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The Persistence in Income Disparities: Evidence from Italian NUTS-2 and NUTS-3 Regions using Dynamic Spatial Panel Models*

César R. Sobrino[a], Edwin Rodriguez[a], Angel Ojeda[a]

[a]*School of Business, Tourism & Entrepreneurship at UAGM, Gurabo, PR 00778*

Abstract: This study investigates stochastic income convergence across Italian regions at two spatial scales—NUTS-2 (regions) and NUTS-3 (provinces)—in a context of an affluent North and the less-developed South. Using dynamic panel data models, both non-spatial and spatial, for 2001–2021, the analysis explores the roles of persistence, unobserved regional heterogeneity, and spatial dependence in income gap dynamics. Models without fixed effects show near-unit-root behavior, indicating high persistence or divergence, whereas including fixed effects substantially reduces persistence, providing evidence of conditional stochastic convergence at both spatial scales. Spatial dependence is limited at the NUTS-2 level, with coefficients generally small and insignificant, but at the NUTS-3 level, spatial interactions are economically meaningful and significant, highlighting localized spillovers in provincial income disparities. Ignoring these interactions at the finer scale can overstate persistence. To correct for Nickell bias in dynamic fixed-effects models, System GMM estimators are employed. Spatial System GMM results show strong but stable persistence, with coefficients around 0.86–0.87. The implied half-life of income shocks is roughly five years at the regional level and four to four-and-a-half years at the provincial level, indicating faster adjustments locally. Overall, the study finds weak but robust conditional stochastic convergence, emphasizing the importance of accounting for both spatial dependence and unobserved heterogeneity in understanding regional income dynamics in Italy. Unlike previous studies, our results quantify the persistence and half-life of income shocks, highlighting the difference between NUTS-2 and NUTS-3.

Keywords: Spatial Models, Time Series, Convergence, Regional Economics
JEL Codes: C21, C32, O47, R10

1. INTRODUCTION

Whether regional income disparities tend to diminish over time has long been a central theme in regional economics and economic growth literature. This inquiry is particularly pertinent

*Sobrino, Rodriguez, and Ojeda are professors in the School of Business, Tourism, and Entrepreneurship at Universidad Ana G. Méndez, Gurabo Campus, Gurabo, PR 00778. *Corresponding Author:* César R. Sobrino, E-mail: sobrinoc1@uagm.edu

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for countries like Italy, which exhibit significant and persistent geographical concentrations of income. Understanding the dynamics of regional income convergence in such contexts is crucial for designing effective regional policies (e.g., increasing schooling budgets, upgrading transportation networks, and reducing market regulations) aimed at fostering cohesion and reducing spatial inequalities.

For Italy, using cross-sectional and panel data models, previous studies have explored β-convergence, where poorer regions catch up to richer ones due to diminishing returns to capital, both with and without spatial econometrics Arbia et al. (2002); Postiglione et al. (2020); Cartone et al. (2021); D'Uva and De Siano (2011). Since Rey and Montouri (1999)'s contribution, one direction in convergence analysis has involved the use of spatial econometrics. Incorporating spatial dependencies helps account for spillover effects (e.g., diffusion of new technologies, labor regulations, infrastructure development, crime, and pollution), yielding more accurate estimates by controlling for regional dynamics that influence neighboring areas. In addition, some literature has examined σ-convergence (Monfort, 2008; Postiglione et al., 2020).

Meanwhile, regional stochastic income convergence focuses on whether income disparities are permanent or temporary. One way to analyze this is by employing unit root or panel unit root tests to examine whether income disparities (regional income minus the benchmark income) are stationary. Studies adopting this approach include Costantini and Arbia (2006) and D'Uva and De Siano (2011). At the NUTS 2 level, Costantini and Arbia (2006) report mixed results, contingent on specific areas and sub-periods in a panel setup accounting for cross-dependence, while D'Uva and De Siano (2011) also yield mixed outcomes when accounting for a structural break in 1992. These studies rely on non-stationary methodologies to assess whether income shocks are temporary but do not address the persistence or half-life of such shocks. While income shocks may be temporary, the implications for half-life differ depending on whether the shock is weakly persistent or nearly a random walk. Furthermore, these studies do not incorporate spatial econometric techniques or explicitly account for time-invariant regional characteristics (e.g., climate, coastline access, political systems). Despite extensive research on regional convergence in Italy across NUTS-2 and NUTS-3, a better understanding of the persistence of regional disparities remains elusive, particularly when considering the crucial roles of spatial interactions and unobserved regional heterogeneity.

Moreover, most empirical literature on Italian regional convergence focuses on a single level of aggregation (either NUTS-2 or NUTS-3). However, aggregation bias can mask finer variations, resulting in divergent conclusions depending on the analytical level. Studies highlighting bias in spatial data aggregation include Monteforte (2007); Persyn (2021); Kunimitsu (2024), and Huck et al. (2025).[1] Although spatial econometrics has increasingly shaped studies on convergence, the interaction between spatial aggregation (NUTS-2 vs. NUTS-3), unobserved time-invariant characteristics, and income shock persistence warrants further investigation.

[1]Monteforte (2007) examined macroeconomic modeling across European countries and the Euro Area; Persyn (2021) showed that wage curve elasticities are steeper at aggregated country levels than at disaggregated regional levels; Kunimitsu (2024) quantified regional aggregation bias in global CGE models; and Huck et al. (2025) identified Focal Area Bias (FAB) in GIS analyses, where peripheral areas within buffers misrepresent core locations.

This study analyzes stochastic income convergence across Italy using a balanced panel of 18 contiguous NUTS-2 regions and their 93 NUTS-3 provinces over the period 2001–2021. It employs dynamic non-spatial and spatial panel data models, including SAR and SEM specifications, to assess whether regional and provincial income gaps relative to the national average exhibit permanent divergence or mean-reverting behavior. Unlike much of the existing literature—which relies primarily on unit root or panel unit root tests and abstracts from time-varying heterogeneity and spatial interactions—this study explicitly accounts for unobserved fixed effects, spatial dependence, and dynamic panel bias within a unified econometric framework. By systematically comparing results across NUTS-2 and NUTS-3 levels, the analysis also addresses the potential role of spatial aggregation bias in shaping conclusions about income convergence.

The results highlight the central importance of unobserved time-invariant heterogeneity. Once fixed effects are introduced, the estimated persistence of income gaps declines substantially at both spatial levels, providing clear evidence of conditional stochastic convergence. Spatial dependence plays a limited role at the NUTS-2 level, where spatial coefficients are generally small and statistically insignificant. In contrast, at the NUTS-3 level, spatial interactions are economically meaningful and statistically significant, indicating the presence of localized spillovers in provincial income dynamics and underscoring the importance of modeling spatial interactions at finer geographical scales.

To address Nickell bias in dynamic fixed-effects models, the study employs Difference and System GMM estimators. Preferred spatial System GMM specifications indicate strong but stable persistence, with coefficients around 0.87 at the NUTS-2 level and approximately 0.86 at the NUTS-3 level. These estimates imply half-lives of income shocks of about five years at the regional level and roughly four to four-and-a-half years at the provincial level, suggesting faster adjustment at finer spatial scales. Overall, the findings point to weak but robust conditional stochastic convergence and demonstrate that ignoring spatial dependence—particularly at the NUTS-3 level—can lead to overstated persistence and misleading inferences about regional income dynamics. Unlike previous studies such as Costantini and Arbia (2006) and D'Uva and De Siano (2011), our outcomes quantify the persistence and half-life of income shocks, highlighting the difference across NUTS-2 and NUTS-3.

The remainder of the study is organized as follows: Section 2 briefly discusses the relevant literature; Section 3 outlines the methodology and describes the data; Section 4 reports the results and discussion; and the final section concludes the study.

2. RELEVANT LITERATURE

The neoclassical economic theory (Solow, 1956, 1957; Swan, 1956) predicts that poor economies will grow faster than rich economies. Basically, in a free capital mobility regime, capital flows to the poor countries, where it is more productive toward achieving income convergence. In addition, this theory suggests that in a free market capital regime, the differences in income across the countries (regions) of a currency area (country) are temporary. Specifically, the disparities in regional income should be minimized in a frictionless economy.

Early convergence studies, such as Baumol (1986) and Barro et al. (1991), focused on β-

convergence, examining whether poorer economies grow faster than richer economies. However, Rey and Montouri (1999) highlighted a critical oversight in these models: the omission of spatial dependence, where economic activity in one region influences its neighbors. Using US states, they provided evidence that accounting for spatial interactions significantly alters β coefficients, leading to more accurate models. Subsequent studies, such as Ertur et al. (2006) and Ramajo et al. (2008), applied spatial econometrics to European NUTS-2 regions, identifying convergence clubs of regions converging to different income levels due to structural or geographic factors.[2]

To address endogeneity and omitted variable bias in cross-sectional regressions, researchers like Arbia et al. (2008); Badinger et al. (2004); Bouayad-Agha and Védrine (2010); Moscone and Tosetti (2011); German-Soto and Brock (2022) employed panel data and Generalized Method of Moments (GMM) techniques, confirming the importance of spatial interactions in the US and EU contexts. These advancements underscore the need for spatially aware models to capture the complex dynamics of regional income convergence.

Another approach is the analysis of stochastic income convergence. In this approach, where regional income disparities are tested for stationarity, implying that shocks to income gaps (the difference between the regional income and the national counterpart) are temporary, the studies mainly employ non-stationary methodologies. Not including spatial interactions are Mello (2011), who finds evidence that supports the hypothesis of stochastic convergence in the US states, and, for Malaysia, Habibullah et al. (2012) support the presence of stochastic convergence for 6 regions. Additional literature on this subject is Genc et al. (2011) who find convergence in US metropolitan and non-metropolitan counties (1969–2001) toward the benchmark income, Carrington (2006) who analyzed 65 EU NUTS-2 regions (1984–1993) and provided evidence that income convergence is sensitive to the choice of time period,[3] and Herrerías and Monfort (2015) who concluded that economic reforms have facilitated convergence across Chinese provinces.

In addition, including spatial interactions Carrion-i Silvestre and German-Soto (2009) find that regional stochastic income convergence holds across Mexican states, Holmes et al. (2014) found stochastic convergence using US Metropolitan Statistical Area data, Cuestas et al. (2021) identify two convergence clubs in real personal disposable income across 14 European countries (12 EU plus Norway and Switzerland, 1975Q1–2019Q2), and, recently, Bozdoğan (2024) does not report stochastic convergence for regions in Turkey.[4]

Specifically for Italian regions, at the NUTS-3 level, Arbia et al. (2002) find a faster convergence rate (conditional β-convergence) when spatial heterogeneity and spatial dependence are corrected. Recent work by Cartone et al. (2021) employs a spatial quantile regression to analyze NUTS-2 regions from 1980–2006, finding conditional β-convergence but highlighting that spatial spillovers from neighboring regions' productivity and human capital significantly influence growth rates. This suggests that neglecting spatial interactions can lead to biased estimates of convergence speed. In addition, using NUTS-3 level data for European provinces including those of Italy, Postiglione et al. (2020) find evidence of conditional β-convergence

[2] Actually, Ramajo et al. (2008) found that EU cohesion-fund countries (Ireland, Greece, Portugal, and Spain) were converging separately from the rest of the EU.

[3] Actually, Carrington (2006) employed a Second-Order Stochastic Dominance approach.

[4] Actually Holmes et al. (2014) and Cuestas et al. (2021) accounted for cross-dependence.

over 1981–2014, using a spatial econometric approach. Their approach accounts for spatial dependence, revealing that provinces with lower initial GDP per capita grow faster, but convergence is slower when spatial spillovers are considered.

Stochastic convergence analyses are less common but offer valuable insights into the persistence of regional income shocks. Using Italian NUTS-2 data, Costantini and Arbia (2006) and D'Uva and De Siano (2011) examined this issue. D'Uva and De Siano (2011), without accounting for spatial dependence, analyze the period 1980–2007 and find mixed evidence of stochastic convergence when allowing for a structural break in 1992. In contrast, Costantini and Arbia (2006) apply recent panel unit root methodologies over 1951–2002 and explicitly account for cross-sectional dependence using SUR and MADF tests.[5] They find no overall convergence across Italian regions, though some convergence is detected among northern regions. Consistent with these findings, recent studies suggest that Italian regions may not converge to a single steady state but instead form "convergence clubs." Cutrini and Mendez (2023) identify two such clubs: a high-income northern group (e.g., Lombardy, Veneto) and a low-income southern group (e.g., Sicily, Calabria), with spatial dependence reinforcing cohesion within clubs. Using finer NUTS-3 data, Novac and Dumitrescu-Moroianu (2020) identify six convergence clubs.

These studies (Costantini and Arbia, 2006; D'Uva and De Siano, 2011) rely on non-stationary methodologies to assess whether income shocks are temporary but do not address the persistence or half-life of such shocks. While income shocks may be temporary, the implications for half-life differ depending on whether the shock is weakly persistent or nearly a random walk. Furthermore, these studies do not incorporate spatial econometric techniques or explicitly account for time-invariant regional characteristics (e.g., climate, coastline access, political systems). Despite extensive research on regional convergence in Italy across NUTS-2 and NUTS-3, a better understanding of the persistence of regional disparities remains elusive, particularly when considering the crucial roles of spatial interactions and unobserved regional heterogeneity.

For Italy, while conditional β-convergence is well explored and some literature has been analyzing convergence clubs, stochastic convergence is less explored, primarily relying on unit root or panel unit root tests. Basically, these studies do not account for time-variant regional characteristics and spatial interactions, whose importance is highlighted by all studies using spatial econometrics. Furthermore, the literature focuses on a single aggregation level, either NUTS-2 or NUTS-3, without comparing results to assess aggregation bias, which may miss intra-regional disparities. Some studies highlighting this bias in spatial data aggregation are: Monteforte (2007) who examined macroeconomic modeling across European countries and the Euro Area; Persyn (2021) who showed that wage curve elasticities are steeper at aggregated country levels than at disaggregated regional levels; Kunimitsu (2024) who quantifies regional aggregation bias in global CGE models; and, Huck et al. (2025) who identifies Focal Area Bias (FAB) in GIS analyses, where peripheral areas within buffers misrepresent core locations.[6]

[5]MADF: Multivariate Augmented Dickey-Fuller unit root test.

[6]Theil (1954) pioneered aggregation bias analysis, comparing aggregate and disaggregate structural models.

3. METHODOLOGY

The concept of stochastic convergence is well-established in the literature, as defined by Bernard and Durlauf (1995) and Bernard and Durlauf (1996). At the regional level, stochastic convergence between a region i and its national counterpart implies that the log difference between their processes becomes a fixed constant at a given time t. This can be formally expressed as:

$$\lim_{t \Rightarrow \infty} E(x_{it} - x_t \,|\, I_t) = u_i \tag{1}$$

where I_t represents the information set available at time t, x_{it} is the process for region i (for all $i \in \{1, 2, \ldots, N\}$) at time t, and x_t is the national process. For a system of N regions, the interpretation of u_i is as follows: (1) if $u_1 = u_2 = \cdots = u_N = 0$, this indicates the presence of absolute convergence; and (2) if some of the u_i values are non-zero, this suggests relative convergence. Fundamentally, regions are considered to converge (diverge) if their deviations from the national process are stationary (non-stationary).

3.1. Dynamic Spatial Panel Model

The general specification for the dynamic spatial panel model, which accommodates both Spatial Autoregressive (SAR) and Spatial Error Model (SEM) structures, is given by the following equations:

$$IGap_{it} = \alpha_i + \theta_1 IGap_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} IGap_{jt} + \sum_{k=1}^{M} \beta_k X_{it,k} + \sum_{k=1}^{M} \gamma_k \sum_{j=1}^{N} w_{ij} X_{jt,k} + u_{it} \tag{2}$$

and the error term u_{it} can follow a spatial process:

$$u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \tag{3}$$

where:

- $IGap_{it}$ represents the difference at time t between the natural logarithm of the income in region i and the natural logarithm of its national counterpart.

- θ_1 is the persistence coefficient. For stochastic convergence (stationarity of the income gap), we require $0 < \theta_1 < 1$. A unit root (non-stationarity) occurs if $\theta_1 = 1$. Given the inclusion of covariates, if the persistence coefficient is statistically significant and less than 1, it indicates conditional stochastic convergence, meaning each region will converge to its own unique steady-state equilibrium.

- W is the $N \times N$ spatial weights matrix, with w_{ij} indicating the spatial relationship between region i and region j.

- α_i captures region-specific fixed effects, representing the particular characteristics of region i. When fixed effects are not included, α_i is replaced by a common intercept term α.

- u_{it} is the unobserved error term. In the absence of a spatial error process (i.e., $\lambda = 0$, as in a pure Spatial Autoregressive (SAR) model), u_{it} represents the stochastic disturbance. When a spatial error process is present (i.e., $\lambda \neq 0$), u_{it} represents the spatially correlated error component, as defined in Equation 3. In both cases, we relax the strict i.i.d. assumption and utilize robust standard errors to account for potential heteroskedasticity and dependence.

- ε_{it} is the idiosyncratic error term (the innovation) in the SEM. Consistent with our estimation strategy, we rely on robust variance-covariance estimators to ensure the validity of our results in the presence of non-i.i.d. disturbances.

- $X_{it,k}$ is the exogenous variable k at time t, for region i

- β_k is the coefficient of exogenous variable k and γ is the coefficient for the spatial lag of exogenous variable k

Regarding the spatial parameters, ρ and λ:

- For a Spatial Autoregressive (SAR) model, $\lambda = 0$, and spatial dependence is captured solely by ρ, which acts on the spatially lagged dependent variable ($\sum_{j=1}^{N} w_{ij} IGap_{jt}$).

- For a Spatial Error Model (SEM), $\rho = 0$, and spatial dependence is modeled through λ, which acts on the spatially lagged error term.

- When $\lambda = 0$ and $\rho = 0$, the equation (2) turns into a dynamic non-spatial panel specification

3.2. Data

Our study utilizes regional economic data from 2001 to 2021, focusing on Gross Domestic Product (GDP) per capita. The data, expressed in constant 2020 US dollars and adjusted for Purchasing Power Parity (PPP), were collected from the OECD Data Explorer webpage. This data is collected at both NUTS-2 and NUTS-3 levels. All data used in the econometric models (including real GDP per capita and covariates) are converted to natural logarithms. The income gap, our dependent variable, is defined as the natural logarithm of real GDP per capita of region i at time t minus the natural logarithm of real GDP per capita of Italy at time t.

In addition, we collected raw data from Eurostat at the NUTS-3 level concerning the number of deaths, total population, employed persons, and population density. From these, we derived regional-level covariates. The mortality rate for a province was calculated as the number of deaths per 1,000 population, and the employment rate as the number of employees per total population.

To obtain the corresponding covariates for NUTS-2 regions, these NUTS-3 raw data and derived provincial rates were aggregated. The mortality rate for a NUTS-2 region i (comprising its constituent NUTS-3 provinces) was calculated as the sum of deaths across its provinces divided by the sum of their populations, multiplied by 1,000. Similarly, the employment rate for a NUTS-2 region i was computed as the sum of employed persons across its provinces divided by the sum of their populations. The population density of a NUTS-2 region i was calculated as the weighted average of the population density of its constituent NUTS-3 provinces, where the weights were the proportion of each province's area relative to the total area of region i.

Our analysis specifically examines Italian regions, categorized according to the Nomenclature of Territorial Units for Statistics (NUTS) classification system. There are 18 contiguous regions at NUTS-2 and at NUTS-3 level, our sample expands to 93 provinces, specifically:

1. **Abruzzo (4):** Chieti, L'Aquila, Pescara, Teramo
2. **Apulia (6):** Bari, Barletta-Andria-Trani, Brindisi, Foggia, Lecce, Taranto
3. **Basilicata (2):** Matera, Potenza
4. **Calabria (5):** Catanzaro, Cosenza, Crotone, Reggio Calabria, Vibo Valentia
5. **Campania (5):** Avellino, Benevento, Caserta, Napoli, Salerno
6. **Emilia-Romagna (9):** Bologna, Ferrara, Forli'-Cesena, Modena, Parma, Piacenza, Ravenna, Reggio Nell'Emilia, Rimini
7. **Friuli-Venezia Giulia (4):** Gorizia, Pordenone, Trieste, Udine
8. **Lazio (5):** Frosinone, Latina, Rieti, Roma, Viterbo
9. **Liguria (4):** Genova, Imperia, La Spezia, Savona
10. **Lombardy (12):** Bergamo, Brescia, Como, Cremona, Lecco, Lodi, Mantua, Milano, Monza and Brianza, Pavia, Sondrio, Varese
11. **Marche (5):** Ancona, Ascoli Piceno, Fermo, Macerata, Pesaro e Urbino
12. **Molise (2):** Campobasso, Isernia
13. **Piedmont (8):** Alessandria, Asti, Biella, Cuneo, Novara, Torino, Verbano-Cusio-Ossola, Vercelli
14. **Tuscany (10):** Arezzo, Florence, Grosseto, Livorno, Lucca, Massa-Carrara, Pisa, Pistoia, Prato, Siena
15. **Trentino-Alto Adige (2):** Bolzano, Trento
16. **Umbria (2):** Perugia, Terni
17. **Valley Aosta (1):** Aosta

18. **Veneto (7):** Belluno, Padua, Rovigo, Treviso, Venezia, Verona, Vicenza

It is important to note that the islands of Sardinia and Sicily are excluded from the analysis. This exclusion is a methodological necessity within the adopted spatial framework, as one of the spatial weight matrices is based on the Queen contiguity criterion and the k-nearest neighbors criterion. The Queen contiguity criterion requires each spatial unit to share at least one common border or vertex with another unit. Since islands have no contiguous neighbors, their inclusion would prevent the proper construction of the contiguity-based weights matrix. The second spatial weights matrix is constructed using a k-nearest neighbors approach with k=3 at the NUTS-2 and k=5 at NUTS-3 levels, which is less restrictive but consistent with the contiguity-based specification.

Before proceeding with the analysis, a preliminary spatial analysis was conducted to assess the presence and patterns of spatial autocorrelation in regional income data. From 2000 to 2021, Figure 1 shows Moran's I across NUTS-2 and NUTS-3. Moran's I values fluctuate between approximately 0.475 and 0.650. Both NUTS-2 and NUTS-3 show similar trends, with a notable dip around 2009–2010, followed by a recovery and some variability.

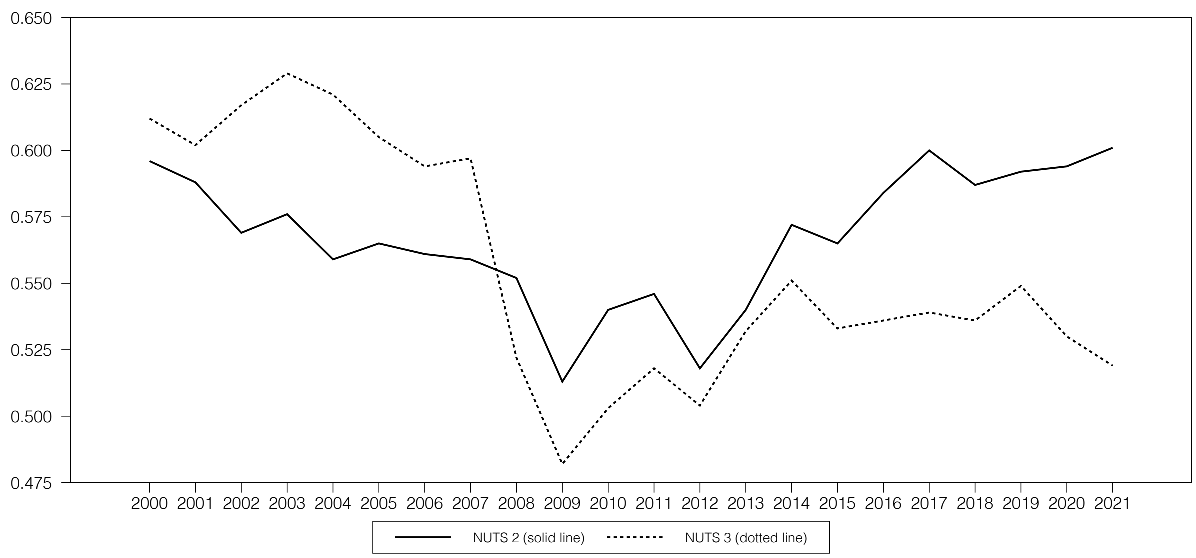
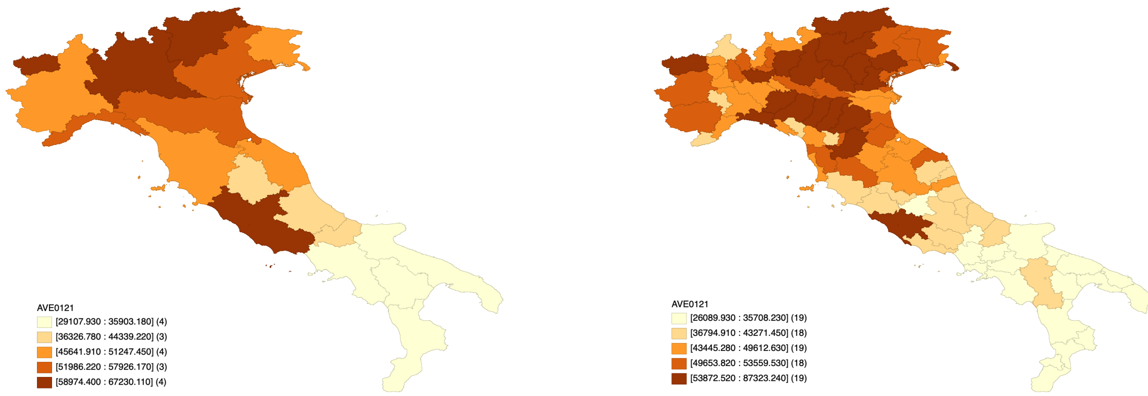


Figure 1: Moran's I: Income level for Italy NUTS-2 and NUTS-3 (2000-2021)

Likewise, Figure 2 presents quintile maps of average income levels in Italy over the period 2001–2021 at both the NUTS-2 and NUTS-3 spatial scales (Queen matrix contiguity). At the NUTS-2 level, the map reveals a clear North–South income difference, with regions in the highest income quintiles concentrated in the North and parts of the Center, while Southern regions predominantly fall into the lowest quintiles. In particular, regions such as Lombardy, Trentino–Alto Adige, Emilia-Romagna, and Aosta Valley occupy the top quintiles, whereas Calabria, Campania, Basilicata, and Apulia are clustered in the bottom quintiles, reflecting strong spatial polarization. The NUTS-3 map reinforces this pattern but also highlights substantial intra-regional heterogeneity. Provinces within high-income NUTS-2 regions display considerable variation across quintiles, with metropolitan and economically dynamic areas occupying the highest income classes alongside neighboring provinces in lower quintiles.[7]



Left Panel: NUTS-2 regions Right Panel: NUTS-3 provinces

Figure 2: Average Regional Income using GDP per Capita (Constant US$, PPP-Adjusted) in Italy, 2001-2021 (excluding Sicily and Sardinia)

Finally, Table 1 and Table 2 present descriptive statistics for the four main variables (income gap ($IGap$), population density (PD), mortality rate (MR), and employment (EP)) at the NUTS-2 and NUTS-3 levels, respectively. At NUTS-2, the income gap ($IGap$) shows a clear North–South divide, with the highest mean in Trentino-Alto Adige (0.34) and the lowest in Calabria (-0.50). Standard deviations of $IGap$ are small (0.01–0.05), and the other variables exhibit similarly low within-region variation, indicating stable regional regimes over 2001–2021. This persistence of disparities motivates our focus on stochastic convergence, while the limited within-region variation supports the use of fixed effects models.

At the NUTS-3 level, however, Table 2 reveals substantially greater heterogeneity across provinces. The income gap ($IGap$) varies widely both across and within provinces, with large positive values in major metropolitan and economically dynamic provinces (e.g., Milano, Roma, Bologna) and strongly negative values in Southern and peripheral ones. Standard deviations of $IGap$—and similarly of employment, mortality, and population density— are markedly higher than at NUTS-2, indicating more pronounced short- and medium-run fluctuations. This increased variability highlights significant intra-regional disparities masked by regional aggregation, with sharp contrasts between urban centers (higher employment intensity, population density, and distinct mortality dynamics) and peripheral areas. Consequently, while persistence remains a defining feature, evidence of stochastic convergence at the NUTS-2 level—interpreted as mean reversion in regional income gaps—does not necessarily extend to the local level.

At NUTS-3, income differentials display greater volatility and heterogeneity, suggesting that shocks may have more persistent or uneven effects across provinces. This reinforces the scale-dependent nature of convergence outcomes in Italy, whereby stability at the regional

[7]For the NUTS-2 and NUTS-3 levels, GeoDa software was used to organize the data, compute Moran's I tests, and generate quintile maps.

Table 1: Regional Statistics for NUTS-2 Regions (2001–2021)

Region	**IGap**		**PD**		**MR**		**EP**	
	mean	SD	mean	SD	mean	SD	mean	SD
Abruzzo	-0.15	0.02	4.79	0.01	2.42	0.06	-3.82	0.05
Apulia	-0.44	0.01	5.36	0.01	2.14	0.09	-3.70	0.04
Basilicata	-0.29	0.03	4.06	0.03	2.20	0.06	-3.52	0.09
Calabria	-0.50	0.02	4.87	0.03	2.20	0.06	-3.41	0.07
Campania	-0.42	0.02	6.07	0.01	2.13	0.08	-4.13	0.09
Emilia-Romagna	0.19	0.01	5.25	0.03	2.48	0.04	-3.81	0.04
Friuli-Venezia Giulia	0.06	0.01	5.06	0.01	2.56	0.05	-3.84	0.06
Lazio	0.20	0.04	5.79	0.05	2.28	0.03	-4.27	0.12
Liguria	0.08	0.01	5.68	0.02	2.62	0.06	-4.73	0.06
Lombardia	0.28	0.01	5.99	0.04	2.27	0.08	-3.81	0.06
Marche	-0.05	0.01	5.12	0.01	2.42	0.05	-3.66	0.06
Molise	-0.28	0.04	4.25	0.02	1.53	0.07	-3.33	0.08
Piemonte	0.06	0.02	5.16	0.01	2.68	0.06	-3.65	0.06
Toscana	0.06	0.01	5.08	0.02	2.44	0.04	-3.71	0.03
Trentino-Alto Adige	0.34	0.04	4.32	0.04	2.13	0.06	-3.39	0.08
Umbria	-0.08	0.05	4.68	0.02	2.43	0.04	-3.73	0.15
Valle d'Aosta	0.29	0.03	3.64	0.02	2.39	0.08	-3.98	0.10
Veneto	0.11	0.01	5.58	0.03	2.30	0.08	-3.62	0.07

level can coexist with pronounced divergence or polarization within regions, and motivates the use of spatial econometric models to capture localized dependence and heterogeneous responses to shocks.

Beyond income disparities, the behavior of mortality rates, employment, and population density further underscores the scale-dependent nature of stochastic convergence in Italy. At the NUTS-2 level, these variables show relatively limited dispersion and stable mean values across regions, suggesting persistent health and labor-market regimes as well as entrenched spatial settlement patterns that evolve slowly. At the NUTS-3 level, however, they display much greater heterogeneity, revealing sharp urban–peripheral contrasts within the same region: provinces with major metropolitan or economic hubs tend to exhibit higher employment intensity, population density, and distinct mortality dynamics, while peripheral provinces follow markedly different trajectories.

Table 2: Regional Statistics for NUTS-3 Provinces (2001-2021)

Province	IGap		PD		MR		EP		Province	IGap		PD		MR		EP	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Chieti	-0.15	0.04	5.02	0.02	2.42	0.06	-3.71	0.08	Cremona	0.08	0.04	5.21	0.04	2.45	0.10	-3.96	0.07
L'Aquila	-0.16	0.05	4.09	0.01	2.45	0.04	-4.02	0.10	Lecco	0.09	0.05	6.19	0.04	2.27	0.09	-5.36	0.21
Pescara	-0.12	0.04	5.57	0.03	2.36	0.06	-4.42	0.15	Lodi	-0.03	0.05	7.63	0.05	3.52	0.09	-5.20	0.35
Teramo	-0.18	0.02	5.05	0.02	2.35	0.06	-3.99	0.10	Mantua	0.07	0.03	5.68	0.05	2.43	0.06	-3.67	0.09
Bari	-0.30	0.02	5.78	0.01	2.14	0.09	-3.72	0.07	Milano	0.60	0.05	7.58	0.04	2.27	0.08	-5.98	0.21
Barletta-A-T	-0.60	0.02	5.54	0.02	2.10	0.10	-3.49	0.14	Monza and Brianza	0.05	0.02	5.17	0.05	1.71	0.06	-4.38	0.10
Brindisi	-0.47	0.03	5.38	0.02	2.24	0.09	-3.31	0.07	Pavia	-0.09	0.08	5.33	0.02	2.57	0.07	-4.51	0.14
Foggia	-0.49	0.02	4.51	0.01	2.09	0.10	-3.14	0.08	Sondrio	0.02	0.03	4.04	0.01	2.34	0.09	-4.13	0.14
Lecce	-0.54	0.02	5.66	0.01	2.26	0.09	-3.70	0.11	Varese	0.07	0.04	6.04	0.04	2.30	0.08	-6.08	0.25
Taranto	-0.45	0.02	5.48	0.02	2.18	0.13	-3.46	0.06	Ancona	0.03	0.02	4.93	0.03	2.42	0.05	-4.70	0.10
Matera	-0.37	0.06	4.08	0.03	2.24	0.10	-3.05	0.09	Ascoli Piceno	-0.10	0.05	5.13	0.01	2.63	1.16	-3.76	1.29
Potenza	-0.25	0.06	4.07	0.04	2.35	0.09	-3.39	0.17	Fermo	-0.11	0.06	5.30	0.02	6.33	2.06	-0.27	2.12
Catanzaro	-0.40	0.06	5.03	0.03	2.24	0.09	-3.26	0.11	Macerata	-0.11	0.02	4.73	0.02	2.45	0.06	-4.12	0.10
Cosenza	-0.57	0.04	4.69	0.03	2.25	0.11	-3.12	0.09	Pesaro E Urbino	-0.07	0.01	5.50	0.02	2.39	0.13	-4.43	0.11
Crotone	-0.47	0.04	4.61	0.02	2.13	0.12	-2.99	0.07	Campobasso	-0.27	0.04	4.36	0.02	1.53	0.07	-4.80	0.16
Reggio Di Calabria	-0.47	0.03	5.17	0.03	2.29	0.07	-2.96	0.07	Isernia	-0.32	0.05	4.05	0.03	3.37	0.08	-2.66	0.10
Vibo Valentia	-0.61	0.02	4.97	0.04	2.25	0.08	-2.94	0.08	Alessandria	-0.01	0.03	4.80	0.02	2.68	0.06	-4.34	0.09
Avellino	-0.44	0.02	5.04	0.02	2.35	0.06	-3.83	0.21	Asti	-0.12	0.03	4.96	0.02	2.61	0.07	-3.59	0.08
Benevento	-0.49	0.04	4.93	0.03	2.40	0.07	-3.23	0.25	Biella	-0.06	0.03	5.31	0.03	2.57	0.08	-5.13	0.11
Caserta	-0.50	0.05	5.84	0.03	2.14	0.07	-4.12	0.13	Cuneo	0.11	0.02	4.44	0.02	2.48	0.05	-3.44	0.10
Napoli	-0.38	0.02	7.88	0.01	2.13	0.08	-5.06	0.28	Novara	0.03	0.04	5.63	0.02	2.41	0.07	-5.20	0.09
Salerno	-0.44	0.01	5.41	0.01	2.25	0.08	-3.63	0.10	Torino	0.11	0.01	5.80	0.02	2.38	0.09	-5.37	0.10
Bologna	0.31	0.03	5.59	0.04	2.49	0.04	-4.98	0.06	Verbano-C-O	-0.17	0.03	4.31	0.01	2.48	0.06	-5.17	0.18
Ferrara	-0.07	0.04	4.93	0.02	2.59	0.05	-3.77	0.07	Vercelli	-0.01	0.05	4.45	0.02	2.60	0.09	-4.49	0.09
Forli' - Cesena	0.09	0.02	5.10	0.03	2.41	0.05	-3.86	0.14	Arezzo	0.00	0.04	4.66	0.02	2.45	0.04	-3.80	0.12
Modena	0.25	0.03	5.55	0.03	2.36	0.04	-4.35	0.15	Florence	0.26	0.03	5.64	0.03	2.44	0.04	-4.84	0.10
Parma	0.26	0.02	4.84	0.04	2.50	0.07	-4.23	0.11	Grosseto	-0.15	0.04	3.90	0.02	2.54	0.04	-3.24	0.09
Piacenza	0.13	0.04	4.71	0.03	2.57	0.08	-4.11	0.12	Livorno	-0.09	0.03	5.62	0.01	2.51	0.04	-4.84	0.10
Ravenna	0.10	0.02	5.35	0.04	2.49	0.05	-3.82	0.08	Lucca	-0.05	0.04	5.40	0.02	2.50	0.04	-4.68	0.21
Reggio Nell'Emilia	0.22	0.03	5.42	0.05	2.39	0.05	-4.42	0.15	Massa Carrara	-0.19	0.04	5.16	0.02	2.53	0.06	-4.83	0.19
Rimini	0.02	0.03	5.91	0.05	2.34	0.06	-4.77	0.09	Pisa	0.07	0.02	5.13	0.03	2.44	0.04	-4.57	0.10
Gorizia	-0.06	0.03	5.77	0.07	2.53	0.05	-4.59	0.11	Pistoia	-0.12	0.02	5.70	0.03	2.44	0.05	-4.05	0.12
Pordenone	0.06	0.03	4.94	0.03	3.03	0.05	-3.67	0.15	Prato	0.10	0.06	6.52	0.04	2.29	0.06	-5.98	0.18
Trieste	0.11	0.06	7.01	0.01	2.76	0.02	-5.72	0.25	Siena	0.06	0.03	4.24	0.02	2.53	0.03	-3.38	0.13
Udine	0.07	0.02	4.72	0.01	1.76	0.07	-4.72	0.13	Bolzano	0.40	0.06	4.22	0.05	2.13	0.06	-3.17	0.11
Frosinone	-0.23	0.03	5.02	0.01	2.17	0.06	-4.17	0.29	Trento	0.27	0.02	4.44	0.05	2.26	0.06	-3.76	0.09
Latina	-0.19	0.06	5.49	0.06	2.14	0.03	-3.43	0.14	Perugia	-0.06	0.05	4.65	0.03	2.43	0.04	-4.01	0.16
Rieti	-0.34	0.06	4.03	0.02	2.25	0.09	-3.66	0.25	Terni	-0.15	0.05	4.68	0.02	2.55	0.04	-4.15	0.13
Roma	0.33	0.05	6.64	0.06	2.28	0.03	-5.32	0.22	Aosta	0.29	0.03	3.65	0.02	2.39	0.08	-3.99	0.10
Viterbo	-0.25	0.06	4.49	0.03	1.95	0.03	-3.51	0.25	Belluno	0.06	0.05	4.06	0.02	2.49	0.04	-4.49	0.20
Genova	0.16	0.03	6.16	0.02	2.62	0.06	-5.94	0.17	Padua	0.13	0.02	6.07	0.04	2.25	0.05	-4.52	0.12
Imperia	-0.15	0.05	5.22	0.02	2.60	0.06	-3.93	0.07	Rovigo	-0.10	0.03	4.96	0.02	2.49	0.07	-3.67	0.10
La Spezia	0.02	0.04	5.53	0.01	2.61	0.05	-5.01	0.18	Treviso	0.12	0.03	5.88	0.03	2.22	0.05	-4.17	0.12
Savona	0.00	0.04	5.20	0.02	2.63	0.05	-4.36	0.09	Venezia	0.07	0.02	5.98	0.06	2.34	0.07	-4.78	0.10
Bergamo	0.16	0.04	5.99	0.05	2.21	0.11	-4.99	0.16	Verona	0.14	0.02	5.73	0.04	2.27	0.06	-4.01	0.12
Brescia	0.17	0.04	5.60	0.05	2.23	0.09	-4.41	0.12	Vicenza	0.13	0.03	5.75	0.03	2.22	0.06	-4.67	0.13
Como	0.03	0.06	6.66	0.04	2.29	0.08	-5.29	0.22									

This intra-regional fragmentation implies that even if income gaps ($IGap$) stabilize or converge at the regional level, underlying demographic, labor-market, and spatial processes remain highly diverse locally. Consequently, stochastic convergence in income does not necessarily extend to health, employment, or spatial concentration, reinforcing the view that convergence outcomes in Italy are highly sensitive to the level of spatial aggregation.

4. OUTCOMES

This section presents the main estimation results of the dynamic panel models for income gaps at both the NUTS-2 and NUTS-3 levels over the period 2001–2021, followed by key diagnostic tests and a discussion of their implications. We begin with pooled OLS, random-effects, and fixed-effects specifications that do not yet incorporate spatial dependence ($\rho = 0$ and $\lambda = 0$).

Table 3 reports the corresponding estimation results. Across all specifications and spatial scales, the coefficient on the lagged dependent variable, θ_1, is positive and highly significant at the 1% level, indicating strong persistence in income gaps and supporting the hypothesis of stochastic conditional convergence.

The Hausman tests decisively reject the random-effects specification in favor of fixed effects—both with and without time effects—at both the NUTS-2 and NUTS-3 levels. This indicates that unobserved regional and provincial characteristics are correlated with the regressors, confirming the appropriateness of fixed-effects estimators. The near-unit-root persistence in pooled and random-effects models reflects dynamic panel bias and the inconsistency of random effects when unit-specific heterogeneity is correlated with the regressors.

In the preferred fixed-effects specifications, the estimated persistence parameter is approximately 0.865–0.871 for NUTS-2 regions and around 0.783–0.785 for NUTS-3 provinces. These values imply mean-reversion rates of roughly 13.8% per year at the regional level and 24.2% per year at the provincial level, corresponding to half-lives of about 5.0 years for regions and 2.9 years for provinces. This suggests that income gaps are more persistent at higher levels of aggregation, while adjustment dynamics are faster at the local level.[8]

By contrast, the structural covariates—employment (EP), population density (PD), and mortality (MR)—are generally not statistically significant in the fixed-effects models. An exception is population density at the NUTS-3 level in the individual fixed-effects specification, where it is significant at the 10% level; however, this effect disappears once time effects are included. Overall, these findings indicate that the evolution of income disparities is driven primarily by their own past dynamics rather than by contemporaneous variation in these structural factors.

Table 4 extends the baseline fixed-effects framework by explicitly accounting for spatial dependence through SAR and SEM specifications, using both Queen contiguity and k-nearest-neighbors (KNN) spatial weight matrices and allowing for individual and two-way fixed effects. Across both NUTS-2 and NUTS-3 levels, the inclusion of spatial interactions leaves the estimated persistence of income gaps largely unchanged. In all specifications, the

[8]The formula of the half-life (h) of the income shocks is $h = \frac{ln(0.5)}{ln(\theta_1)}$, where θ_1 is the persistence coefficient.

Table 3: Dynamic Panel Estimates for Italian Regions at NUTS-2 and NUTS-3, 2002–2021

	Pooling	**Random Effects**	**Fixed Effects**	**Fixed Effects (with time effects)**
Dependent Variable: $IGap_t$				
		NUTS-2		
$IGap_{t-1}$	0.999***	0.999***	0.865***	0.871***
	(0.002)	(0.002)	(0.034)	(0.031)
EP_t	0.003	0.003	0.005	0.004
	(0.002)	(0.002)	(0.012)	(0.015)
PD_t	0.000	0.000	-0.015	-0.017
	(0.001)	(0.001)	(0.056)	(0.064)
MR_t	0.002	0.002	-0.000	-0.003
	(0.002)	(0.002)	(0.013)	(0.023)
Constant	0.002	0.002	–	–
	(0.007)	(0.007)		
Observations	360	360	360	360
Hausman test (FE vs RE)	$\chi^2(4) = 19.33$, $p = 0.0007$			
Hausman test (FE-tw vs RE-tw)	$\chi^2(4) = 17.30$, $p = 0.0017$			
		NUTS-3		
$IGap_{t-1}$	0.995***	0.995***	0.783***	0.785***
	(0.003)	(0.003)	(0.018)	(0.018)
EP_t	-0.001	-0.001	0.003	0.002
	(0.001)	(0.001)	(0.004)	(0.005)
PD_t	-0.001	-0.001	-0.053*	-0.034
	(0.001)	(0.001)	(0.025)	(0.029)
MR_t	-0.001	-0.001	-0.005	-0.003
	(0.001)	(0.001)	(0.005)	(0.006)
Constant	-0.000	-0.000	–	–
	(0.006)	(0.006)		
Observations	1,860	1,860	1,860	1,860
Hausman test (FE vs RE)	$\chi^2(4) = 232.2$, $p < 0.001$			
Hausman test (FE-tw vs RE-tw)	$\chi^2(4) = 225.0$, $p < 0.001$			

Standard errors in parentheses (clustered robust). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

coefficient on the lagged dependent variable remains positive, highly significant at the 1% level, and very close in magnitude to the corresponding non-spatial fixed-effects estimates. This indicates that the stochastic conditional convergence dynamics identified in the baseline models are robust to alternative forms of spatial interaction.

At the regional (NUTS-2) level, evidence of spatial dependence is relatively weak. The spatial autoregressive parameter (ρ) is positive but only marginally significant in a limited

Table 4: Fixed Effects: Spatial Dynamic Panel Estimates for NUTS-2 and NUTS-3

	SAR				**SEM**			
	Queen		KNN		Queen		KNN	
Time effects	No	Yes	No	Yes	No	Yes	No	Yes
Dependent Variable: $IGap_t$								
	NUTS-2							
$IGap_{t-1}$	0.858***	0.865***	0.865***	0.869***	0.865***	0.868***	0.867***	0.869***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)	(0.031)
EP_t	0.001	0.000	0.003	0.001	0.001	-0.001	0.003	0.000
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
PD_t	-0.020	-0.016	-0.023	-0.014	-0.019	-0.012	-0.021	-0.013
	(0.036)	(0.040)	(0.036)	(0.041)	(0.035)	(0.039)	(0.036)	(0.040)
MR_t	0.002	0.000	-0.002	-0.002	-0.001	0.001	-0.002	-0.001
	(0.012)	(0.023)	(0.012)	(0.023)	(0.013)	(0.023)	(0.013)	(0.023)
ρ	0.083*	0.052	0.026	0.003				
	(0.049)	(0.050)	(0.049)	(0.049)				
λ					0.113*	0.057	0.088	0.031
					(0.063)	(0.064)	(0.068)	(0.069)
	NUTS-3							
$IGap_{t-1}$	0.783***	0.785***	0.780***	0.784***	0.785***	0.786***	0.785***	0.786***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
EP_t	0.003	0.002	0.002	0.002	0.003	0.002	0.003	0.001
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
PD_t	-0.049**	-0.034	-0.044*	-0.031	-0.049**	-0.033	-0.048*	-0.032
	(0.018)	(0.021)	(0.018)	(0.021)	(0.018)	(0.021)	(0.019)	(0.021)
MR_t	-0.005	-0.003	-0.004	-0.003	-0.005	-0.003	-0.005	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ρ	0.024	-0.002	0.069**	0.041				
	(0.023)	(0.024)	(0.026)	(0.027)				
λ					0.095**	0.045	0.149***	0.091*
					(0.033)	(0.033)	(0.036)	(0.037)

Notes: Robust standard errors in parentheses. For NUTS-2, K=3 and for NUTS-3, K=5.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

subset of SAR specifications, while the spatial error parameter (λ) in SEM models is small and becomes statistically insignificant once time effects are included. These findings suggest that, after controlling for unobserved regional heterogeneity and common time shocks, cross-regional spillovers in income gaps are limited, and convergence dynamics are driven primarily by internal persistence rather than strong spatial interactions.

By contrast, at the provincial (NUTS-3) level, spatial dependence is more pronounced. Both SAR and SEM models yield positive and statistically significant spatial parameters, particularly under the KNN specification, indicating meaningful localized spillovers across neighboring provinces. The stronger and more robust significance of the spatial error component in SEM models points to the presence of spatially correlated unobserved shocks—such as local labor market conditions, institutional features, or province-specific economic disturbances—that influence income disparities at finer spatial scales.

Despite the inclusion of spatial dependence, the structural covariates—employment (EP), population density (PD), and mortality (MR)—remain weakly significant or insignificant across most specifications. This reinforces the conclusion that income gap dynamics are dominated by persistence and spatial interaction effects rather than contemporaneous socioeconomic controls.

Overall, the spatial estimates highlight a clear scale effect: while spatial dependence is modest at the regional level, it is substantially stronger at the provincial level, where economic interactions are more localized. Importantly, accounting for spatial dependence does not overturn the convergence results but rather complements them, showing that stochastic convergence operates alongside localized spillovers, especially in more disaggregated spatial units.

Although non-spatial and spatial fixed-effects models deliver very similar results, dynamic fixed-effects estimators are subject to Nickell bias due to the presence of a lagged dependent variable. To address this issue and obtain consistent estimates of persistence, the analysis therefore proceeds by implementing Difference GMM and System GMM estimators as the following.

Table 5 reports System GMM and Difference GMM estimates for Italian NUTS-2 regions over 2002–2021. Across all System GMM specifications, the coefficient on the lagged income gap is large, positive, and highly significant, with values ranging between 0.87 and 0.89. A coefficient strictly below unity implies mean reversion in income disparities: shocks to regional income gaps are not permanent, but gradually dissipate over time. However, the magnitude of the coefficient indicates that this reversion process is slow, reflecting strong persistence in regional inequality.

Using the preferred spatial System GMM specification with KNN-3 weights (column 3), the implied speed of adjustment corresponds to a half-life of approximately five years. This means that roughly half of the effect of a shock to regional income disparities remains even after five years, highlighting substantial inertia at the regional level.

Spatial dependence is weak at this level of aggregation. The spatial autoregressive parameter is small and statistically insignificant across System GMM specifications, regardless of the spatial weights matrix. This suggests that, once persistence and common shocks are accounted for, regional income disparities evolve largely independently of neighboring regions and are driven primarily by internal dynamics rather than contemporaneous spatial spillovers.

From a diagnostic perspective, System GMM performs well. We report the Hansen test for over-identifying restrictions, which is robust to heteroskedasticity and autocorrelation, unlike the standard Sargan test. These results are interpreted as conditional diagnostics of instrument suitability. The preferred specification passes the Hansen test of overidentifying restrictions (p = 0.207), shows no evidence of second-order serial correlation, and relies on a highly parsimonious instrument set. Difference GMM models, by contrast, yield substantially lower persistence estimates and require many more instruments, raising concerns about weak

Table 5: System GMM and Difference GMM Results in Italian NUTS-2, 2002-2021

	(1) Non-Spatial System GMM	(2) Spatial System GMM (Queen)	(3) Spatial System GMM (KNN-3)		(4) Spatial Difference GMM (Queen)	(5) Spatial Difference GMM (KNN-3)
Dependent Variable:		$IGap_t$			$\Delta IGap_t$	
$IGap_{t-1}$	0.870***	0.894***	0.870***	$\Delta IGap_{t-1}$	0.343	0.304
	(0.204)	(0.139)	(0.206)		(0.220)	(0.222)
Spatial Lag (ρ)		-0.027	-0.003		0.260	0.258*
		(0.063)	(0.065)		(0.161)	(0.144)
EP_t	0.007	0.010	0.007	ΔEP_t	-0.012	-0.010
	(0.018)	(0.018)	(0.019)		(0.016)	(0.016)
PD_t	-0.011	-0.007	-0.011	ΔPD_t	-0.005	-0.014
	(0.018)	(0.012)	(0.019)		(0.169)	(0.182)
MR_t	0.033	0.029	0.033	ΔMR_t	0.003	0.003
	(0.041)	(0.032)	(0.042)		(0.017)	(0.017)
Hansen Test (p-value)	0.056	0.328	0.207		0.978	0.978
AR(2) Test (p-value)	0.900	0.903	0.919		0.737	0.757
Observations	360	360	360		342	342
# of Instruments	7	6	6		32	32
Time Dummies (2008, 2009)	Yes	No	No		No	No
Instrument Set	lags 2–3	lags 2–3	lags 2–3		lags 2–3	lags 2–3
Estimation Method	One-step	One-step	One-step		One-step	One-step

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust (Windmeijer-corrected) standard errors in parentheses. All models estimated with a minimal instrument set appropriate for small $N = 18$. Model (3) is preferred, balancing strong persistence, valid instruments (Hansen $p = 0.207$), and absence of second-order serial correlation.

identification and finite-sample bias. Accordingly, System GMM with minimal instruments is clearly preferred at the NUTS-2 level.

Table 6 presents analogous results for Italian provinces (NUTS-3), revealing both similarities and important differences. As at the regional level, income disparities exhibit strong persistence, with the lagged income gap coefficient in the preferred System GMM specification equal to 0.861 and highly significant. Because this coefficient remains well below unity, income disparities at the provincial level are also mean-reverting, but the adjustment process is faster than at the regional level.

The implied half-life of a shock is approximately 4.5 years, indicating that convergence toward long-run differentials occurs more rapidly at finer spatial scales. This faster mean reversion is consistent with greater mobility, localized labor-market adjustment, and stronger short-distance economic interactions across provinces.

Table 6: System GMM and Difference GMM Results: in Italian NUTS-3, 2002-2021

	(1) Non-Spatial System GMM	(2) Spatial System GMM (Queen)	(3) Spatial System GMM (KNN-5)		(4) Spatial Difference GMM (Queen)	(5) Spatial Difference GMM (KNN-5)
Dependent Variable:		$IGap_t$			$\Delta IGap_t$	
$IGap_{t-1}$	0.907***	0.815***	0.861***	$\Delta IGap_{t-1}$	0.392**	0.404***
	(0.04)	(0.07)	(0.06)		(0.14)	(0.10)
Spatial Lag (ρ)		0.231**	0.125**		0.612***	0.508**
		(0.10)	(0.06)		(0.15)	(0.18)
EP_t	-0.017**	0.003	-0.004	ΔEP	0.000	-0.003
	(0.01)	(0.01)	(0.00)		(0.01)	(0.01)
PD_t	-0.007	0.006	-0.003	ΔPD_t	0.028	-0.044
	(0.01)	(0.01)	(0.01)		(0.08)	(0.06)
MR_t	0.014*	-0.007	-0.001	ΔMR_t	-0.001	0.003
	(0.01)	(0.01)	(0.00)		(0.01)	(0.01)
Hansen Test (p-value)	0.056	0.009	0.062		0.114	0.143
AR(2) Test (p-value)	0.14	0.13	0.12		0.055	0.052
Observations	1,860	1,860	1,860		1,767	1,767
# of Instruments	7	9	5		51	51
Time Effects	Yes	No	No		No	No
Instrument Set	lags 2–5	lags 2–5	lag 2 only		lags 2–3	lags 2–3
Instrument Validity	Marginal	Invalid	Valid		Valid	Valid

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust (Windmeijer-corrected) standard errors in parentheses. All models include individual fixed effects. Models (1)–(3) are two-step System GMM; (4)–(5) are one-step Difference GMM. Model (3) is preferred as it is the only System GMM specification achieving instrument exogeneity (Hansen $p > 0.05$) while identifying significant spatial spillovers.

In contrast to the NUTS-2 results, spatial dependence is economically meaningful and statistically significant at the provincial level. In the preferred System GMM specification with KNN-5 weights, the spatial autoregressive coefficient is positive and significant, indicating the presence of local spillovers whereby increases in income disparities in neighboring provinces raise local disparities. Difference GMM models yield substantially larger spatial coefficients, but these estimates are likely inflated due to weaker identification and instrument proliferation.

Diagnostic tests favor the preferred System GMM specification, which achieves instrument validity, no evidence of second-order serial correlation, and a very parsimonious instrument set. This combination allows both temporal persistence and spatial interaction to be identified without confounding one with the other.

Time dummies play an important but limited role in the dynamic specification. At the NUTS-2 level, including time effects in the non-spatial System GMM model confirms strong persistence even after controlling for common macroeconomic shocks such as the Great Recession and the sovereign debt crisis. When spatial interactions are introduced, time dummies are excluded to preserve instrument parsimony, yet the estimated persistence and implied half-lives remain remarkably stable. This indicates that persistence reflects genuine regional and provincial inertia rather than spurious dynamics driven by aggregate trends.

Taken together, the System GMM results point to three main conclusions. First, income disparities in Italy are persistent but mean-reverting at both regional and provincial levels: shocks fade over time, but only gradually. Second, the speed of mean reversion differs by spatial scale, with half-lives of roughly five years at the regional level and about 4–4.5 years at the provincial level. Third, while spatial spillovers are negligible at the regional level, they are economically meaningful at the provincial level, indicating that convergence dynamics operate alongside localized spatial interactions. Importantly, accounting for spatial dependence does not overturn the evidence of mean reversion, but clarifies how persistence and spatial spillovers jointly shape the evolution of income disparities in Italy.

An important additional consideration is the dynamic stability of the estimated models. In all preferred System GMM specifications, the coefficient on the lagged income gap lies strictly below unity and is precisely estimated, as indicated by standard errors that are small relative to the point estimates. This confirms that the dynamic process is stable and implies mean reversion rather than explosive behavior. In other words, income disparities follow a persistent but stationary process, with shocks that gradually dissipate over time.

This issue is particularly relevant at the NUTS-3 level. In non-spatial System GMM specifications, the estimated persistence parameter is substantially larger and, in some cases, close to or above unity, raising concerns about near-unit-root behavior and overstated inertia. Once spatial interactions are explicitly introduced, the persistence parameter falls below one and becomes more precisely estimated. This indicates that part of what would otherwise be attributed to temporal persistence actually reflects spatial dependence across neighboring provinces. Ignoring spatial interactions therefore risks inflating the degree of persistence and obscuring the true mean-reverting nature of provincial income disparities.

At the NUTS-2 level, the inclusion of spatial interactions has a more limited impact on persistence, consistent with weaker spatial dependence at higher levels of aggregation. Nevertheless, controlling for common macroeconomic shocks remains important. Because including a full set of time dummies in spatial System GMM models is computationally difficult and can induce singularity and instrument proliferation, the analysis instead includes crisis-period dummies for 2008 and 2009. Even this limited control for aggregate shocks is sufficient to reduce the estimated persistence and ensure a stable, mean-reverting dynamic process at the regional level.

At the NUTS-3 level, a similar trade-off arises. Including both spatial interactions and a full set of time dummies in System GMM is infeasible in small panels without severely weakening identification. However, the results show that introducing spatial dependence—while omitting time effects—already leads to lower persistence estimates and clear mean reversion. This suggests that spatial interactions absorb a substantial portion of the cross-sectional comovement that would otherwise be captured by time dummies. In this sense, spatial interactions and time effects play complementary roles, and including at least one of them is crucial for avoiding upward bias in persistence estimates.

Overall, the preferred System GMM specifications strike a balance between dynamic stability, instrument validity, and economic interpretation. At both spatial scales, models that adequately control for either common shocks (through crisis dummies) or spatial dependence yield persistence parameters below unity, implying finite half-lives and genuine mean reversion. At finer spatial scales (NUTS-3), accounting for spatial dependence is essential: without it, persistence is overstated and may approach non-stationarity, whereas with spatial interactions the dynamics are stable, economically plausible, and consistent with localized spillovers shaping the evolution of income disparities.[9]

4.1. Non-Spatial Panel Unit Root Tests

The results show that including fixed effects substantially affects the conclusions. In the pooling specification (no constant), the LLC test fails to reject non-stationarity in both NUTS-2 and NUTS-3 across all lags. When fixed effects (constant) are included, the LLC and standard IPS tests strongly reject the unit root null in NUTS-3, indicating stationarity. In NUTS-2, however, these tests continue to fail to reject non-stationarity.

The heterogeneity-adjusted IPS test provides more conservative results: it fails to reject non-stationarity in NUTS-2 at all lags, and in NUTS-3 it rejects only at 1 lag (mixed evidence). The Hadri test strongly rejects stationarity in NUTS-2 but fails to reject it in NUTS-3, suggesting possible non-stationarity in the former and stationarity in the latter.

Overall, the evidence is mixed and sensitive to the inclusion of fixed effects and heterogeneity adjustment. This underscores the importance of controlling for time-invariant unobserved heterogeneity and, potentially, spatial dependence when assessing the persistence of income gaps.[10]

4.2. Discussion

The empirical results provide a coherent picture of income gap dynamics in Italy once persistence, unobserved heterogeneity, spatial dependence, and dynamic panel bias are jointly accounted for. Across all specifications, the lagged income gap is positive and highly significant, indicating strong persistence and supporting the hypothesis of conditional stochastic convergence.

A first key result concerns the role of fixed effects. In pooled and random-effects models, the persistence coefficient is extremely close to unity at both the NUTS-2 and NUTS-3 levels, suggesting near–unit-root behavior. However, Hausman tests decisively reject the random-effects specification in favor of fixed effects, indicating that unobserved region- and

[9] All estimations were conducted in RStudio. Dynamic spatial panel models, including System GMM (Blundell and Bond, 1998) and Difference GMM, were implemented to account for the expanded 2001–2021 sample period. Spatial weight matrices, including both Queen-contiguity and K-nearest neighbors (KNN-3 for NUTS-2 and KNN-5 for NUTS-3), were constructed and row-normalized using the `spdep` package. Diagnostic tests for spatial autocorrelation and over-identifying restrictions (Hansen J-test) were performed to ensure model stability and instrument validity.

[10] RATS software was employed for standard panel unit root tests.

Table 7: Panel Unit Root Tests for NUTS-2 and NUTS-3 Regions, 2001-2021 (p-values)

Test	**1-lag**	**2-lag**	**3-lag**
	NUTS-2		
Pooling			
Levin–Lin	0.8746	0.8746	0.8746
Fixed Effects			
Levin–Lin	0.9986	0.9974	0.9985
Im–Pesaran–Shin	0.7339	0.6437	0.5203
Im–Pesaran–Shin (adjusted heterogeineity)	0.8317	0.7493	0.6551
Hadri	0.0000	0.0000	0.0000
	NUTS-3		
Pooling			
Levin–Lin	0.9999	0.9999	0.9999
Fixed Effects			
Levin–Lin	1.0000	1.0000	1.0000
Im–Pesaran–Shin	0.0002	0.0000	0.0000
Im–Pesaran–Shin (adjusted heterogeineity)	0.0757	0.0096	0.0060
Hadri	0.9820	0.9999	1.0000

Note: Pooling: not including a constant; and Fixed Effects: including a constant.

province-specific characteristics are correlated with the regressors. Once fixed effects are introduced, the estimated persistence declines substantially—to about 0.87 at the NUTS-2 level and around 0.78 at the NUTS-3 level. These estimates imply clear mean reversion: income gaps are not permanent but gradually revert toward long-run differentials.

Interpreting these coefficients in dynamic terms highlights an important scale effect. At the regional level (NUTS-2), the implied mean-reversion rate is approximately 13–14% per year, corresponding to a half-life of about five years. At the provincial level (NUTS-3), the adjustment process is faster, with mean-reversion rates of roughly 22–24% per year and half-lives of around three years. This indicates that income disparities dissipate more rapidly at finer spatial scales, consistent with greater labor mobility, localized economic adjustment, and more intensive short-distance interactions.

Introducing spatial dependence through SAR and SEM specifications does not materially alter these convergence dynamics. Across both NUTS-2 and NUTS-3, the estimated persistence coefficients remain remarkably stable when spatial interactions are included, confirming that the conditional stochastic convergence identified in non-spatial fixed-effects models is robust. spatial interactions therefore complement rather than overturn the temporal dynamics.

That said, spatial dependence itself exhibits strong heterogeneity across spatial scales. At the NUTS-2 level, spatial autoregressive and spatial error parameters are generally small and weakly significant at best, and they lose significance once time effects are included. This suggests that, after controlling for unobserved heterogeneity and common macroeconomic shocks, regional income gaps evolve largely independently of neighboring regions. By contrast, at the NUTS-3 level, spatial dependence is economically meaningful and statistically significant, especially under KNN weighting schemes. The prominence of spatial error dependence in SEM models points to spatially correlated unobserved shocks—such as localized labor market conditions or institutional features—that are more relevant at finer spatial resolutions.

While fixed-effects estimates reveal relatively fast mean reversion, dynamic fixed-effects estimators are known to suffer from Nickell bias in the presence of lagged dependent variables. To address this issue, the analysis proceeds with Difference GMM and System GMM estimators. The System GMM results confirm strong persistence but continue to imply mean reversion, as the lagged income gap coefficient remains strictly below unity in all preferred specifications.

At the NUTS-2 level, the preferred spatial System GMM model yields a persistence coefficient of approximately 0.87, corresponding to a half-life of about five years—closely aligned with the fixed-effects estimates. Spatial spillovers remain weak and statistically insignificant, reinforcing the conclusion that regional income dynamics are driven primarily by internal persistence rather than cross-regional interactions.

At the NUTS-3 level, System GMM estimates point to a persistence coefficient of about 0.86 in the preferred specification, implying a half-life of roughly 4–4.5 years. Importantly, at this level the inclusion of spatial interactions is crucial. Spatial dependence is statistically significant and economically meaningful, indicating that provincial income disparities are influenced by neighboring provinces. Moreover, failing to account for spatial dependence would tend to inflate the persistence parameter, potentially overstating temporal inertia. Thus, at finer spatial scales, spatial interactions play an essential role in stabilizing the dynamic specification and correctly allocating variation between persistence and spillovers.

A practical challenge emerges in the GMM framework: jointly including spatial interactions and full sets of time dummies is difficult due to instrument proliferation and singularity problems, especially in panels with small cross-sectional dimensions. In the NUTS-2 analysis, this issue is mitigated by including targeted time dummies for 2008 and 2009 to capture the Great Recession, while maintaining instrument parsimony. At the NUTS-3 level, time effects are excluded in spatial GMM specifications to preserve identification. Nevertheless, the estimated persistence parameters remain stable across alternative treatments of time effects, indicating that the observed mean reversion reflects genuine regional and provincial dynamics rather than spurious responses to common shocks.

While much of the early spatial literature focuses on conditional β-convergence (e.g. Pfaffermayr (2009)), we adopt a stochastic convergence framework to better capture the time-series properties and persistence of income shocks. Nonetheless, we follow the spatial econometric tradition by accounting for the geographic interdependence and scale-specific interactions that Pfaffermayr (2009) identifies as critical to understanding regional growth dynamics and the resulting aggregation bias between NUTS scales.

Finally, the panel unit root tests provide complementary but inconclusive evidence. Results are sensitive to the inclusion of fixed effects and heterogeneity adjustment, with mixed conclusions regarding stationarity——particularly at the NUTS-2 level. This ambiguity reinforces the value of dynamic spatial panel models, which allow persistence, heterogeneity, and spatial dependence to be assessed jointly rather than in isolation.

Taken together, the results lead to three main conclusions. First, income disparities in Italy are highly persistent but mean-reverting at both regional and provincial levels, consistent with conditional stochastic convergence. Second, convergence is faster at finer spatial scales, with shorter half-lives at the provincial level. Third, spatial dependence matters primarily at the local level, where ignoring spatial interactions can distort persistence estimates. Properly accounting for fixed effects, spatial interaction, and dynamic bias is therefore essential for understanding the true nature of income inequality dynamics and for designing effective, spatially targeted policy interventions.

5. CONCLUSION

This study investigates stochastic income convergence across Italian regions over the period 2001–2021, comparing dynamics at two spatial scales: NUTS-2 (regional) and NUTS-3 (provincial). The empirical analysis combines non-spatial and spatial dynamic panel models with fixed effects and System GMM estimators, allowing persistence, unobserved heterogeneity, spatial dependence, and dynamic panel bias to be jointly addressed. The results provide robust evidence of conditional stochastic convergence, but also reveal substantial persistence and important scale-dependent differences in adjustment dynamics.

A central finding is the critical role of fixed effects. In pooled and random-effects specifications, the persistence coefficient on the lagged income gap is extremely close to unity at both spatial levels, suggesting near–random-walk behavior. Hausman tests decisively reject random effects in favor of fixed effects, indicating that unobserved region- and province-specific characteristics are correlated with the regressors. Once fixed effects are introduced, persistence declines markedly—to approximately 0.87 at the NUTS-2 level and around 0.78 at the NUTS-3 level—implying clear mean reversion. These estimates indicate that income gaps are not permanent but gradually converge toward long-run differentials once time-invariant heterogeneity is controlled for.

Interpreting these coefficients in dynamic terms highlights a pronounced scale effect. At the regional level, the implied speed of adjustment is about 13–14% per year, corresponding to a half-life of roughly five years. At the provincial level, mean reversion is faster, with adjustment rates of around 22–24% per year and half-lives of approximately three years. This suggests that income disparities dissipate more rapidly at finer spatial scales, consistent with stronger localized adjustment mechanisms, labor mobility, and short-distance economic interactions.

Introducing spatial dependence through SAR and SEM specifications leaves the estimated persistence largely unchanged, confirming that the convergence dynamics identified in non-spatial fixed-effects models are robust. However, the importance of spatial interactions differs sharply across spatial scales. At the NUTS-2 level, spatial autoregressive and spatial error parameters are generally small and weakly significant at best, and they lose significance once time effects are included. This suggests that, after controlling for unobserved heterogeneity and common macroeconomic shocks, regional income gaps evolve primarily through internal dynamics rather than strong cross-regional spillovers.

By contrast, at the NUTS-3 level spatial dependence is economically meaningful and statistically significant. Both SAR and SEM models—particularly those based on KNN weight matrices—indicate positive spatial spillovers and spatially correlated unobserved shocks. These findings imply that provincial income disparities are shaped not only by their own past but also by conditions in neighboring provinces, underscoring the importance of local spatial interactions at finer geographical resolutions.

While fixed-effects models indicate relatively fast convergence, dynamic fixed-effects estimators are subject to Nickell bias. To obtain consistent estimates of persistence, the analysis therefore employs Difference GMM and System GMM estimators. The System GMM results confirm strong persistence but continue to imply mean reversion, as the coefficient on the lagged income gap remains strictly below unity in all preferred specifications.

At the NUTS-2 level, the preferred spatial System GMM specification yields a persistence coefficient of approximately 0.87, closely aligned with the fixed-effects estimates and implying a half-life of about five years. Spatial spillovers remain weak and statistically insignificant, reinforcing the conclusion that regional income dynamics are dominated by internal persistence rather than contemporaneous spatial interaction.

At the NUTS-3 level, the preferred System GMM specification yields a persistence coefficient of about 0.86, corresponding to a half-life of roughly 4–4.5 years. Importantly, accounting for spatial dependence is crucial at this level. In non-spatial System GMM models, persistence is substantially higher and, in some cases, close to unity, raising concerns about near-unit-root behavior. Once spatial interactions are introduced, the persistence coefficient falls below one and becomes more precisely estimated, confirming dynamic stability. This indicates that part of what would otherwise be attributed to temporal persistence actually reflects spatial spillovers across neighboring provinces. Ignoring spatial dependence, therefore, risks overstating inertia and obscuring the true mean-reverting nature of provincial income disparities.

A practical challenge arises in the GMM framework: jointly including spatial interactions and a full set of time dummies is difficult due to instrument proliferation and singularity problems, particularly in panels with small cross-sectional dimensions. At the NUTS-2 level, this issue is mitigated by including targeted time dummies for 2008 and 2009 to capture the Great Recession. Even this limited control for aggregate shocks is sufficient to ensure stability and mean reversion. At the NUTS-3 level, spatial System GMM models exclude time effects to preserve instrument validity, but the resulting persistence estimates remain stable and below unity. This suggests that spatial interactions absorb an important share of cross-sectional comovement that might otherwise be captured by time dummies, highlighting a degree of complementarity between spatial and temporal controls.

Panel unit root tests provide mixed and model-sensitive evidence, particularly at the NUTS-2 level, and their conclusions depend heavily on the inclusion of fixed effects and heterogeneity adjustment. This ambiguity reinforces the value of dynamic spatial panel models, which allow persistence, heterogeneity, and spatial dependence to be assessed jointly rather than relying on unit root tests alone.

Overall, the results lead to three main conclusions. First, income disparities in Italy are highly persistent but mean-reverting at both regional and provincial levels, consistent with stochastic conditional convergence rather than divergence. Second, convergence is faster at finer spatial scales, with shorter half-lives at the provincial level. Third, spatial dependence matters primarily at the local level: at NUTS-3, ignoring spatial interactions inflates persistence and risks mischaracterizing the dynamics as nearly non-stationary.

From a policy perspective, the findings imply that while convergence is present, it is far from rapid. Persistent local disparities—especially at the provincial level—highlight the need for long-term, place-based interventions, such as those embedded in Italy's National Recovery and Resilience Plan, including investments in green transition, digitalization, human capital, and institutional quality. Future research could further refine these conclusions by exploring alternative spatial weighting schemes, explicitly incorporating geographically isolated regions such as Sardinia and Sicily, and extending the set of covariates to include capital accumulation, productivity, and innovation. Such extensions would deepen our understanding of how spatial structure and regional characteristics jointly shape long-run income convergence in Italy.

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