specification (i.e. Equation 5), in Table 5 in Appendix D, we report the estimates from the pooled Poisson regression model, i.e. without imposing any clustering structure; they are reported in the Appendix in Table 5. The estimates are made by considering one year at a time (i.e., year-specific regression) and aggregating all observations present in 2019–2022 (i.e., pooling all observations).

5.3 Model Comparison and Selection

The identification of the best model for each year and specification is based on statistical goodness-of-fit measures. To this extent, we use the Bayesian Information Criterion (BIC) that, when minimized, provides a statistical insight into the optimal number of groups/clusters and the corresponding estimate of the local parameters (Di Mari et al. 2023; Cerqueti et al. 2025b). In the context of SCR, in fact, Italian municipalities are categorized into internally homogeneous clusters, ensuring that the influence of economic indicators remains consistent within each group, while varying between different spatial groups.

The choice of the BIC compared to other criteria is instigated by its parsimony property, which, in this context, leads to preferring a smaller number of groups, improving the overall interpretability of the socioeconomic phenomena under investigation. To this purpose, consider the following. In Italy there are approximately 8 thousand municipalities. When considering a classification with $G = 25$ groups, there would be on average 320 municipalities in each cluster; becoming 160 when the number of groups is increased to $G = 50$. In an effort to preserve the asymptotic statistical properties of the regression estimators, it is necessary to maintain the highest possible sample size in each cluster. Therefore, for each specification, year, and number of neighbors, we estimate the five specifications with a number of groups ranging from $G = 1$ to $G = 50$, where $G = 1$ indicates the pooled or global regression (which is, therefore, without local effects). However, it is worth noting that, as the number of groups increases, the understanding of the estimates reduces. In this sense, BIC minimization guarantees an adequate compromise between complexity and interpretability.

Overall, the total number of econometric models estimated is equal to 3000 (given by 4 years $\times$ 50 clusters $\times$ 3 neighboring structures $\times$ 5 specifications). Despite the computational burden and the use of automatic selection criteria, the visual inspection of the results and their economic interpretation act as main guidelines for the evaluation of the results.

Empirical results about the spatially-clustered regression models can be reproduced in the R language (R Core Team 2023) using the SCDA library (Cerqueti et al. 2025b).

6 Results

For the sake of brevity, in what follows we discuss the results provided by the main empirical specification expressed in Eq. (5). Extended results related to the other robustness specifications can be found in the Supplementary Materials.

In general, the empirical results reveal the historical geographical dualism characterizing the Italian socioeconomic development, that is, the one between northern and southern regions (Salvati and Carlucci 2014; Lagravinese 2015; Guzzardi et al. 2024). At the same time, they also show marked differences within the same territories and regions. In particular, they highlight a positive correlation between low levels of municipal per capita income and high local share of poverty characteristic of the number of beneficiary families. Spatially discordant values, due to the structural characteristics of the Italian economy are, instead, observed in areas characterized by high-income inequalities. In other words, a greater territorial inequality can influence the participation rates of families and individuals in income support policies, since in these areas the average level of income is higher. Similar results are also obtained in the other specifications of the model, formally illustrated in the equations of Appendix C.

These results suggest that the GMI policy has been more effective in reaching households in need in areas with lower average income and higher poverty rates. However, it also raises questions about the extent to which these policies address deeper structural inequalities rather than merely alleviating short-term economic distress. In particular, greater attention to region-specific dynamics, and policy approaches capable of adapting to continuously changing socioeconomic challenges should be taken into account. This signals the need for more targeted and flexible public policies, capable of interpreting and responding to territorial specificities, especially in a context of increasing inequalities and global economic changes such as those brought about by the pandemic.

6.1 Optimal Number of Groups and Complexity of the Social Phenomenon

First, let us start by analyzing the temporal dynamics of the optimal number of groups in the period 2019–2022. In Fig. 3 we report the BIC associated with models assuming a number of clusters from $G = 1$ to $G = 50$ for all the pairwise combinations of number of neighbors (columns) and years (rows).

The plot shows that the optimal model is associated with a number of groups between $G^* = 25$ and $G^* = 48$. The BIC, at least for 2019, shows a parsimonious approach in establishing the optimal number of groups (i.e., 25 groups with about 320 municipalities in each group), as adding additional groups would not significantly improve the model fit. This observation of the BIC highlights an additional aspect of considerable relevance, pertaining to the optimal group number. Indeed, one can

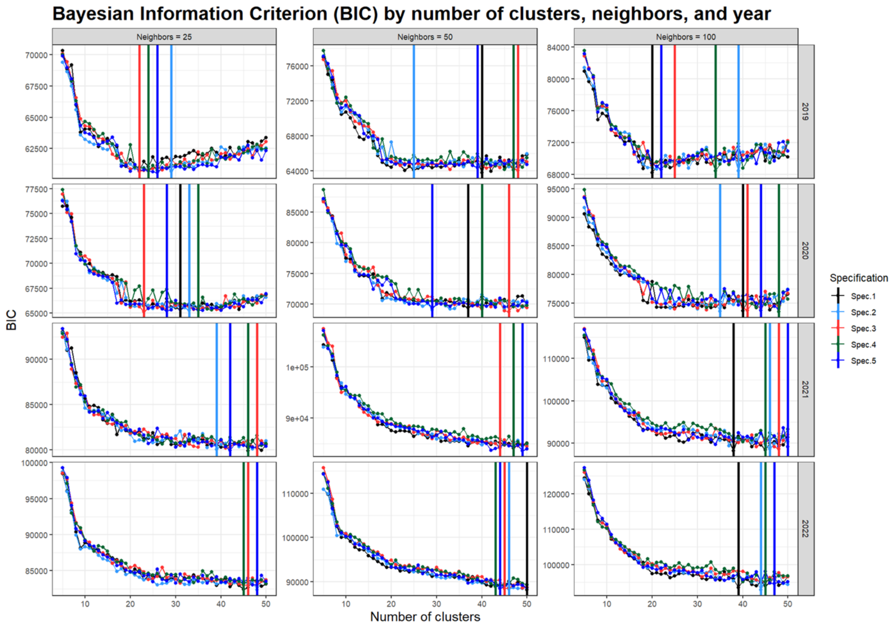

Fig. 3 Bayesian Information Criterion (BIC) by number of clusters, neighbors, and year

easily notice that, moving from one year to the next, the number of optimal groups grows substantially, even almost doubling from 25 groups in 2019 to 48 groups in 2022. We interpret such increases as the growth in the complexity[11] of the contextual and socioeconomic phenomena underlying the willingness to participate in income support programs, such as the RdC. This suggests that, over time, the phenomenon has taken on more complex and geographically-specific dynamics, further complicating the effectiveness of the measure in reaching the desired target. A possible reason for this result could be due to the recessive effects of the COVID-19 pandemic, which have worsened the inequalities that were already present in the country (Palomino et al. 2020; Brunori et al. 2021; INPS 2022a, b; Gallo and Raitano 2023). According to our analytical perspective, the increase in the degree of complexity is directly linked to the increase in spatial heterogeneity in the investigated relationships. Therefore, in the following Sects. 6.2, 6.3, 6.4, we explore in detail the apparent increase in the underlying socioeconomic complexity by analyzing whether it is associated with local patterns (i.e., signs and magnitudes) of income inequality, average declared income, and the share of poverty, respectively.

Moreover, comparing the graphs based on the number of neighbors considered, it is clear that K is a minor factor that does not influence the increasing socioeconomic

[11] In this context, the Economy and the Society are understood as “complex” systems characterized by the dynamic interactions between individuals across various levels within interconnected frameworks of social, economic, educational, scientific, technological, and environmental domains. The inherent complexity of these systems is further compounded by their dynamic nature, characterized by continuous change and evolution, which makes the development of comprehensive analytical models for their systematic study a formidable challenge (Drożdż et al. 2021).

complexity; in fact, regardless of the number of neighbors, the BIC has a monotonically decreasing tendency, and the optimal number is identified for progressively larger G values over the years. Therefore, in the following section, we will only comment on the case with the smallest number of neighbors, i.e. $K^* = 25$.

6.2 Heterogeneity in Income Inequality

The estimates of the coefficients associated with income inequality, calculated at the municipal level, show a heterogeneous spatial influence on the demand for income support, with marked differences between the macro-areas of the country (see Fig. 4[12]).

Northern Italy hosts the clusters with higher (in absolute terms) negative regression coefficients (i.e. an increase in the income inequality is associated with a decrease in the number of recipient families). Specifically, Trentino-Alto Adige (North-East) and large part of the North-West, together with parts of Lombardy, Liguria and Tuscany, show estimates that are significantly negative, especially in the first year of operation of the GMI (i.e., 2019). We recall from the exploratory analysis that northern territories present both the highest levels of inequality and the highest average per capita income; thus, a direct relationship between income inequality and demand for the GMI could be unrealistic due to the presence of high average income levels, which hinder access to the support measure. Conversely, positive and statistically significant coefficients are found in areas like Friuli-Venezia Giulia (North-East at the border with Slovenia) in which marked inequalities are also present along with high average income levels. This indicates that in some contexts, despite the presence of high inequalities, the GMI has managed to intercept households in conditions of greater economic difficulty. However, the overall effect in the north appears fragmented and, in all the years of observation, the GMI does not correctly reach the most vulnerable population. The explanation for this phenomenon lies in the structural conditions of the local economy, in which higher income levels act as a barrier to obtaining the benefit, given that the access thresholds are determined mainly on a declaration basis. On these terms, families in difficulty could be excluded from the benefit due to a declared income higher than the limits set by the policy, despite higher living costs and possible situations of economic vulnerability not immediately captured by the GMI selection criteria.

It is interesting to note that even in some areas of the center-south, typically characterized by lower income levels and generally lower internal inequalities, negative coefficients emerge, albeit with territorial differences. In particular, a part of the center-south regions presents clusters with significantly negative coefficients, suggesting that, even in these contexts, the GMI has not always been able to effectively reach families

[12] Notice that, Figs. 4, 5, and 6 report the map of spatial clusters generated by the year-specific regressions (from 2019 to 2022) and the corresponding estimated cluster-wise coefficients. Across the three figures, the shape of the clusters in a specific year is fixed. Also, clusters are characterized by an internal color (filler), which can either be reddish (positive coefficient), greenish (negative coefficient), or whitish (null coefficient), according to the estimated local coefficient. The intensity of the color depends on the absolute value of the estimated coefficient (i.e. darker areas are associated with higher coefficients in absolute terms). Information about the statistical significance for each group is synthesized through the cluster boundary; groups with a thicker border are those whose estimated coefficient is statistically significant at 5%. The colors (red or green) reflect the sign of the estimate.

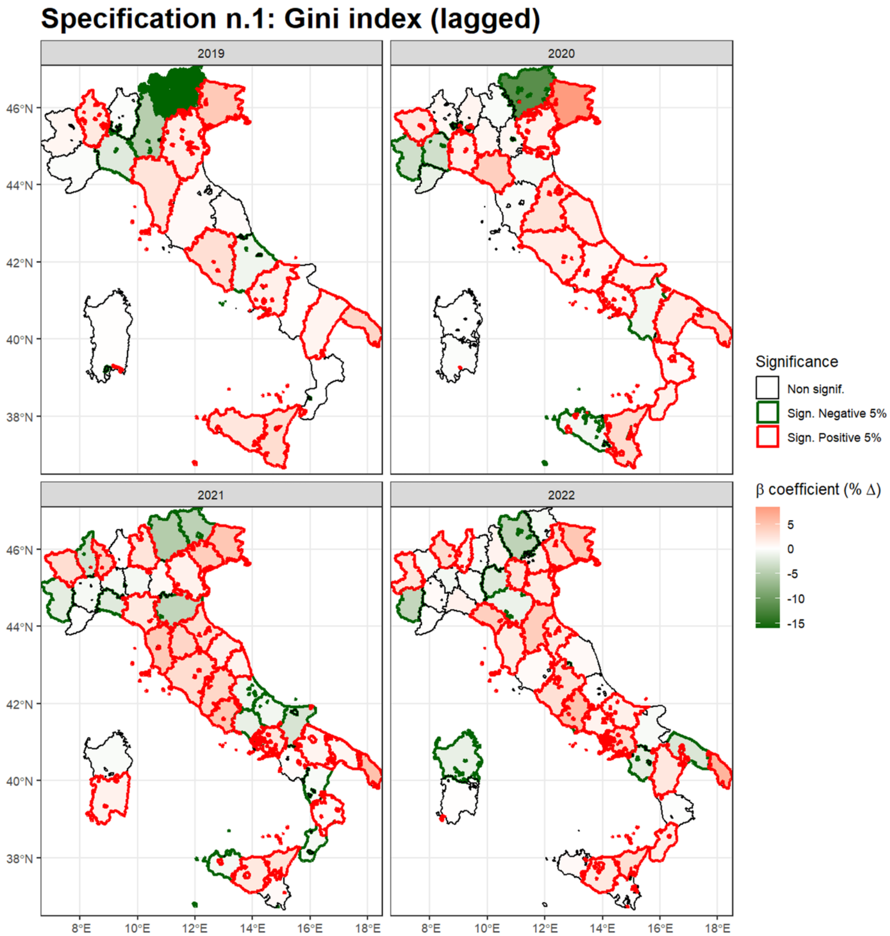

Fig. 4 Estimated clusterwise regression coefficients (and statistical significance) of income inequality by year

in greatest difficulty. This result highlights that, on the one hand, the areas with the highest income present structural obstacles to accessing the benefit, and, on the other, that there are phenomena of selective exclusion even in regions with lower economic capacity, probably linked to bureaucratic access mechanisms or to the distribution of the poor population across the territory.

Furthermore, the map highlights the presence of some municipalities that, despite being located within compact clusters, are assigned to distinct groups. This phenomenon could reflect economic, social, or institutional characteristics peculiar to these territories, which differentiate them from the surrounding areas. These discrepancies suggest that, alongside a broader territorial dynamic, there are also specific local factors that affect the relationship between income inequality and participation in the GMI. The integration of this evidence in the analysis of public policies could contribute to a better understanding of the dynamics of access to the measure, avoiding distortions in the allocation of resources.

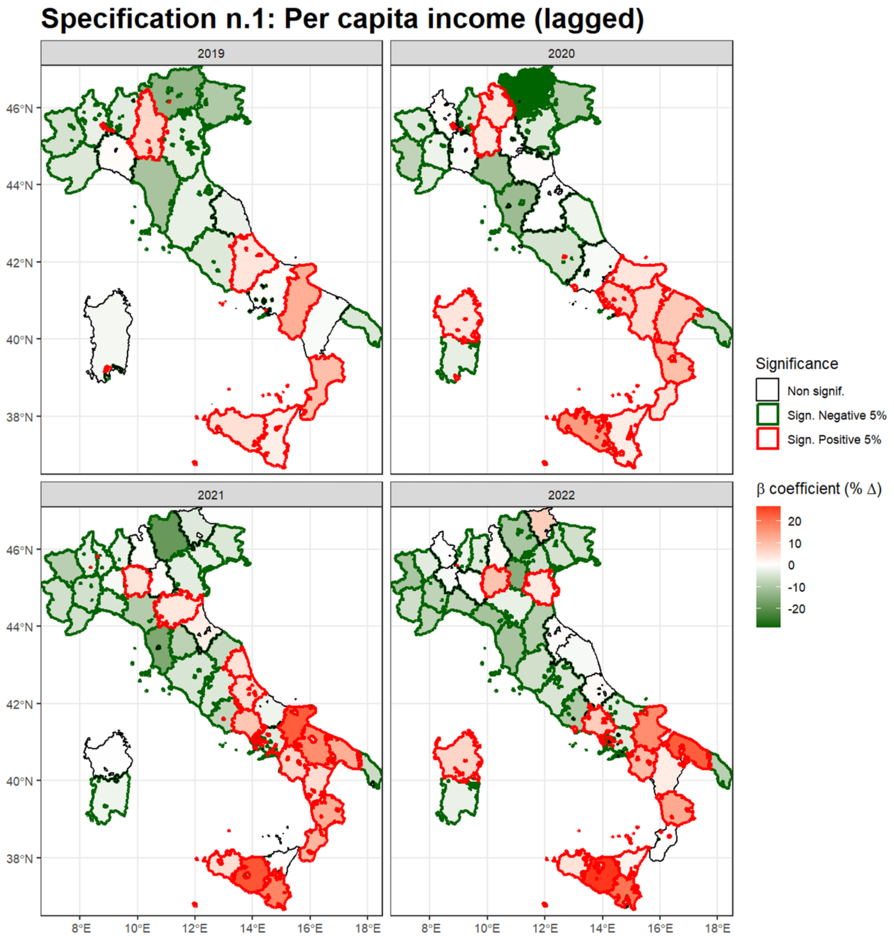

Fig. 5 Estimated clusterwise regression coefficients (and statistical significance) of per capita income by year

In general, the empirical findings confirm how the GMI, despite being a national measure, interacts with territorial specificities that, in turn, affect its effectiveness. The increasing fragmentation and widening spatial heterogeneity between 2019 and 2022 reinforce the idea that more flexible and local-based income support policies could improve the targeting of the measure, ensuring a fairer distribution of resources and encouraging participation in the measure that better responds to the conditions of vulnerability and social exclusion present.

6.3 Heterogeneity in per Capita Income

Figure 5 shows the clusterwise estimated coefficients for *Specification 1* relative to the municipal per capita income.

In the Northern regions, negative and statistically significant coefficients are found throughout the observed series, particularly in the municipalities of the North-East.

These municipalities, which are characterized by the highest levels of municipal income per capita (as highlighted in Fig. 2 and Table 4), show the most negative correlations between average income level and number of GMI recipients. Negative and significant coefficients are also present in the middle and upper Tyrrenian regions (i.e., Lazio and Tuscany). Positive correlations, on the other hand, are observed along the municipalities of the Adriatic regions (excluding the South of Apulia) and in the territories of the South and Islands, where the lowest levels of per capita income are present. Therefore, the results show that the different levels of per capita income found in the Italian territory are properly correlated with the number of households benefiting from the GMI monetary transfer. In this sense, the GMI appears to correctly intercept vulnerability situations at the local level. In fact, the results suggest effective policy targeting in areas of the country with lower income levels.

We can also detect an increase in the correlation between the number of recipients and social exclusion situations during the reference period, evidenced by an increasing number of positively estimated coefficients with higher values in terms of magnitudes.

Even with reference to income levels, many municipalities, although included within specific clusters, are assigned to distinct groups varying in the years of observation. This highlights not only differences in spatial dynamics, but also a notable temporal variability, suggesting that the processes of participation in the GMI evolve over time in a non-uniform way among the different geographical areas.

Furthermore, we detect the same trend shown for the income inequalities, with the increase in the degree of complexity and spatial heterogeneity from 2019–2022 (see Fig. 5). In particular, the maps in Fig. 5 show, for 2019, an almost exact overlap between the spatial boundaries created by the clusters and the administrative boundaries of the Italian regions. However, in 2022, the increase reveals deeper spatial differences. Again, the weight of the pandemic may have been decisive in the link between income differentials and the number of households that benefit from the measure (Palomino et al. 2020; Brunori et al. 2021; INPS 2022a, b; Gallo and Raitano 2023).

6.4 Heterogeneity in the Share of Poverty

As with income levels, the estimates of the coefficients associated with the municipal proportion of people living in poverty (see Fig. 6) also show results consistent with the typical Italian spatial dynamics (shown in Fig. 2 and Table 4).

Indeed, in the municipalities of Northern Italy, there is a largely negative and significant correlation between citizens in poverty and GMI's households. In particular, in the municipalities of the North-East, the values of the coefficients remain fairly constant in terms of sign, direction, and intensity, over the four years of observation, showing some stability. However, in specific areas of Northern Italy, negative coefficients are recorded. We recall from Fig. 2 that the distribution of income in these territories is less uniform but the average income is higher than in the southern regions. This means that some northern families, who are in conditions of socio-economic vulnerability, do not join the GMI program despite having the income requirements. Similar results, but with opposite signs, are recorded in the municipalities of the South and Islands, where the coefficients of the Eq. (5) show, instead, a positive and statistically significant link

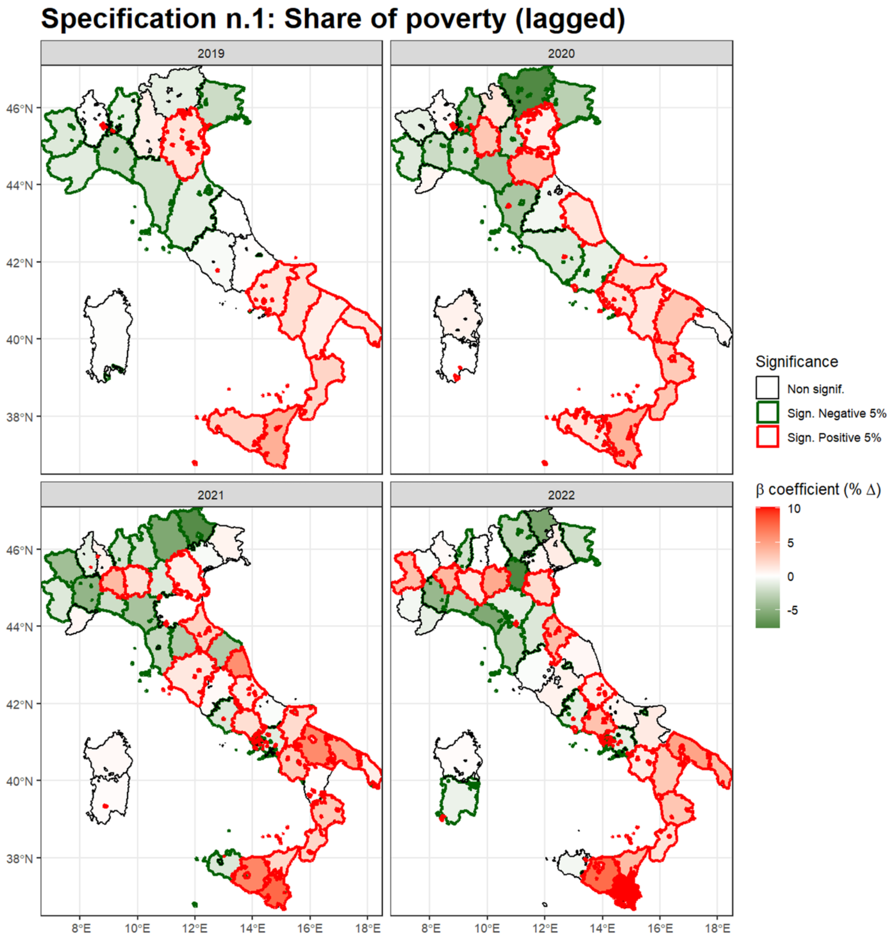

Fig. 6 Estimated clusterwise regression coefficients (and statistical significance) of the share of poverty by year

between poverty and receipt of the monetary benefit. The presence of municipalities belonging to clusters which differ from the surrounding ones is confirmed, highlighting heterogeneous spatial and temporal dynamics.

The results obtained for share of poverty are thus in line with the well-known socioeconomic vulnerabilities present in the Italian territory. Consequently, the share of poverty conditions seems to be well related to GMI's participation.

In the case of the municipal poverty rate, the growth of complexity along the years observed (2019–2022) is also revealed by the increase in clusters and the magnitude of the coefficients, with more positive magnitudes, especially in the municipalities of southern Italy. Specifically, in the last years of operation of the GMI, numerous socio-spatial differences can be observed linked to phenomena of social exclusion even in similar geographical contexts.

7 Discussion and Concluding Remarks

7.1 Discussions on GMI Impacts and Territorial Dynamics

In this study, we used municipal-level data to investigate the role of three local socioeconomic and well-being indicators, namely the index for income inequality, the average per capita income, and the share of poverty, in determining geographical differences and heterogeneity in the number of Italian families that required income support from central government between 2019 and 2022.

In particular, we considered a guaranteed minimum income (GMI) support policy implemented in Italy to support families and individuals affected by socioeconomic exclusion, namely the Italian Citizenship Income (in Italian language, *Reddito di Cittadinanza*) adopted between 2019 and 2023. The main research question focused on whether the GMI policy was able to effectively reach the target families in light of the geographical patterns shown by the three local indicators. Specifically, we were interested in studying whether limited wealth resources (i.e., low disposable income), poverty, and income inequality were able to influence households' choices to participate in public programs of economic and social support by fragmenting the country into sub-areas that are heterogeneous in terms of response.

To answer this question, we implemented numerous econometric specifications with spatially-varying coefficients, namely the spatially-clustered regression (SCR) models, grasping the strong spatial heterogeneity exhibited by the GMI recipient households by grouping municipal units into homogeneous and (potentially) spatially contiguous groups. The SCR methodology allowed us to evaluate how geography and local factors influenced the effective coverage of income support policies. We considered, as response variable of the regression, the count of households benefiting from the policy, while the local socioeconomic and well-being indicators acted as exogenous variables, in addition to a large set of socio-political and economic controls. To account for potential temporal dependencies and mitigate issues related to simultaneity, these socioeconomic indicators were lagged by one year relative to policy implementation.

Our findings showed that the spatial heterogeneity of socioeconomic proxies across the Italian municipalities significantly influenced participation in income support. Indeed, both the sign and magnitude of the estimated correlation strongly depend on the type of indicator used and on local structural characteristics, as well as on the year under inspection. To summarize the results, Fig. 7 illustrates the cluster-wise relationship between the estimated coefficients (as well as their estimated variability) and the average value for the three socioeconomic determinants of interest within the study period.[13]

In general, we obtained positive and statistically significant correlations between the level of per capita income and the share of municipal poverty. In particular, the highest positive magnitudes were recorded in areas marked by higher socioeconomic issues and low-income levels (i.e. southern Italy). In addition, Fig. 7 shows that average

[13] Notice that, Fig. 7 presents a 4×3 matrix structure in which the columns are the three socioeconomic drivers discussed in the paper (i.e., Gini index, per capita income, and share of poverty), while the rows represent years. We report both the group-wise point estimate of the coefficient and the corresponding confidence interval (fixing $\alpha = 5\%$) as in an error bar plot.

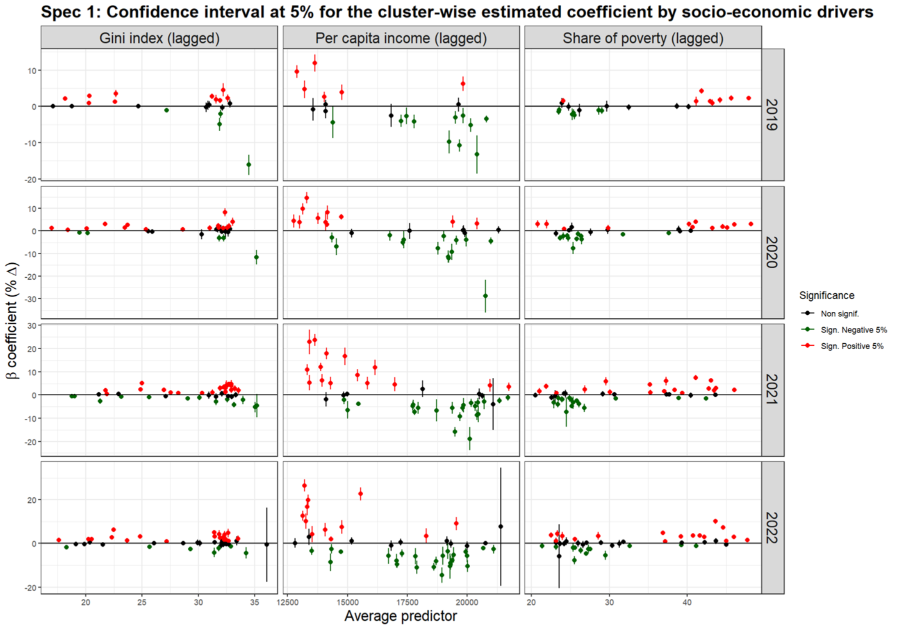

Fig. 7 Cluster-wise error-bars reporting the confidence interval at $\alpha = 5\%$ significance level for the estimated regression coefficients evaluated at group-specific average Gini index, average per capita income, and average share of municipal poverty during the period of interest4

per capita income (middle column) and poverty rate (right column) can clearly distinguish clusters with a positive effect (i.e., an increase in the number of GMI-recipient households) from those with a negative effect (i.e., a decrease in the number of recipient households). Specifically, as per capita income increases, the estimated coefficient changes from significant and positive to significant and negative; conversely, as the share of people in poverty increases, the coefficient changes from negative to positive, while remaining highly significant. The dynamics appear to be stable over the years considered, although the year 2021 (as a result of the COVID-19 pandemic) shows more complex patterns than the other years.

Concerning income inequality, the situation becomes more entangled. Specifically, we assessed the simultaneous presence of areas characterized by marked income inequalities which present negative correlations with the number of beneficiary families (e.g., north-western Italy), and areas showing positive and statistically significant values of correlation (e.g., north-eastern Italy). In fact, according to the left column of Fig. 7, positive and negative coefficient clusters are evenly distributed for each value of the index. However, in general, it can be observed that most clusters have a positive and statistically significant coefficient (i.e. the number of red clusters is higher than the number of green or black clusters), especially in the years following the pandemic.

These results, which may seem contradictory, are intrinsically linked to the examined dimensions. In fact, in areas where both average per capita income and income inequality are high (e.g., North-West), the GMI, which by definition applies only to low-income households, was unable to reach potential household targets, leaving the level of income inequality unchanged and leading to a negative correlation. In contrast, in southern Italy, mainly characterized by low income levels but lower levels of income inequality, the GMI reached a high number of households, leading to a positive and significant correlation. Eventually, the results highlighted a remarkable augmentation of the complexity of the social phenomenon throughout the period 2019–2022. Such a complexity was proxied by the number of relevant groups identified through the SCR algorithm. Empirically, we noticed that, from the second year of activity of the GMI policy (i.e., 2020) onwards, with the arrival of the COVID-19 pandemic, the number of clusters with statistically significant but spatially-varying coefficients increased substantially, leading to a more scattered and complex scenario.

In general, the empirical results obtained are mutually consistent with each other, but they must be interpreted in light of the spatial exploratory analysis reported in Fig. 2 and in Table 4. We recall that all three indicators are constructed, starting from the same source of information, that is, the declared incomes provided by the Ministry of Finance. In particular, the maps in Figs. 4, 5, 6 clearly showed how, in comparison to southern Italy, the north has both a higher average wealth and a lower share of families in poverty, but also a greater disparity in income distribution. Furthermore, the econometric models considered directly take into account the number of families residing in each municipality (i.e., the number of families is included as an offset), thus controlling for a possible scale effect. Therefore, since access to the GMI is based on proof of income, it seems plausible to assume that in the territories with higher declared income, the number of potentially reachable families is lower, or in any case more difficult to identify, compared to areas where there is a high number of families with incomes below the access thresholds. This interpretation could be useful to justify the different strengths in the estimated correlation between the number of families requesting the GMI and the three indicators considered (i.e. while the results are more straightforward and precise for the average per capita income, the estimates are more vague for the poverty rate and even more so for the Gini index.)

Starting from the results obtained through the spatial regression, we conducted an empirical exercise that evaluates the financial impact of a reallocation of funds, based on the optimization of resource allocation. The calculation procedure is illustrated in Appendix E. In particular, by leveraging on the simultaneous presence of positive and negative regression coefficients associated with the Gini index, we were able to estimate the economic impact of a realignment of funds based on the actual need detected in the different clusters. Indicatively, under the assumption that a negative sign of the Gini index is incongruent with prevailing expectations, we estimated the amount of additional resources that would have enabled the groups to transition (on average) from a negative to a positive sign, thereby ensuring the empirical result's consistency across the country. This transition comes from the difference in the averages of the economic support received by households in clusters with positive beta coefficients compared to those with negative beta coefficients, indicating the need for a reallocation towards areas where the GMI has demonstrated greater effectiveness. Estimates highlighted a significant margin for optimization of resource targeting. In fact, we estimate that an optimized allocation of resources could lead to an adjustment of the budget allocated to the GMI of approximately 2.78 billion euros. This sum, if added to the total of 23 billion actually allocated in the four years and distributed evenly across the territories, could have significantly increased the effectiveness of the intervention.

7.2 Policy Recommendations

The Italian Citizen's Income has been the subject of numerous criticisms, mainly regarding its actual capacity to identify and support families in need of assistance. This article provides fresh and positive evidence in relation tothe primary objectives of the GMI policy, namely, to reach and be useful for families in conditions of socioeconomic exclusion, taking into account the specific characteristics of different territories. The main result we find is that local socioeconomic conditions decisively matter in the implementation of national policies. Today, this measure has been abolished and replaced with other forms of income support less generous in terms of amounts to be paid and the number of eligible families. In the light of these regulatory changes, we argue for a constant evaluation of income support policies, exploiting the role of spatial heterogeneity to respond to the non-homogeneous economic and social contexts typical of the Italian landscape. Specifically, the variability of the effectiveness of the GMI in relation to the different contexts of inequality, suggests that adapting policies to local realities could not only improve their effectiveness, but also ensure a more equitable and sustainable impact. Consequently, future policy interventions should allow for more differentiated and flexible approaches, adapted to the specific needs of different geographical areas. In general, therefore, the results of our study demonstrate how income inequality within areas can have a significant impact on the distribution of the GMI. In particular, we observe that, in contexts characterized by high inequality and high income, the GMI does not always reach the families which might need it most. This phenomenon is partly due to the selection criteria based on declared income or other asset categories, which tend to exclude those families who, despite having a nominal income above the threshold established by the policy, are, nevertheless, in vulnerable situations.

The increasing complexity of the socioeconomic system, as evidenced by the results of this study, underscores the absence of a "one-size-fits-all" solution to the issue of providing support to individuals in need, a duty for which governments are expected to be responsible. Consequently, there is a need to review selection and participation mechanisms, in the light of local economic and social realities, so that support measures can be more inclusive and tailored to the specific needs of each territorial context. Our findings open up new perspectives for policymakers, as a more nuanced understanding of local inequality dynamics can lead to a more equitable and targeted implementation of support measures, as highlighted, for example, by Autor (2014) and Piketty (2014). In particular, the link between internal inequalities and access to minimum income measures could stimulate the development of regional policies that are more suited to heterogeneous economic contexts, promoting a more effective redistribution of income and a greater involvement of local communities in the policy formulation process. Also, we stress that areas with different levels of internal inequality are prone to respond differently to policies. The strategic adaptation of measures to such contexts has the potential to enhance the efficacy of interventions and ensure a more equitable and sustainable impact of welfare policies. Therefore, a thorough evaluation of resource targeting and allocation strategies is recommended, so that economic support effectively reaches those in vulnerable conditions, while reducing inequalities within and between different territorial areas.

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Author Contributions Paolo Maranzano: Contributed to *all sections* of the paper (Sect. 1, *Introduction*; Sect. 2, *Guaranteed Minimum Income Policies: Theoretical Frameworks and the Italian Application*; Sect. 3, *Further Socioeconomic Data*; Sect. 4, *Estimating Spatially-Varying Relationship via Spatially Clustered Regression*; Sect. 5, *Empirical Strategy*; Sect. 6, *Results*; Sect. 7, *Conclusions*). He collaborated to the study conception, design, code implementation, drafting, and revising the manuscript. Gianluca Monturano: Contributed to *all sections* of the paper (Sect. 1, *Introduction*; Sect. 2, *Guaranteed Minimum Income Policies: Theoretical Frameworks and the Italian Application*; Sect. 3, *Further Socioeconomic Data*; Sect. 4, *Estimating Spatially-Varying Relationship via Spatially Clustered Regression*; Sect. 5, *Empirical Strategy*; Sect. 6, *Results*; Sect. 7, *Conclusions*). He collaborated to the study conception, design, code implementation, drafting, and revising the manuscript. Pasquale Tridico: Contributed primarily to Sect. 1 (*Introduction*), Sect. 2, *Guaranteed Minimum Income Policies: Theoretical Frameworks and the Italian Application*; Sect. 6 (*Results*), and Sect. 7 (*Conclusions*). He collaborated on the theoretical framework of the study, final discussion, policy implications of the results, and revision of the manuscript.

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Data Availability The municipal dataset on Citizenship Income used in the study is provided by the Italian Institute of Social Security (INPS) and is available to the public upon request. The authors accessed the data through a non-disclosure agreement. All results presented in this paper can be reproduced using the `R` software. The codes were developed entirely by the authors. For reproducibility purposes, all the scripts and a masked-version of the dataset (i.e., containing data not covered by non-disclosure agreements and simulated data for municipal INPS GMI) are made available for the public on the following GitHub repository: https://github.com/PaoloMaranzano/PM_GM_PT_IEJ2025_RdCSpatClust.git. Recall that, due to the non-disclosure of INPS data, actual results of the paper cannot be reproduced; however, the public codes allow to verify the validity of the empirical findings, respecting GDPR rules.

Declarations

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

Appendix A Eligibility Criteria for Italian Citizenship Income

See Table 2.

Table 2 Detailed eligibility criteria for access to GMI

Income	ISEE value less than 9360 euros
Economic	Family income of less than 6000 Euros per year, multiplied by the equivalence scale parameter, with increased thresholds for access to the citizenship pension and for rented households
Wealth and assets	Real estate assets, excluding the home, not exceeding 30,000 Euros
	Movable assets not exceeding 6000 Euros for singles, with increases by number of members, children beyond the second, and members with disabilities
	Family income of less than 6000 Euros per year, multiplied by the equivalence scale parameter, with increased thresholds for access to the citizenship pension and for rented households
Citizenship and residence	Italian or European Union citizens
	Citizens of third countries with an EU long-term residence permit, or stateless persons with a similar permit
	Third country citizens who are family members of an Italian or EU citizen with the right of residence or permanent residence
	Holders of international protection
	Residence in Italy for at least 10 years, of which the last two are continuous
Other requirements	No member must own motor vehicles registered in the 6 months preceding the request or with a displacement greater than 1,600 cc, or motor vehicles greater than 250 cc registered in the previous 2 years, excluding vehicles for the disabled
	No possession of ships and pleasure boats
	The applicant must not be subjected to personal precautionary measures or definitively convicted in the previous ten years for certain crimes
Employment status	Compatible with NASPI, DIS-COLL and other income support tools for involuntary unemployment
	Exclusion for voluntary resignation in the previous 12 months (except for just cause), state detention or long-term hospitalization, and for members subjected to personal precautionary measures or final convictions for specific crimes in the previous 10 years

Source Author's processing of Italian Government data

Appendix B Descriptive Statistics on GMI and Economic Variables

See Tables 3 and 4.

Table 3 Distribution of GMI by territorial area, 2019–2022

Territorial	Number of households receiving GMI				Share of households receiving GMI on total households			
	2019	2020	2021	2022	2019	2020	2021	2022
Abruzzo	18,197	23,522	40,448	43,689	2.92	3.69	6.07	6.61
Basilicata	9176	10,657	17,083	19,758	4.01	4.59	7.27	8.35
Calabria	58,774	78,214	135,680	155,902	6.69	8.78	14.60	16.92
Campania	160,853	249,541	450,921	502,973	5.43	7.82	13.22	14.56
EM	27,252	36,818	68,091	66,248	1.13	1.49	2.80	2.75
FVG	8979	11,236	18,432	18,283	1.09	1.31	2.31	2.31
Lazio	73,480	110,533	221,152	236,378	3.53	4.92	8.57	9.21
Liguria	17,129	24,285	43,747	42,262	1.87	2.56	4.69	4.84
Lombardy	65,013	94,639	184,317	168,206	1.16	1.55	2.92	2.85
Marche	11,974	15,682	26,923	26,156	1.66	2.10	3.60	3.53
Molise	5077	6631	11,238	12,031	3.63	4.99	8.29	8.82
Piedmont	46,069	64,045	116,903	117,995	1.47	2.05	3.79	3.95
Puglia	78,260	106,819	194,233	213,635	4.12	5.73	9.87	10.65
Sardinia	37,892	47,248	79,150	87,146	5.06	6.11	9.61	10.08
Sicily	148,898	215,302	380,350	438,769	6.06	8.39	13.69	15.72
Tuscany	30,955	39,567	70,199	69,260	1.70	2.17	3.79	3.71
TAA	2405	3489	7584	6705	0.38	0.51	1.06	0.94
Umbria	8640	11,748	19,977	20,515	1.92	2.58	4.42	4.51
Valle d'Aosta	908	1068	1812	1634	1.10	1.26	2.08	1.87
Veneto	23,789	30,818	55,895	53,232	0.94	1.19	2.09	2.04
North-East	62,425	82,361	150,002	144,468	0.89	1.14	2.08	2.02
North-West	129,119	184,037	346,779	330,097	1.34	1.82	3.38	3.42
Center	125,049	177,530	338,251	352,309	2.43	3.27	5.68	5.89
South	330,337	475,384	849,603	947,988	4.85	6.58	11.02	12.27
Islands	186,790	262,550	459,500	525,915	5.57	7.27	11.69	12.95
Italy	833,720	1,181,862	2,144,135	2,300,777	2.60	3.47	5.95	6.40

Source Author's processing of INPS data
The data are obtained by aggregating municipal data provided by the INPS

Table 4 Average per capita income and average share of poverty by territorial area, 2018–2021

Territorial	Average per capita income				Average share of poverty			
	2018	2019	2020	2021	2018	2019	2020	2021
Abruzzo	14,901.66	15,057.54	15,098.77	15,760.44	37.86	37.18	37.18	35.28
Basilicata	13,910.99	13,965.20	14,072.04	147,20.24	41.51	40.70	39.90	38.08
Calabria	12,730.35	12,849.30	12,867.45	13,384.31	48.10	47.22	47.00	45.43
Campania	14,198.66	14,293.76	14,218.47	14,899.26	42.98	42.15	42.37	40.22
EM	19,981.44	20,161.18	19,788.60	20,872.62	23.51	23.10	23.43	22.31
FVG	19,129.32	19,313.80	19,120.46	20,008.52	25.43	24.97	25.08	24.01
Lazio	16,686.23	16,769.11	16,701.81	17,397.22	34.13	33.43	33.68	31.75
Liguria	18,167.64	18,143.74	17,784.65	18,729.52	29.40	29.02	30.12	28.52
Lombardy	20,531.92	20,535.43	20,149.30	21,225.59	23.70	23.46	24.36	22.94
Marche	16,955.62	17,173.78	17,007.16	17,937.82	29.07	28.33	28.39	26.87
Molise	13,056.98	13,165.56	13,206.27	13,807.45	44.98	44.01	43.70	41.90
Piedmont	19,186.02	19,225.76	18,929.11	19,918.88	25.48	25.18	25.52	24.29
Puglia	14,124.38	14,231.69	14,257.25	14,913.95	41.88	41.14	41.19	39.24
Sardinia	14,011.69	14,169.18	14,206.48	14,733.04	40.14	39.09	39.23	37.52
Sicily	13,634.56	13,753.58	13,704.98	14,325.24	43.65	42.83	43.08	40.92
Tuscany	18,637.47	18,771.97	18,364.43	19,480.18	27.11	26.58	27.32	25.71
TAA	19,983.33	20,161.27	19,815.55	20,659.54	27.22	26.52	26.53	26.27
Umbria	17,306.11	17,498.55	17,398.27	17,741.37	29.08	28.67	29.02	28.95
Valle d'Aosta	19,885.15	19,965.56	19,665.50	20,032.98	24.17	23.84	24.86	25.41
Veneto	19,406.38	19,577.21	19,238.95	20,280.69	24.75	24.24	24.56	23.43
North-East	19,616.80	19,792.29	19,469.04	20,454.86	25.06	24.55	24.77	23.84
North-West	19,799.65	19,817.63	19,470.86	20,485.68	24.86	24.58	25.28	23.97
Center	17,357.98	17,496.37	17,307.41	18,144.92	30.50	29.87	30.22	28.64
South	13,867.21	13,977.84	13,985.49	14,606.02	43.15	42.34	42.27	40.40
Islands	13,819.67	13,957.31	13,951.65	14,525.35	41.93	41.00	41.19	39.25
Italy	17,541.57	17,634.11	17,445.99	18,295.21	31.40	30.85	31.13	29.69

Source Author's processing of Ministry of the Economy data
The data are obtained by aggregating municipal data provided by the Ministry of Economy

Appendix C Additional *Specifications* of the Empirical Model

In the following, the empirical specifications of the Poisson regression model for a generic cluster g and year t are described in the Eqs. C1, C2, C3, C4.
Specification 2: (Gini is omitted from the main covariates)

$$
\begin{aligned}
log[E(y_{s_g t}|\boldsymbol{X}_{s_g t})] = \beta_{0gt} &+ \beta_{1gt} PerCapitaIncome_{s_g t-1} \\
&+ \beta_{2gt} ShareOfPoverty_{s_g t-1} \\
&+ LogNumFam_{s_g t} + \boldsymbol{\gamma}_{gt} X_{s_g t} \\
&\forall t = 2019, \ldots, 2022 \text{ and } \forall g = 1, \ldots, G
\end{aligned}
\tag{C1}
$$

where $y_{s_g t} \sim Poisson(\eta_g)$ are the observed number of recipient families for year t in group g, β_{1gt} is the coefficient associated with the per capita income for group g at year $t-1$, β_{2gt} is the coefficient associated with the share of poverty for group g at year $t-1$, $LogNumFam_{s_g t}$ represents the logarithm of the number of families living in municipality s at time t (recall that, being an offset, the associated coefficient is fixed to 1), and $\boldsymbol{\gamma}_{gt}$ is the set of $q = 21$ contemporaneous coefficients associated with the control variables.

Specification 3: (only Gini as main covariate)

$$\begin{aligned} log[E(y_{s_g t}|\boldsymbol{X}_{s_g t})] = \beta_{0gt} &+ \beta_{1gt} Gini_{s_g t-1} \\ &+ LogNumFam_{s_g t} + \boldsymbol{\gamma}_{gt} X_{s_g t} \\ &\forall t = 2019, \ldots, 2022 \text{ and } \forall g = 1, \ldots, G \end{aligned} \tag{C2}$$

where $y_{s_g t} \sim Poisson(\eta_g)$ are the observed number of recipient families for year t in group g, β_{1gt} is the coefficient associated with the income inequality (index) for group g at year $t-1$, β_{2gt} is the coefficient associated with the share of poverty for group g at year $t-1$, $LogNumFam_{s_g t}$ represents the logarithm of the number of families living in municipality s at time t (recall that, being an offset, the associated coefficient is fixed to 1), and $\boldsymbol{\gamma}_{gt}$ is the set of $q = 21$ contemporaneous coefficients associated with the control variables.

Specification 4: (only share of poverty as main covariate)

$$\begin{aligned} log[E(y_{s_g t}|\boldsymbol{X}_{s_g t})] = \beta_{0gt} &+ \beta_{1gt} ShareOfPoverty_{s_g t-1} \\ &+ LogNumFam_{s_g t} + \boldsymbol{\gamma}_{gt} X_{s_g t} \\ &\forall t = 2019, \ldots, 2022 \text{ and } \forall g = 1, \ldots, G \end{aligned} \tag{C3}$$

where $y_{s_g t} \sim Poisson(\eta_g)$ are the observed number of recipient families for year t in group g, β_{1gt} is the coefficient associated with the income per capita income for group g at year $t-1$, β_{2gt} is the coefficient associated with the share of poverty for group g at year $t-1$, $LogNumFam_{s_g t}$ represents the logarithm of the number of families living in municipality s at time t (recall that, being an offset, the associated coefficient is fixed to 1), and $\boldsymbol{\gamma}_{gt}$ is the set of $q = 21$ contemporaneous coefficients associated with the control variables.

Specification 5: (only per capita Income as main covariate)

$$\begin{aligned} log[E(y_{s_g t}|\boldsymbol{X}_{s_g t})] = \beta_{0gt} &+ \beta_{1gt} PerCapitaIncome_{s_g t-1} \\ &+ LogNumFam_{s_g t} + \boldsymbol{\gamma}_{gt} X_{s_g t} \\ &\forall t = 2019, \ldots, 2022 \text{ and } \forall g = 1, \ldots, G \end{aligned} \tag{C4}$$

where $y_{s_g t} \sim Poisson(\eta_g)$ are the observed number of recipient families for year t in group g, β_{1gt} is the coefficient associated with the share of poverty for group g at year $t-1$, β_{2gt} is the coefficient associated with the share of poverty for group g at year $t-1$, $LogNumFam_{s_g t}$ represents the logarithm of the number of families living in municipality s at time t (recall that, being an offset, the associated coefficient is fixed to 1), and $\boldsymbol{\gamma}_{gt}$ is the set of $q = 21$ contemporaneous coefficients associated with the control variables.

Appendix D Comparison Between Spatially Clustered and the Pooled Regression Results

Table 5 shows the estimates of the pooled Poisson regression for the selected variables, offering an overall view of the phenomenon studied, without considering the spatial component and local specificities.

In particular, the coefficients of the constant term show negative and significant values in 2019, indicating a low initial propensity to benefit from the GMI. In the following years up to 2022, these coefficients become positive and statistically significant, signaling an improvement in participation in the support program. A similar trend is observed in the coefficient of the intercept for the time-pooled model that includes all the years of observation together.

Regarding the three main drivers, the behaviors are more stable and consistent with the group-wise results, highlighting a continuous and significant impact of these socioeconomic indicators in shaping access to the GMI policy.

These robustness estimates, despite the possibility of masking regional disparities and local nuances, provide crucial information on the influence of spatial heterogeneity on the effectiveness of the GMI. The adopted approach allows for a comparative analysis with the results of the spatially pooled benchmark regression (see Figs. 4, 5, 6) and with other model specifications. The influence of local socioeconomic well-being variables is found to be significantly heterogeneous across regions in the spatial models, confirming that the same factors can have different effects depending on the territorial contexts. These observations emphasize the importance of integrating multiple econometric approaches to analyze both general trends and local ones, thus ensuring more targeted and effective policy interventions. The results highlight the need to adapt policies such as the GMI to regional characteristics to effectively address disparities.

In conclusion, while pooled regressions provide useful baseline information, the spatially pooled analysis underlines the critical importance of regional economic dynamics and local socioeconomic factors in influencing policy outcomes. This dual approach is essential for policymakers who aim to design interventions that are effective and equitable across geographic areas.

Table 5 Specification 1 of Poisson regression: pooled estimates (no spatial clustering) of regression coefficients for year-specific regression (columns 2–5) and time-pooled (all data from 2019 to 2022) regression (column 6)

	2019	2020	2021	2022	2019:2022
(Intercept)	−0.72***	0.09	0.69***	1.81***	0.20***
	(0.06)	(0.06)	(0.04)	(0.04)	(0.02)
Per capite income	−0.00***	−0.00***	−0.00***	−0.00***	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share of poverty	0.01***	0.01***	0.01***	−0.00**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gini Index	0.02***	0.02***	0.02***	0.02***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of taxpayers	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Local Units	−0.00***	−0.00***	−0.00***	−0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employees of local units	0.00***	0.00***	0.00***	0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment rate 20–64 years	−0.06***	−0.06***	−0.06***	−0.07***	−0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Distance to essential services	−0.01***	−0.01***	−0.00***	−0.01***	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Resident population	0.00***	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share of immigration	0.00***	0.00***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Register for foreigners	0.00	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Population growth rate	−0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Population dependency index	−0.00***	−0.00***	−0.01***	−0.01***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Population density	0.00	−0.01***	−0.02***	−0.01***	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Population 25–64 with low school	−0.00***	0.00***	0.00***	−0.00***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 5 continued

	2019	2020	2021	2022	2019:2022
Level of urbanisation	−0.09***	−0.10***	−0.10***	−0.08***	−0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Territorial surface	−0.00***	−0.00	0.00	−0.00	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Altitude of the center	−0.00*	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Protected natural areas	−0.00***	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Landslide hazard zones	−0.00**	0.00**	0.00***	0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Land consumption	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
High emission motor rate	0.01***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Undifferentiated urban waste	−0.00***	−0.00***	0.00	−0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of mayor	−0.00***	−0.00***	−0.00***	−0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average age of councilors	0.00***	0.00***	0.00***	0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Resid.SD	75.90	79.42	155.10	154.70	594.86
Num. obs	7852	7803	7789	7848	31,292
Num. pars	26	26	26	26	26
Log likelihood	− 51,315	− 59,987	− 80,933	− 90,005	− 720,055
AIC	102,681	120,027	161,918	180,063	1,440,162
BIC	102,863	120,208	162,099	180,244	1,440,379
Deviance	64,707	80,055	117,765	135,346	1,273,503

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Appendix E Calculation Procedure for Optimizing Resource Allocation of GMI

To assess the financial impact of the optimized allocation of funds from the GMI, we followed the calculation procedure below using the data available to us and the results of Spatially Clustered Regression. In particular:

1. We divide the municipalities into two groups based on the beta coefficients obtained from the spatial analysis:
   - *Municipalities with a negative beta coefficient;*
   - *Municipalities with a positive beta coefficient.*

2. We calculate the average positive total amount for municipalities with positive beta coefficients:

$$AveragePositiveTotalAmount = \frac{\sum(PositiveHouseholdsGMI \times GMIAverageMonthlyAmounts)}{\sum WeightedPositiveHouseholdsGMI} \tag{E5}$$

3. The average negative total amount of municipalities with negative beta coefficients is obtained by selecting the product values $PositiveHouseholdsGMI \times GMIAverageMonthlyAmounts$ lower than the $AveragePositiveTotalAmount$ value (in our case, 572.80 euros).
4. The average monthly total amount for the filtered municipalities with negative beta coefficients is calculated:

$$AverageNegativeTotalAmount = \frac{\sum(NegativeHouseholdsGMI \times GMIAverageMonthlyAmounts)}{\sum WeightedNegativeHouseholdsGMI} \tag{E6}$$

5. The average difference between the average amounts of the two groups of municipalities is:

$$\Delta AverageTotalAmount = AveragePositiveTotalAmount - AverageNegativeTotalAmount \tag{E7}$$

6. The estimate of the necessary budget adjustment for an optimized allocation of resources (in our result 2,78 billion euros) is based on the calculated average difference and the number of beneficiary households is obtained with:

$$Total\ Adjustment = GMI\ Number\ Households \times \Delta\ Average\ Total\ Amount \times Months\ GMI\ operation \tag{E8}$$

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