Unpacking Structural Polarisation: Economic Complexity and Productivity across Italian Territories

Giuseppe Simone

Papers in Evolutionary Economic Geography

25.36

Utrecht University Human Geography and Planning

Unpacking Structural Polarisation: Economic Complexity and Productivity across Italian Territories

Giuseppe Simone
giuseppe.simone1@uniba.it *

September 2025

Unpacking Structural Polarisation: Economic Complexity and Productivity across Italian Territories

Abstract

This paper investigates the structural foundations of regional productivity divergence in Italy through the lens of economic complexity. Leveraging a newly constructed Economic Complexity Index (ECI) at the NUTS-3 level, we examine how the sophistication and diversity of local productive structures shape long-run productivity trajectories of Italian provinces over the period 2000–2021. Empirical approach combines panel data models with instrumental variable (IV-GMM) techniques, spatial econometrics, and simultaneous equation systems (3SLS) to capture the direct, spatial, and bidirectional relationships between complexity and productivity. The findings reveal that economic complexity is a robust and consistent predictor of regional labour productivity. This association is particularly strong in Northern provinces, where institutional density and innovation ecosystems amplify the returns to complexity, and where spatial spillovers from neighbouring territories enhance local outcomes. In contrast, Southern regions experience lower returns and limited externalities, reflecting persistent development traps. Crucially, I provide the first integrated empirical evidence of a cumulative, self-reinforcing loop between complexity and productivity: more complex regions become more productive, and more productive regions are better equipped to diversify into complex activities.

*Personal Addres: giuseppe.simone91@gmail.com.
Postdoctoral Researcher at the Department of Political Science, University of Bari "Aldo Moro". Research interests: economics of innovation, local and regional development, and applied economics. I am especially indebted to Professor Peiró-Palomino for his suggestions and comments during the mentored review process that materially enhanced the paper. The work also benefited from comments at the 22nd Annual STOREP . I warmly acknowledge the support from the Italian Ministry of University and Research under the PRIN2022 project (2022Z78M8J): The Digital Transition and the World of Work: Labour Markets, Organisations, Job Quality, and Industrial Relations (DIGITWORK).

1 Introduction

Metropolitan cores swell, drawing in young talent and leading technologies as peripheral regions lose ground through economic decline and depopulation. High-margin corporate and producer services concentrate in a few large cities, while historic manufacturing districts and traditional industries decline (Feldman et al., 2021). Complex technologies cluster within dense urban ecosystems where deep labour markets and robust infrastructure generate cumulative advantages, widening spatial imbalances (Simone, 2025). Meanwhile, many other places remain locked into traditional and low-complexity sectors, facing deep barriers to diversification and upgrading (Balland and Boschma, 2024). This process of selective agglomeration has widened territorial gaps not only in productivity, but also in innovation capacity, income levels, employment quality, and life opportunities in what has been called the "urban crisis" (Florida, 2017).

As a result, understanding the drivers of regional productivity disparities remains a central challenge for policymakers as the gap between territories continues to widen (OECD, 2025). The role of productive capabilities and knowledge accumulation—captured through the lens of economic complexity– has gained renewed prominence as a theoretical and empirical framework for explaining why some places grow, diversify, and innovate, while others stagnate or decline (Balland et al., 2019, Pinheiro et al., 2025).

Against this backdrop, this paper contributes to the growing literature on structural polarisation by examining the role of economic complexity in shaping productivity trajectories across 103 Italian provinces (NUTS-3) between 2000-2021. Moving beyond national averages and embracing a more granular territorial perspective allows us to link the uneven geography of the productive capabilities with the regional divergence (Balland and Boschma, 2024, Dijkstra et al., 2015). While the economic complexity literature has produced robust evidence at the national level, its subnational application remains relatively underexplored, especially in the context of long-term productivity dynamics (Hidalgo, 2021). Italy offers a compelling empirical setting to fill this gap: a country marked by persistent macro-regional dualisms and increasing within-region inequalities, where productivity stagnation and heterogeneous industrial dynamics affected long-run provincial trajectories (Simone, 2025, Viesti, 2021). Yet, similar patterns of internal divergence and territorial polarisation are increasingly shared across advanced economies, rendering these findings highly relevant beyond the Italian context(OECD, 2024, Rodríguez-Pose, 2025). This study addresses three main research questions: (i) Does local economic complexity foster productivity? (ii) Are there present spatial spillovers from the complexity of neighbouring territories? Do these effects differ across structurally advanced and lagging macro-regions? (iv) Can the interplay between economic complexity and productivity be understood as a self-reinforcing, demand-led process of regional divergence across Italian territories? To answer these questions, we gather insights from evolutionary economic geography (Balland and Boschma, 2024), structural change theory and cumulative causation model (Hirschman, 1958, Myrdal, 1957), and complexity economics (Hidalgo, 2021, Pinheiro et al., 2025), providing fresh empirical evidence on how subnational capabilities shape economic performance.

The work adopts a rigorous empirical strategy combining two-way fixed effects panel regressions (TWFE) with Driscoll–Kraay standard errors, instrumental variable estimation, Generalised method of moment approach (IV-GMM) to mitigate endogeneity, spatial modelling to assess inter-territorial spillovers, and simultaneous equations to capture feedback mechanisms between productivity and complexity. The work presents multiple novelties. Expanding on the work of Basile and Cicerone (2022), this paper offers a substantial advancement in both methodological depth and analytical scope. First, it delivers a comprehensive assessment of the positive link between local capabilities and productivity across multiple specifications and controlling for a wide array of demographic, structural, and economic fundamentals. Second, it moves beyond a unidirectional interpretation by formally modelling the cumulative and looping feedback between complexity and productivity. Third, providing granular evidence that complexity returns are systematically stronger in the Centre-North and largely absent in the Centre-South, this study identifies spatial spillovers and regional asymmetries across macro–regions. Together, these enhancements deepen our understanding of the structural roots of territorial polarisation and offer a more comprehensive empirical platform for evaluating regionally differentiated development strategies.

Policy implications are straightforward. One-size, sectoral-neutral and place-blind policies are inconsistent in addressing spatial and structural heterogeneity of territories and are unable to catch the looping mechanism at the roots of regional development that can either foster or trap regional economies depending on their starting structural conditions. In more advanced regions, particularly in northern Italy, the policy priority should be to consolidate and extend productive ecosystems, enabling further diversification into high-complexity sectors such as advanced services, green technologies, and digital manufacturing. These territories already benefit from dense innovation networks, skilled labour pools, and strong institutions that can be further leveraged through targeted support for scale-ups, smart specialisation policies, and export promotion. Conversely, in structurally lagging provinces, especially in the South, the emphasis must shift toward capability deepening. This entails enabling firms to enter into the production of more complex activities, expanding local production space through technological upgrading, skills enhancement, and access to knowledge and finance. In these areas, a weak enabling environment contributes to what Balland and Boschma (2024) refer to as a ”regional development trap.” Sustained public investment and sectoral industrial policies that support diversification, open market opportunities, and new specialisations are essential to boost a ”virtuous circle” of regional development. The rest of the paper is structured as follows. Section 2 reviews the relevant literature on economic complexity, productivity, and regional divergence. Section 3 presents data, variables and descriptive evidence. Section 4 outlines the empirical strategy and describes the model. Section 5 discusses the main results, and Section 6 concludes with implications for policy and future research.

2 Literature Review

The rise of inequality across territories is particularly striking in light of the process of convergence that occurred until the late 1980s, primarily driven by the expansion of industrial manufacturing across many peripheral regions and the extensive diffusion of interventionist policies inspired by Keynesian principles (Viesti, 2021). The “great inversion” of regional development trajectories refers to the growing divergence between leading regions–which concentrate demographic gains, technological production, and skilled labour–and lagging regions, experiencing economic decline, high unemployment, deindustrialisation, and negative demographic balance. Technological advancements and structural change have played a key role in the new wave of regional inequality (Bathelt et al., 2024). High-tech, knowledge-intensive activities become heavily concentrated in a small number of leading areas where firms benefit from labour market sorting, dense innovation ecosystems, and cumulative externalities (Sassen, 2018). Meanwhile, other places remain locked into low-complexity, low-productivity sectors, facing major barriers to diversification and upgrading. Pinheiro et al. (2025) portrayed the uneven distribution of advanced productions across territories, with technologically sophisticated and complex activities clustering in already leading territories, warning about the reinforcing structural imbalances across European territories. .

For these reasons, territorial divides not only occur between macro–regions but also within them, requiring a massive geographic granularity to be investigated. Many rural territories and small-to-medium metropolitan areas, once engines of growth, have been marked by job losses, declining labour-force participation, and falling per capita incomes relative to national averages (Iammarino et al., 2018). Evidence from OECD countries shows that between 2000 and 2018, the GDP per capita gap among small regions (TL3) consistently widened, revealing a persistent trend of spatial divergence even within the same region (OECD/EC, 2020), while Kemeny and Storper (2024) documented increasing economic disparities even among U.S. metropolitan areas. OECD (2025) shows that the gap in productivity between metropolitan and non–metropolitan zones has widened across OECD countries. Velthuis et al. (2025) clustered European NUTS-3 regions based on economic performance, labour market characteristics, and demographic dynamics, highlighting varying degrees of “left behindness” even within the same regions. Viesti (2021) observed the huge disparities between Italian NUTS3 territories of the same region, especially striking in regions with leading metropolitan zones that outperform other territories. For these reasons, going beyond the most adopted regional level of analysis, this study focuses on the Italian provinces, addressing the need to capture at the finest geographic scale how structural economic characteristics relate to localised productivity trajectories (Dijkstra et al., 2015, Iammarino et al., 2018).

The concept of economic complexity has emerged as a powerful analytical framework to understand the structural foundations of economic development and regional performance (Hidalgo, 2021). Building on the seminal work of Hidalgo and Hausmann (2009), this approach shifts the focus from traditional input-based analysis of economic growth to investigate the latent capabilities embedded in the economic structure of territories. These capabilities, which are rarely observable directly, are inferred through data-driven measures of the diversity and complexity of products and services that regions can competitively produce. More complex economies, indeed, produce and export sophisticated goods marked by dense and functionally integrated productive networks that combine knowledge-intensive and technological-advanced processes. By contrast, low-complexity economies specialised in more traditional productions with simpler, more standardised processes embedded in lower technological content and less specialised know-how.

At the core of this framework lies the Economic Complexity Index (ECI), a measure that captures both the diversity of a region –how many different products a territory redcompetitively exports – and the ubiquity or rarity of products– the number of regions able to export the same goods. Regions with high ECI scores excel in producing and exporting a broad array of sophisticated products that few other regions can replicate, highlighting their advanced productive knowledge and unique capabilities endowment (Hidalgo and Hausmann, 2009).

From an empirical standpoint, ECI proved its effectiveness as a robust seminal work of Hidalgo and Hausmann (2009) and Hausmann et al. (2014) showed that countries with higher complexity tend to grow faster, have better export quality, innovation capabilities, income levels, and sustainability outcomes (Sbardella et al., 2018).

Subnational applications of the ECI proved that economic complexity is also a strong predictor of regional performance, where agglomeration effects, local labour markets, and innovation systems play a central role (Balland et al., 2020, Mewes and Broekel, 2022, Pintar and Scherngell, 2022). Recent studies adopted ECI to examine the link between structural change and territorial divergence, providing new perspectives on the ongoing debate about the factors influencing regional development.

On the one hand, this research agenda, building upon classical development theories of cumulative causation and regional divergence (Hirschman, 1958, Myrdal, 1957), emphasises the role of self-reinforcing mechanisms such as agglomeration externalities, capital flows, infrastructure spillovers, and selective migration as key drivers of persistent regional disparities. On the other hand, this approach highlights the spatially bounded, path-dependent, and capability-driven nature of innovation and diversification processes (Audretsch and Feldman, 1996, Boschma and Lambooy, 1999, Ciccone and Hall, 1996) grounded in the contributions of evolutionary economic geography.

Complex activities—defined as those requiring a broad set of complementary capabilities that are difficult to acquire and imitate—tend to concentrate in urban agglomerations and knowledge-intensive regions with advanced economic structures. Balland et al. (2020) show that more complex technological and economic activities disproportionately cluster in US metropolitan areas, where proximity fosters collaboration and knowledge spillovers. These metropolitan hubs benefit massively from agglomeration economies, enabling higher productivity, wage growth and resilience through technological upgrading and persistent diversification into advanced sectors (Fritz and Manduca, 2021). The European context presents similar patterns. Antonelli et al. (2017) highlights the spatial concentration of knowledge production across EU regions. Likewise, Pintar and Scherngell (2022) finds that the most complex knowledge crowd particularly in already leading regions, reinforcing the distance of lagging regions from the technological frontier. Balland and Boschma (2024), for example, defines regional traps as the structural inability of certain European regions to develop new and complex activities, showing that this condition negatively affects both employment and wage growth in these areas.

In the Italian context, Simone (2025) shows that innovation activities and technologically advanced services, such as ICT and finance and insurance industries, are largely concentrated in a few of the fourteen Italian metropolitan areas, both in terms of employment and value-added, fostering divergent growth trajectories not only between metropolitan and non–metropolitan territories, but also within the same metropolitan areas. Indeed, only a few technological hotspots across the country benefit from the sorting dynamics and monopolistic nature of the new digital and service sectors, while most territories are overlooked (Fiorentino and Phelps, 2025).

Looking specifically at the interplay between complexity and productivity, findings are both nuanced and inconclusive. Antonelli et al. (2022), find that although knowledge complexity significantly enhances innovation, it may dampen productivity in the short run across EU regions.

Çınar et al. (2022) examined the link between economic complexity and sectoral regional productivity in Turkey, finding that economic fitness positively influences overall labour productivity, with the most pronounced effects observed in the industrial sector.

In the Italian context, Basile and Cicerone (2022) show that economic complexity strongly predicts provincial manufacturing productivity polarisation. High-ECI provinces in the North systematically outperform the Southern ones, which remain constrained in low-complexity structures. The authors estimate a growing differential in the ergodic productivity distribution between 2000 and 2015, witnessing the divergent growth trajectories of Italian territories.

In summary, economic complexity plays a decisive role in shaping regional productivity through a dynamic interplay of capability endowments, structural diversification, and agglomeration economies. Regions with sophisticated capabilities leverage complexity to achieve higher growth, foster innovation, and sustain productivity improvements, whereas low-complexity regions face diversification barriers that sustain productivity gaps. Understanding how complexity drives productivity is crucial for clarifying the relationships between structural change, technological upgrading, and economic performance. It also provides critical insights for designing effective regional development policies and promoting inclusive growth. Nevertheless, subnational evidence on this relationship remains limited and inconclusive.

This paper addresses that gap by investigating the reinforcing mechanisms connecting the complexity of regional economic structures and productivity. In doing so, it contributes to the broader debate on territorial inequality and the structural polarisation observed across European regions.

3 Empirical framework

3.1 Data and Variables

This study employs a novel panel dataset covering 103 Italian NUTS-3 provinces over the period 2000–2021 to investigate the relationship between economic complexity and regional productivity. The long time span and fine spatial resolution provide a unique opportunity to analyse how structural capabilities influence productivity dynamics at the local level. To ensure spatial consistency across years, administrative boundaries were harmonised by aggregating provinces affected by territorial reforms, thereby preserving comparability over time.

The dependent variable is labour productivity, measured as the logarithm of real value added per employee. To account for economic, demographic, and structural fundamentals potentially correlated with both complexity and productivity, a comprehensive set of control variables is included. Capital intensity is measured as the logarithm of gross fixed capital formation per capita (GFCF per capita (ln)). Labour market differences are captured through the logarithm of total hours worked per employee (Hrs worked per capita (ln)) and hourly labour compensation (Hrs compensation (ln)), which account for variations in both the quantity and quality of labour inputs. Local demand-side dynamism is proxied by value added (VA per c. (ln)), controlling for regional income disparities and the scale of internal markets.

Trade openness is defined as the natural logarithm of the ratio of total exports plus imports to value added (Openess (ln)). Innovation capacity is proxied by patent intensity, measured as the logarithm of the number of patents per capita (ln_patent_pop). Patent data are drawn from the Italian Patent and Trademark Office, which provides more accurate regional coverage than international datasets such as REGPAT (Diodato et al., 2024), where peripheral regions are often under-represented due to the lower propensity of firms located in these places to international intellectual property protection. Population density (Density (ln)), captures agglomeration effects. Demographic structure is controlled for using the shares of young and female populations at the provincial level. Structural characteristics of the local economy are further examined using the shares of employment in ICT services (ICT. Empl. Share) and manufacturing sectors (Manuf. Empl. Share), capturing regional differences in industrial specialisation and technological intensity. Additionally, in order to assess possible differences in infrastructure endowments across provinces, I estimate the density of railways and motorways for Italian provinces by weighting data at the regional level with the limited information available at the NUTS 3 level. Similarly, three waves of Census data–2001, 2011, 2021– are used to estimate the share of the population with at least a high-school degree and obtain a proxy of the province's human capital. Finally, in order to control for institutional quality heterogeneity across Italian territories, Nifo and Vecchione (2015) index of corruption score is adopted. It is worth noting that while the last three variables account for crucial features of Italian territories, their temporal coverage differs from that of the others, making sample estimations less comparable. Descriptive statistics, source and time coverage are shown in detail in Table 1. All monetary variables are expressed in constant euros and log-transformed to reduce skewness and facilitate interpretation.

Table 1: Descriptive statistics

Variable	Period	Mean	SD	Source
Outcome				
Labour productivity	2000–2021	64 971.7620	8127.1779	ARDECO
Key explanatory				
Economic Complexity Index (ECI)	2000–2021	0.0000	1.0002	Calculation based on COEWEB
Controls				
GFCF per person	2000–2021	5345.0940	1763.8610	ARDECO
Hours worked	2000–2021	1771.4819	79.0119	ARDECO
Openness	2000–2021	0.4100	0.2700	Calculation based on COEWEB
Patents per person	2000–2021	0.0002	0.0006	UIBM
Population density (per km^2)	2000–2021	252.7802	337.2778	ISTAT
Female share	2000–2021	0.5107	0.0300	DEMO–ISTAT
Young share	2000–2021	0.2251	0.0354	DEMO–ISTAT
VA per capita	2000–2021	14 660.0000	22 252.0000	ARDECO
ICT employment share	2000–2021	0.1640	0.0790	ISTAT – Territorial Accounts
Manufact. empl. share	2000–2021	0.1700	0.0820	ISTAT – Territorial Accounts
Compensation per hour	2000–2021	21.7996	1.9215	ARDECO
Corruption	2004–2021	0.8100	0.1700	Nifo and Vecchione (2015)
Infrastructure density	2001–2021	0.2167	0.0905	Authors' calculations (EUROSTAT; ISTAT)
Graduated Share	2001–2021	0.5083	0.0605	ISTAT Census

Notes: Provincial statistics are averages over the period. Monetary variables are in constant 2015 euros. Descriptive statistics are computed before log transformation.

3.2 Economic Complexity Index

To quantify the structural capabilities of local economies, we compute the Economic Complexity Index (ECI) at the NUTS-3 level for Italy using export data from ISTAT's Coeweb archive. This database provides detailed annual foreign trade data by product and province, disaggregated at the three-digit NACE Rev. 2 classification. The ECI is a widely established measure that captures the amount of productive knowledge embedded in an economy, inferred from the diversity and exclusivity of the goods it can competitively produce and export (Hidalgo and Hausmann, 2009).

Grounded in the idea that economies grow and diversify not randomly but by accumulating and recombining capabilities, the ECI captures the sophistication of an economy by analysing the products in which it is specialised (Hausmann et al., 2014, Hidalgo and Hausmann, 2009). Sophisticated regions are not only diversified but also specialised in exporting goods that are rarely produced elsewhere. This duality is reflected in the recursive structure of the ECI: economies are complex if they produce complex products, and products are complex if only complex economies can produce them (Hidalgo, 2021).

The construction of the ECI follows the method of reflections introduced by Hidalgo and Hausmann (2009). In this framework, complexity reflects both the diversity of the products that a region exports with revealed comparative advantage (RCA), and the ubiquity of those products—that is, how many other regions also export them. Formally, the RCA for each province p and product i is defined as:

$$\mathrm{RCA}_{ip} = \frac{\frac{X_{ip}}{\sum_i X_{ip}}}{\frac{\sum_p X_{ip}}{\sum_{i,p} X_{ip}}} \tag{1}$$

where X_{ip} denotes the export value of product i from province p. The numerator represents the share of product i in province p's total exports, and the denominator reflects the national share of product i. Provinces with $\mathrm{RCA}_{ip} \geq 1$ are considered specialised in product i. We then define a binary province–product matrix M_{ip} where $M_{ip} = 1$ if $\mathrm{RCA}_{ip} \geq 1$, and $M_{ip} = 0$ otherwise.

From this matrix, two key characteristics are calculated: the *diversity* of a province p as $M_p = \sum_i M_{ip}$, and the *ubiquity* of a product i as $M_i = \sum_p M_{ip}$.

The ECI is obtained by diagonalising the normalised similarity matrix:

$$\tilde{M}_{pp'} = \sum_i \frac{M_{ip} M_{ip'}}{M_p M_i} \tag{2}$$

This matrix compares the export baskets of provinces p and p', with products weighted inversely by their ubiquity and normalised by the diversity of province p. The ECI corresponds to the eigenvector K_p associated with the second-largest eigenvalue of $\tilde{M}$. The final ECI score is then standardised:

$$\mathrm{ECI}_p = \frac{K_p - \langle K \rangle}{\sigma_p} \tag{3}$$

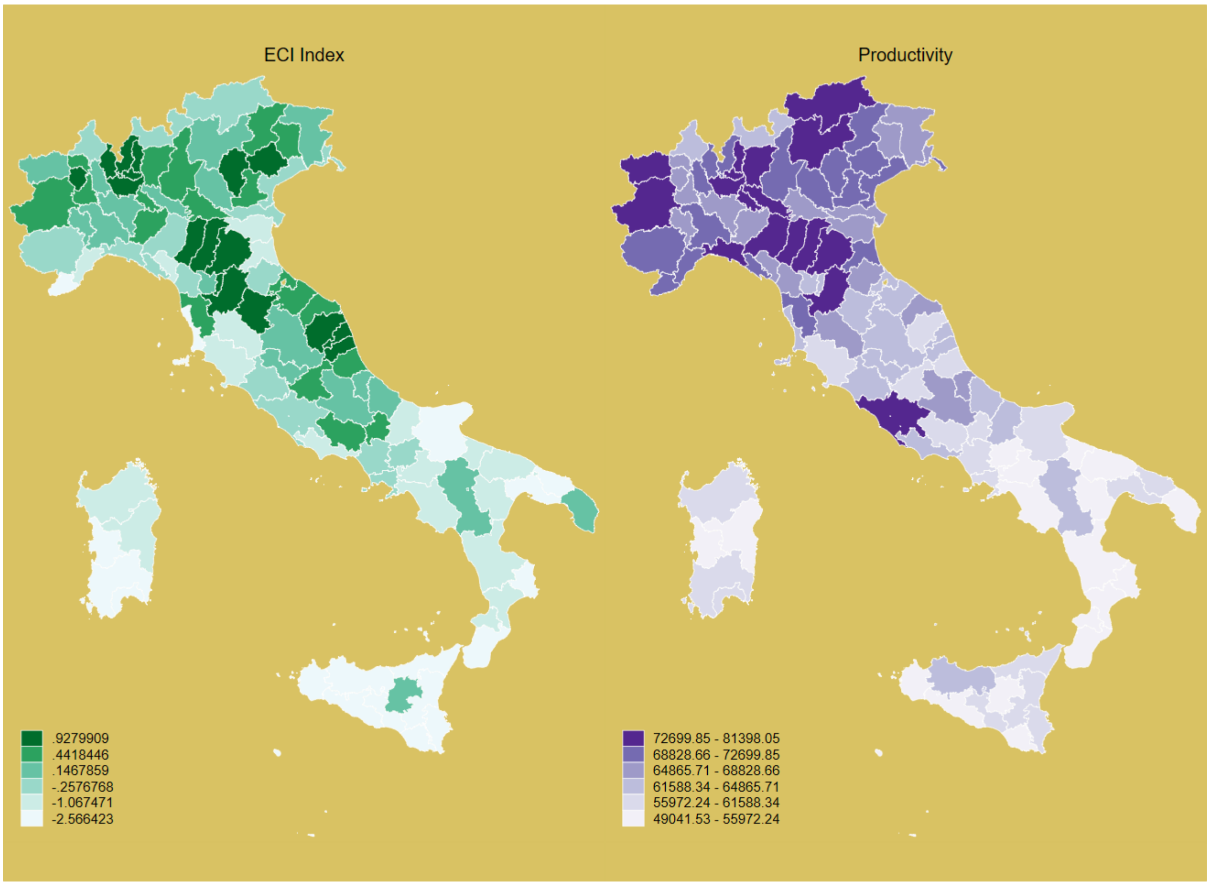
where $\langle K \rangle$ is the mean of K_p across provinces and σ_p its standard deviation. This algorithm operationalises the idea that complex provinces export rare products, and rare products are those exported by a few, highly diversified provinces.

Following seminal contributions (Basile and Cicerone, 2022, Hidalgo, 2021, Reynolds et al., 2018), we compute an *ECI* by excluding resource-intensive products, such as fossil fuels, mineral ores, electricity, gas, and products containing many zeros, to avoid distortions from factor endowments or scale effects (Hausmann et al., 2014, Hidalgo, 2021).

Although the ECI is derived from export data, it captures far more than simple diversification. As demonstrated by Kemp-Benedict (2014) and Mealy et al. (2019), the ECI and the initial diversity index are orthogonal, implying that the ECI reflects more quality of production, including knowledge intensity and exclusivity, and not just product variety (Antonietti and Burlina, 2023). High-ECI provinces specialise in technologically advanced, knowledge-intensive goods, while low-ECI provinces remain focused on basic and more traditional outputs. The resulting indicator serves as the key explanatory variable in our empirical models, providing a dynamic measure of how structural production complexity relates to spatial patterns of regional productivity.

3.3 Descriptive statistics

Figure 1: Provincial averages (2000–2021) of ECI (left) and Labour Productivity (right)

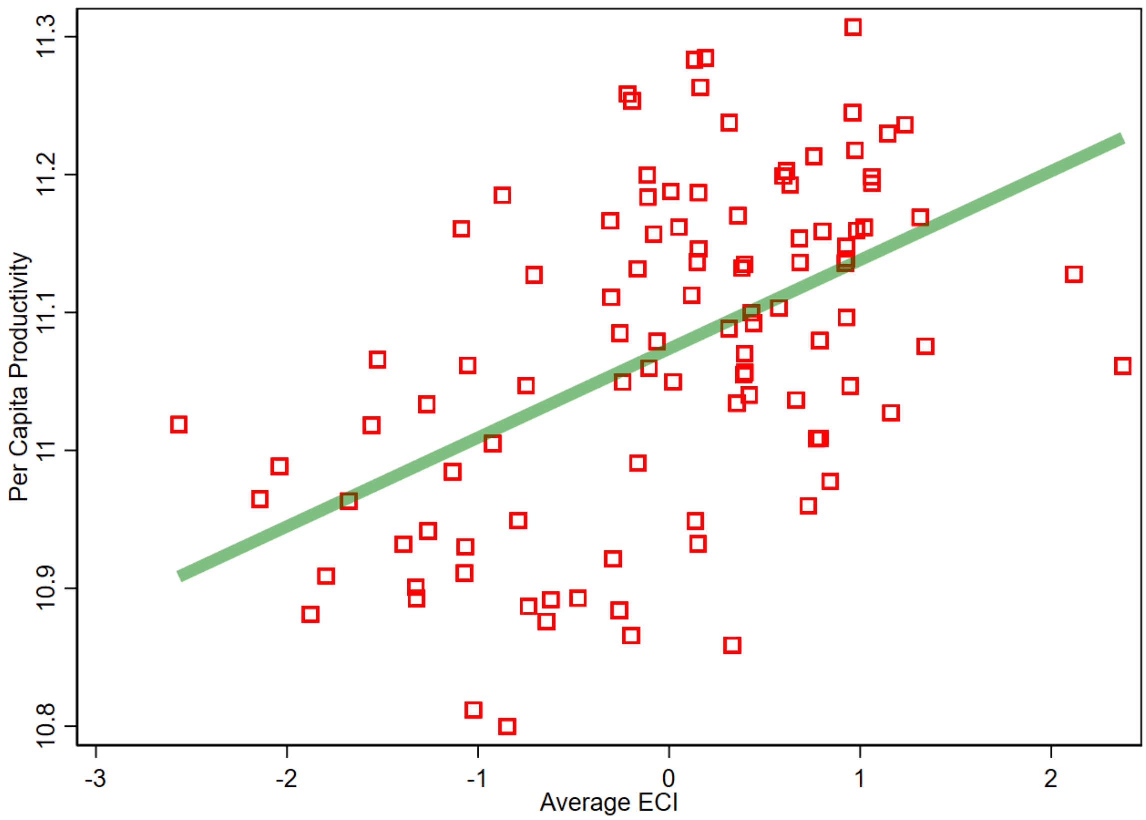


Source: Author's elaboration. Note: ECI's legend (left) indicates lower-bound brackets.

Figure 1 illustrates the geography of complexity and labour productivity across Italian provinces over 2000–2021. The maps reveal a clear pattern of spatial sorting: high values of both indicators cluster systematically in the Centre–North, while the Mezzogiorno and the islands remain concentrated in low and medium–low brackets(check 9 for the detailed division of provinces across macro–areas). In the North, nodes of a dense, capability-rich ecosystem, including industrial districts and service-specialised territories, record the highest scores in complexity and productivity, anchored by metropolitan hubs such as Milan and Bologna, and by specialised industrial ecosystems in Emilia-Romagna (Parma, Modena) and the Northeast. In Central Italy, Rome peaks as a distinctive metropolitan pole, although neighbouring provinces show mixed performances. By contrast, the Mezzogiorno and the islands exhibit extended middle–to–low scores on both variables, particularly in non-metropolitan and internal areas. Outside a few industrial centres, provinces distant from the main metropolitan systems tend to exhibit lower capability endowments and lower productivity levels.

The spatial diagnostic strongly suggests a sorting dynamics of ECI across Italian territories. Global Moran's I for `ECI` is very large and positive: $I = 0.7774$ (expected $E(I) \approx -0.0004$), $p < 0.001$. The Local Moran summary further documents extensive spatial concordance: 1,131 High–High and 857 Low–Low observations in the full sample, with 618 High–High and 513 Low–Low cells significant at the 1% level. These diagnostics indicate pronounced spatial clustering of economic complexity (high-ECI provinces bordering high-ECI provinces and low-ECI provinces bordering low-ECI provinces). A more detailed assessment of the recent evolution of the ECI Index during the last two decades witnessed the strong spatial divergence occurring among leading areas and the immobilism of lagging regions, particularly in the South Capriati et al. (2025). These patterns are shown in 3 in 6.2, reflecting the divergent trajectories of structural capabilities of Italian macro—areas.

Figure 2: Scatter EC–Productivity



Source: Author's elaboration.

Figure 2 plots average ECI against productivity, depicting a robust and positive correlation between the two variables. The dispersion widens at intermediate values, depicting differentiated specialisation paths and mixed industrial portfolios. Although descriptive, these patterns document interesting patterns. First, they report a persistent macro–regional dualism in the structural capabilities of territories that appears to correlate with productivity performance. Second, spatial sorting of the variables seems to indicate the presence of potential spatial spillovers interacting in the link between economic complexity and productivity and possible heterogeneous returns to complexity by macro–region.

4 Model specification and empirical strategy

The empirical strategy encompasses an extensive and rigorous econometric approach designed to robustly analyse the link between economic complexity and productivity across Italian provinces. Baseline specification encompasses the TWFE panel estimator, formally described as follows:

$$Y_{it} = \beta_1 \mathrm{ECI}_{i,t-1} + \beta_2 X_{i,t-1} + \phi_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where Y_{it} denotes the logarithm of real labour productivity (real value added per employee) for the province i at time t, $\text{ECI}_{i,t-1}$, is the lagged measure of province complexity, $X_{i,t-1}$ and represents the set of control variables. Province–level fixed effects (ϕ) and year fixed effects (γ_t) are included to capture unobserved heterogeneity and temporal shocks, respectively. The vector of control variables includes an extensive array of demographic, economic, and structural covariates carefully selected based on theoretical relevance and empirical robustness from existing regional economic literature.

Specifically, given the negative demographic balance of many Italian provinces, the share of young populations and the share of females are included to account for demographic asymmetries across territories and the different composition of labour demand. These groups—typically more exposed to market shocks, precarious employment, and flexible work arrangements—reflect heterogeneity in local labour market supply (Capriati et al., 2024). In addition, variables such as total hours worked per employee and hourly labour compensation help to capture both the quantitative and qualitative characteristics of local employment. Population density serves to reflect agglomeration externalities and productivity advantages typically observed in densely populated, metropolitan regions (Moretti, 2012).

GFCF and patenting activity, rescaled for local population, aim to grasp differences respectively in capital accumulation and innovation dynamics across Italian local economies. Following (Basile and Cicerone, 2022), openness reflects the exposure of local economies to international competition and their integration in global markets. Taken together, these variables support the understanding of supply-side factors driving local economic performance.

Structural variables such as employment shares in the ICT services and manufacturing sectors explicitly account for the industrial specialisation and sectoral characteristics of provincial economies. In addition, local demand patterns are further proxied by the value-added, providing additional control for regional income disparities and local market scale that may influence productivity outcomes.

The share of the population with at least a high school degree proxies the difference in human capital stock across Italian territories, while infrastructure density accounts for the heterogeneous endowments of railway and motorway. To gain additional control, the effect of institutional quality is analysed using the corruption level index from Nifo and Vecchione (2015), though the temporal coverage of this variable does not fully align with the sample.

To ensure the robustness and consistency of the findings, multiple specifications of the baseline model are provided following a systematic, step-wise approach: adding control variables incrementally to observe their effects, including potential changes in the estimated coefficient for ECI.

Recognising the inherent econometric challenges of panel data, notably serial correlation, heteroscedasticity, and cross-sectional dependence, Driscoll–Kraay standard errors are adopted. This estimation strategy produces robust standard errors under spatial and temporal correlation, making it particularly suitable for panel datasets with our dimensions (Hoechle, 2007). Moreover, to explicitly mitigate potential simultaneity-related endogeneity, all regressors are lagged by one year, ensuring temporal precedence and reducing contemporaneous feedback loops between productivity and explanatory variables.

Despite lagging regressors, to further mitigate endogeneity and reverse causality bias, instrumental variable generalised method of moments (IV-GMM) estimation with a heteroscedasticity-robust covariance matrix was implemented. Specifically, the complexity index is instrumented using its deeper lagged values (up to three periods prior), following the approach adopted by Basile and Cicerone (2022). Further specifications with ECI predicted by ten-year lags confirm the robustness of the empirical strategy; results are available upon request. The IV-GMM estimator leverages internal panel structure to provide consistent and efficient estimates even in the presence of heteroscedasticity, autocorrelation, or endogenous regressors.

Considering the geographical patterns of the relation investigated and the potential spatial spillover involved, spatial econometric methods are incorporated into the analytical framework. Precisely, ECI spatial spillover effects are estimated by an inverse-distance spatial weighting matrix (W). This approach assigns higher weights to nearby provinces and progressively lower weights to more distant ones, thereby reflecting the empirically grounded assumption that spatial externalities—such as knowledge diffusion, supply chain linkages, or labour mobility—tend to decay with distance. Crucially, we opted not to truncate the matrix, allowing for a fully connected spatial structure in which each province can, in principle, exert influence on every other province, albeit at a decaying rate. This decision was driven by both empirical considerations and theoretical alignment with complexity literature, highlighting the non-local nature of structural spillovers, particularly in integrated economies such as Italy. The resulting matrix is row-standardised and symmetric, ensuring comparability of spatial effects across provinces and mitigating issues related to scale heterogeneity. The use of an inverse-distance specification is well-established in spatial econometrics (Elhorst et al., 2014), and is especially appropriate in the absence of sharp administrative or functional boundaries that would justify cutoffs or contiguity-based definitions. As such, the constructed spatial matrix offers a flexible and theoretically grounded platform for estimating spatially lagged effects of complexity while preserving a continuous and fully observed spatial interaction surface.

Furthermore, using various spatial matrices, such as the six-nearest neighbours, or an economic distance-based spatial weights matrix based on the province's level of openness, does not affect the estimation results. In addition, spatial weight matrices with a cut-off of 300 and 150 Km are tested, along with a Contiguity matrix, without altering the main results. The spatial econometric approach follows a multi-level and nested process. First, the inclusion of the spatially lagged $W_{t-1}ECI_{t-1}$ captures the potential spillover effects of neighbouring provinces' complexity on local productivity outcomes. In addition, we account for North-South differences by splitting the estimation sample and using interaction terms. Second, a range of specifications that account for potential alternative and different spatial dynamics are provided, specifically including Spatial autoregressive (SAR), spatial error model (SEM) and spatial Durbin model (SDM).

To explicitly address the potential looping and cumulative relationship between productivity and economic complexity, we implement a system of simultaneous equations using the Three-Stage Least Squares (3SLS) estimator. This approach is appropriate when some explanatory variables are potentially endogenous to the system and may also be correlated with the error terms. In the context of this study, productivity and economic complexity are likely to influence each other over time. Productivity growth may enhance the development of new productive capabilities and promote diversification into complex activities, while increasing complexity can, in turn, stimulate productivity improvements through innovation, technological upgrading, and more efficient resource allocation. Neglecting this mutual dependence could result in biased and inconsistent parameter estimates, limiting the full understanding of the systematic mechanism of cumulative causation fuelling economic development (Myrdal, 1957). However, while this approach is more commonly used in innovation studies (Carboni and Medda, 2020, Pianta, 2018, Simone et al., 2024), it remains underutilised in development literature. The complexity equation is specified as:

$$\mathrm{ECI}_{it} = \pi_1 \ln Y_{i,t-1} + \pi_j Z_{i,t-1} + \delta_i + \eta_t + \nu_{it} \tag{5}$$

where $\ln Y_{i,t-1}$ captures the feedback effects from productivity to complexity $\ln Y_{i,t-1}$ and control variables $Z_{j,t-1}$ include demographic factors (young and female population shares), and population density.

The 3SLS estimation proceeds in three stages. First, each endogenous variable is regressed on all exogenous explanatory variables to generate fitted values, which serve as instruments. Second, the covariance matrix of cross-equation disturbances is estimated consistently using the residuals from a 2SLS estimation of each structural equation. Third, the system of equations is estimated using the GLS method that incorporates both the fitted values and the second-step estimated variance-covariance matrix. This procedure yields consistent and efficient parameter estimates while explicitly accounting for simultaneity and the feedback mechanisms linking productivity and economic complexity.

This comprehensive empirical strategy enables a robust identification of the dynamics and relationships between regional economic complexity and productivity, while rigorously controlling for potential challenges and confounders.

5 Results

In this section, results from the econometric exercise are analysed in order to assess the link between ECI and complexity across Italian provinces.

5.1 Panel estimations

Table 2 presents estimations across four increasingly comprehensive specifications, progressively introducing blocks of controls for economic, structural, demographic, and institutional features. In all columns `ECI` coefficients result in positive and significant values, mirroring the straightforward link between territorial structural sophistication and provincial labour productivity.

Column (1) provides the baseline estimate where productivity is explained only by provincial-level ECI, controlling for unobserved individual and temporal fixed effects. Results echo the macro-level findings of Hidalgo and Hausmann (2009) and the recent regional application of Basile and Cicerone (2022) in which complexity records as a robust predictor of productivity. In Column (2), we introduce core economic controls such as capital intensity and total hours worked per employee. While the number of hours worked is not statistically significant in this specification, capital intensity exerts a positive and highly significant effect on productivity, confirming the expected role of capital accumulation in supporting productivity growth. This result contrasts with the negligible effect of capital investments on productivity witnessed for the manufacturing sector by Basile and Cicerone (2022).

Column (3) extends the model by introducing structural and demographic controls. Population density enters positively and significantly, supporting the idea that urban scale and agglomeration externalities—such as knowledge spillovers and matching—foster productivity, as theorised by Moretti (2012) and empirically validated by Balland et al. (2020). Trade openness also shows a positive and statistically significant association with productivity, suggesting that more international regions tend to engage in higher-value activities and benefit from exposure to external competition, as in Basile and Cicerone (2022). Demographic composition also plays a clear role: a higher female employment share is positively associated with productivity, potentially reflecting inclusion and human capital utilisation, while the youth share seems to exert a negative effect on productivity levels, virtually capturing lower average experience in the labour market and more flexible jobs (Capriati et al., 2024).

Sectoral specialisation shows asymmetric effects. While manufacturing employment appears weakly correlated with productivity in the full model, the ICT share is negatively signed and highly significant. This is consistent with the spatial concentration of high-tech services in a few urban cores, and the difficulty for peripheral regions to convert ICT specialisation into productivity gains—a pattern also highlighted by Antonelli et al. (2017) and Simone et al. (2024).

In Column (4), innovation (patent intensity), wage structure (labour compensation), and local demand (value added per capita) are included. While value added per capita and hourly labour compensation are both strongly significant and positively signed, capturing the role of local demand and labour market conditions in reinforcing productivity growth as emphasised in demand-led growth models(Capriati et al. (2024) and cumulative causation frameworks (Hirschman, 1958, Myrdal, 1957), patent intensity in this specification is not statistically significant mirroring the puzzling link between knowledge creation and productivity gains across Italian territories evinced by (Antonelli et al., 2017).

These results are largely confirmed by models (5) and (6), which account for additional controls such as human capital endowment, infrastructure density and institution quality. While the density of infrastructure in (5) positively impacts productivity, the other additional controls do not show a statistically significant effect.

Overall, the ECI coefficient remains remarkably stable and significant across all specifications, increasing slightly in the full model (0.0051, $p < 0.01$). The progressive increase in model fit (pseudo-R^2 rising from 0.561 to 0.697) highlights the prediction power of incorporating structural, demographic, and institutional controls, mirroring the multidimensional nature of regional development.

Yet, the persistent effect of complexity across all specifications confirms that the nature and composition of what a territory produces remains central to understanding long-run productivity performance. Nonetheless, the persistent and robust association between ECI and productivity indicates that productive capabilities reflect a deeper, structural dimension of economic performance that is not reducible to conventional growth factors. Table 8 in the appendix supports these findings by describing compelling results from the stepwise procedure with contemporaneous control variables, marked by improved statistical precision and reinforcing the central role of complexity in shaping regional development trajectories.

Table 2: Stepwise FE estimates

	(1) FE-DK	(2) FE-Controls	(3) FE-Structural	(4) FE-Demand	(5) FE-FULL	(6) FE-Institutional
L.ECI	0.0035*	0.0035**	0.0035**	0.0048**	0.0051***	0.0045**
	(0.0019)	(0.0016)	(0.0015)	(0.0018)	(0.0017)	(0.0016)
L.GFCF per capita (ln)		0.0528***	0.0601***	-0.0074	-0.0072	-0.0135
		(0.0112)	(0.0106)	(0.0096)	(0.0102)	(0.0100)
L.Hrs worked per capita (ln)		0.0679	0.1042	0.5826***	0.5924***	0.5729***
		(0.0823)	(0.0921)	(0.1287)	(0.1352)	(0.1609)
L.Density (ln)			0.104**	-0.1541***	-0.1961***	-0.2021***
			(0.0446)	(0.0489)	(0.0421)	(0.0329)
L.Openess (ln)			0.0096***	0.0055**	0.0057**	0.0094**
			(0.0023)	(0.0026)	(0.0027)	(0.0037)
L.Female Share			0.3162***	0.319***	0.2814***	-1.3957
			(0.0837)	(0.0615)	(0.0882)	(0.8303)
L.Young Share			-0.4242**	-0.5572***	-0.5542***	-0.5496***
			(0.1558)	(0.1118)	(0.1448)	(0.1788)
L.ICT Empl Share			-0.1367	-1.6509***	-1.5993***	-1.2569**
			(0.3183)	(0.3203)	(0.3807)	(0.4824)
L.Manuf. Empl. Share			0.0024***	-0.0007	-0.0008	-0.0011
			(0.0006)	(0.0006)	(0.0008)	(0.0012)
L.Patent per c. (ln)				0.0003	0.0002	-0.0014
				(0.0016)	(0.0017)	(0.0015)
L.VA per c. (ln)				0.2404***	0.2455***	0.2564***
				(0.0223)	(0.0231)	(0.0296)
L.Hrs compensation (ln)				0.5575***	0.5793***	0.5167***
				(0.0564)	(0.0693)	(0.0610)
L.Infrastructure Density (ln)					0.0153**	0.006
					(0.0062)	(0.0066)
L.Gradueted Share					-0.0088	0.0002
					(0.0423)	(0.0517)
L.Corruption						-0.0058
						(0.0143)
Constant	11.048***	omitted	omitted	omitted	3.4549***	4.3869**
	(0.001)	/	/	/	(1.1427)	(1.6114)
Observations	2163	2163	2163	2163	2060	1648
Pseudo R^2	0.561	0.576	0.589	0.671	0.666	0.687
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	D-KRAAY	D-KRAAY	D-KRAAY	D-KRAAY	D-KRAAY	D-KRAAY

Notes: The table depicts the estimations of the stepwise procedure. In each model, a more comprehensive set of control variables is included. Driscoll–Kraay robust standard errors in parentheses. Significance: $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.10$.

In order to mitigate at least partially endogeneity and reverse causality bias,table 3 reports the results of the instrumental variable estimation IV-GMM approach.

This method provides efficient estimates in the presence of arbitrary heteroskedasticity and intra-cluster correlation by computing a heteroskedasticity- and cluster-robust covariance matrix. Standard errors are clustered at the province level to account for unobserved serial correlation and spatial dependence within Italian NUTS-3 territories. The endogenous regressor (`ECI`) is instrumented using its previous lags to soften, at least partially, simultaneity and reverse causality bias, following a similar approach in literature (Basile and Cicerone, 2022). The top panel of the table shows the first-stage estimates, confirming that both lagged instruments are strong and statistically significant predictors of current complexity levels. The right panel displays the second-stage results, where the estimated coefficient on the instrumented complexity index is positive and statistically significant at the 5% level. Several identification diagnostics were applied to strengthen the robustness of the result of this approach. The Kleibergen-Paap LM statistic rejects the null hypothesis of underidentification, while the Kleibergen-Paap Wald rk F statistic equals 29.9, comfortably exceeding the Stock-Yogo critical value for weak identification at the 10% level (19.93). These results support the idea that instruments are relevant and the model is not weakly identified. Overall, the IV-GMM estimation provides consistent and efficient estimates of the positive link between economic complexity and regional productivity, accounting for potential endogeneity through strong internal instruments and a rich econometric framework, and at least partially may help to address reverse causality concerns.

Table 3: IV-GMM Estimation Results

Variable	**First stage (ECI)**	**Second stage (Productivity)**
ECI (IV)	–	0.01146**
		(0.00553)
L3.ECI	0.3073***	–
	(0.0397)	
L4.ECI	0.0893***	–
	(0.0303)	
GFCF per capita (ln)	0.1917	-0.02380
	(0.2335)	(0.01640)
Hrs worked per capita (ln)	0.4098	0.5401***
	(1.6507)	(0.1240)
Openess (ln)	0.0037	0.00885*
	(0.1436)	(0.00480)
Patent per c. (ln)	-0.0315	-0.00191
	(0.0269)	(0.00219)
Density (ln)	1.2638	-0.33909***
	(0.7725)	(0.07605)
Female Share	-18.9001	-1.11701
	(14.3259)	(0.77644)
Young Share	-4.22895	-0.72785**
	(5.14715)	(0.29186)
VA per c. (ln)	-0.3457	0.42925***
	(0.5451)	(0.03822)
ICT. Empl. Share	8.3371	-1.75777***
	(7.5458)	(0.54290)
Manuf. Empl. Share	0.0243	-0.00102
	(0.0192)	(0.00153)
Hrs compensation (ln)	-0.3831	0.51573***
	(0.9112)	(0.07759)
Infrastructure Density (ln)	-0.0848	0.01702**
	(0.1529)	(0.00743)
Graduated Share	-2.9513**	0.01918
	(1.1183)	(0.08800)

Centered R^2 = 0.4505
Sanderson–Windmeijer $F(2, 102) = 29.92$.
Kleibergen–Paap rk LM: Chi-sq(2) = 22.340, p = 0.0000.
Cragg–Donald = 103.813
Kleibergen–Paap rk Wald F = 29.920.
Hansen J: $J = 0.643$, Chi-sq(1), p = 0.4225.

Notes: Cluster-robust standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.2 Spatial Estimations

Table 4 reports the results of spatially augmented fixed-effects estimations in which the geographical heterogeneity is explicitly addressed throughout an inverse distance spatial matrix and accounting for North–South Italian macro-areas. This specification allows the examination not only of the direct impact of local economic complexity on productivity, but also accounts for spatial spillovers and territorial heterogeneity in the relationship between complexity and productivity.

Columns (1) and (2) present separate estimations for Northern and Southern Italian provinces. In the Northern macro-area, the `ECI` coefficient is positive and statistically significant, confirming its relevance for regional productivity; meanwhile, in the South, the link is less statistically robust and smaller in scale, consistent with the hypothesis that institutional quality, innovation ecosystems, and infrastructural integration improve complexity returns (Balland and Boschma, 2024, Balland et al., 2019).

Column (3) further investigates this territorial heterogeneity by including an interaction term between ECI and macro-regions that records a negative and statistically robust difference for the Southern zones.

Columns (4)-(6) introduce a spatially lagged complexity term ($W_{t-1}ECI_{t-1}$), constructed using an inverse distance spatial matrix, to control whether a province's productivity is influenced by the complexity of its neighbours. While in the national sample, the spatial lagged variable missed statistical significance, Columns (5) and (6) report spatial estimations disaggregated by macro-area. In the North (Column 5), the spatial complexity term is large, positive, and statistically robust (0.105, $p < 0.01$), indicating that provinces embedded in highly complex regional environments benefit from positive spillovers—likely via inter-firm linkages, supply chain complementarities, and regional knowledge diffusion (Mewes and Broekel, 2022, Pintar and Scherngell, 2022). Conversely, in the South (Column 6), the spatial lag coefficient is less robust and smaller. These patterns suggest that lagging areas may struggle to convert existing complexity into sustained economic upgrades without complementary structural conditions, as contended by the recent literature on regional development traps (Balland and Boschma, 2024).

Turning to control variables, the results are broadly consistent with theoretical expectations and remain stable across specifications. Total hours worked and labour compensation are consistently and significantly positively associated with productivity, highlighting the relevance of both quantity and quality of labour inputs. Value added per capita also enters positively, reflecting the role of local demand conditions in sustaining productivity (Hirschman, 1958). Capital intensity, in contrast, does not show a significant association in most models. Demographic composition variables exhibit strong and asymmetric effects. The share of the young is positively and significantly associated with productivity in the North but negatively in the South, pointing to differences in inclusion and labour market structure. (Capriati et al., 2024). Similarly, the female share is negatively correlated with productivity in the North, while it becomes positively signed in the South, albeit with weaker significance, potentially reflecting regional differences in the local labour market composition. Population density is significantly negative in the South but not in the North, indicating that urbanisation does not necessarily translate into productive efficiency in lagging areas due to congestion effects, informal economies, or weak governance. Sectoral variables confirm prior findings: manufacturing share does not exhibit a stable relationship with productivity, while ICT employment shows a strong negative effect, particularly in the North, mirroring the tendency to crowd in a few large metropolitan hubs with advanced capabilities (Simone, 2025). Infrastructure density correlates positively with productivity, but this effect is stronger in the Northern provinces. As a robustness check, in Table 10, estimations also include provincial–level corruption as an additional control variable, confirming the reduced and less statistical relevance of ECI spatial spillover across Southern provinces.

Table 4: Spatial baseline estimations

	(1) North	(2) South	(3) Interaction NS	(4) SLX	(5) SLX-N	(6) SLX-S
L.ECI	0.0112***	0.0037	0.0101***	0.0050***	0.0109***	0.0040*
	(0.0026)	(0.0022)	(0.0029)	(0.0016)	(0.0029)	(0.0022)
L.GFCF per capita (ln)	-0.0377*	-0.0195	-0.0090	-0.0080	-0.0314	-0.0184
	(0.0198)	(0.0192)	(0.0104)	(0.0104)	(0.0192)	(0.0197)
L.Hrs worked per capita (ln)	0.7727***	0.3732***	0.6001***	0.5705***	0.6965***	0.3434**
	(0.1230)	(0.1242)	(0.1373)	(0.1446)	(0.1244)	(0.1259)
L.Openess (ln)	0.0019	0.0054	0.0072**	0.0076**	0.0031	0.0057*
	(0.0044)	(0.0032)	(0.0026)	(0.0027)	(0.0045)	(0.0031)
L.Patent per c. (ln)	-0.0033	0.0007	-0.0002	0.0000	-0.0030	0.0009
	(0.0024)	(0.0024)	(0.0017)	(0.0016)	(0.0023)	(0.0024)
L.Density (ln)	-0.0835	-0.4500***	-0.2038***	-0.2074***	-0.0830	-0.4498***
	(0.0592)	(0.0859)	(0.0414)	(0.0418)	(0.0613)	(0.0884)
L.Female Share	-3.1634***	2.1018	-1.1331*	-1.2834**	-2.7633***	2.0654
	(0.8717)	(1.4259)	(0.5711)	(0.5921)	(0.8435)	(1.4413)
L.Young Share	-1.2040***	0.6880**	-0.6620***	-0.6892***	-1.2437***	0.6802**
	(0.2215)	(0.2761)	(0.1585)	(0.1568)	(0.2018)	(0.2718)
L.VA per c. (ln)	0.2563***	0.3396***	0.2537***	0.2495***	0.2464***	0.3397***
	(0.0347)	(0.0595)	(0.0255)	(0.0244)	(0.0331)	(0.0604)
L.ICT Empl Share	-1.6470**	-0.7278	-1.5359***	-1.4498***	-1.5198**	-0.6998
	(0.5842)	(0.6039)	(0.4397)	(0.4431)	(0.5739)	(0.6045)
L.Manuf. Empl. Share	-0.0009	-0.0047**	-0.0014	-0.0013	-0.0004	-0.0049**
	(0.0012)	(0.0019)	(0.0009)	(0.0010)	(0.0011)	(0.0018)
L.Hrs compensation (ln)	0.6492***	0.4847***	0.5949***	0.5900***	0.6443***	0.4905***
	(0.0893)	(0.0832)	(0.0762)	(0.0782)	(0.0889)	(0.0853)
L.Infrastructure Density (ln)	0.0106	-0.0088	0.0152**	0.0151**	0.0178**	-0.0130
	(0.0082)	(0.0087)	(0.0066)	(0.0066)	(0.0078)	(0.0097)
L.share_uppersec_school	0.0672	-0.0240	0.0100	-0.0090	0.0314	-0.0260
	(0.0396)	(0.0998)	(0.0432)	(0.0399)	(0.0385)	(0.1010)
ECI × South			-0.0087**			
			(0.0036)			
Spatial ECI				0.0248	0.1253***	0.0412
				(0.0145)	(0.0157)	(0.0376)
Constant	0.0000	0.0000	3.9962***	4.3942***	0.0000	0.0000
	(0.0000)	(0.0000)	(1.2155)	(1.2750)	(0.0000)	(0.0000)
Observations	1273	684	1957	1957	1273	684
Pseudo R^2 (within)	0.7169	0.6747	0.6674	0.6664	0.7222	0.6751
Provinces Dummy	YES	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES	YES
Robust SE	D–KRAAY	D–KRAAY	D–KRAAY	D–KRAAY	D–KRAAY	D–KRAAY

Notes: The table depicts the result of the spatial baseline estimations. Column (1) and (2) are estimated using macro–areas subsamples. In column (3) ECI is interacted with macro–area variable. In column (4) the spatial lagged ECI is introduced. Model (4) and (5) include SLX term and are estimated using macro–areas subsamples. Driscoll–Kraay robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Given the spatial dimension of the two main variables of interest, namely productivity and ECI, depicted both through the graphical inspection and spatial autocorrelation test, multiple spatial model specifications are implemented in order to capture potential different spatial processes in a composite empirical framework. Table 5 compares alternative spatial specifications (SAR, SEM, SDM and three SDM variants with macro-area interactions). The spatial autoregressive parameter is large and highly significant (ρ ≈ 0.45-46) in the SAR (column 1) and SDM (column 4-6), while the SEM (column 2) reports a significant error spatial parameter, which together indicate that both lagged outcomes and spatially correlated shocks matter. Due to the relevance of spatial dynamics both in the outcome and regressors, SDM specification appears to be the most suited framework to model the link between ECI and productivity.

The direct effect of ECI is positive and robust across specifications, even after modelling different spatial dynamics. Looking at the geographical asymmetries, the SDM variants that explicitly include spatially lagged ECI and macro-area interactions (Cols. 4-6) reveal important heterogeneity. In the SDM baseline estimation in column 3 (without interaction), spatially lagged ECI is small and not statistically significant, suggesting that the sign and magnitude of spillovers are conditioned by macro-regional context rather than uniform across the country. In column 5, the spatial ECI interacted with the Northern macro-area is positive and significant (Spatial ECI × North: ≈ 0.0596, p<0.05), whereas the interaction with the Southern macro-area is negative and significant (Spatial ECI × South: ≈ -0.0789, p<0.01). Similar results are found in column 6, where the direct effect of ECI is also interacted with regional dummies. While spatial ECI echoes macro—regional asymmetries recorded in column 5, local ECI effects do not reveal any statistical difference across Centre–Northern and Centre–Southern provinces.

In other words, provinces embedded in more complex northern neighbourhoods benefit from positive spillovers, while southern neighbourhood complexity is associated with a significantly weaker spatial effect. In light of these results, the SDM variants (Cols. 4–6), which allow for heterogeneous spillovers, are the most informative specifications for our substantive question.

Turning to the covariates, coefficients are stable across specifications and broadly conform to the previous spatial specifications. Results recorded using different spatial matrices, shown in Table 11 and controlling for institutional level with a more limited temporal coverage, depicted in Table 12, draw a very similar picture, backing the validity of the integrated approach proposed.

Table 5: Composite spatial specifications

	(1) SAR	(2) SEM	(3) SDM	(4) SDM-1	(5) SDM-2
L.ECI	0.0045**	0.0045**	0.0045**	0.0046**	0.009***
	(0.0018)	(0.0018)	(0.0018)	(0.0019)	(0.0031)
L.GFCF per capita (ln)	-0.0082	-0.007	-0.0083	-0.0098	-0.0105
	(0.0107)	(0.0111)	(0.0106)	(0.0105)	(0.0105)
L.Hrs worked per capita (ln)	0.4466***	0.4481***	0.448***	0.4759***	0.4861***
	(0.1306)	(0.1283)	(0.1363)	(0.1330)	(0.1288)
L.Openess (ln)	0.0064**	0.0047	0.0064**	0.0059**	0.0056**
	(0.0030)	(0.0032)	(0.0030)	(0.0029)	(0.0027)
L.Patent per c. (ln)	-0.0002	-0.0001	-0.0002	-0.0003	-0.0003
	(0.0018)	(0.0018)	(0.0017)	(0.0016)	(0.0017)
L.Density (ln)	-0.1973***	-0.2152***	-0.1972***	-0.1992***	-0.1976***
	(0.0461)	(0.0427)	(0.0467)	(0.0460)	(0.0460)
L.Female Share	0.2802***	0.2939***	0.2792***	0.2723***	0.2784***
	(0.0831)	(0.0750)	(0.0787)	(0.0739)	(0.0690)
L.Young Share	-0.4902***	-0.5260***	-0.4884***	-0.4717***	-0.4768***
	(0.1392)	(0.1287)	(0.1299)	(0.1243)	(0.1179)
L.VA per c. (ln)	0.2502***	0.2488***	0.2504***	0.2495***	0.2518***
	(0.0205)	(0.0197)	(0.0203)	(0.0205)	(0.0215)
L.ICT. Empl. Share	-1.489***	-1.3309***	-1.4925***	-1.4581***	-1.491***
	(0.4285)	(0.3983)	(0.4464)	(0.4434)	(0.4508)
L.Manuf. Empl. Share	-0.001	-0.0004	-0.001	-0.0008	-0.0008
	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0008)
L.Hrs compensation (ln)	0.5815***	0.5772***	0.5819***	0.5805***	0.5796***
	(0.0686)	(0.0695)	(0.0703)	(0.0713)	(0.0713)
L.Infrastructure Density (ln)	0.0157**	0.0171***	0.0156***	0.0178***	0.0185***
	(0.0062)	(0.0062)	(0.0060)	(0.0056)	(0.0056)
L.share_upperhcl	-0.0088	-0.0150	-0.0084	-0.0032	0.0091
	(0.0412)	(0.0440)	(0.0404)	(0.0409)	(0.0445)
ρ	0.4477***		0.4488***	0.4816***	0.4893***
	(0.0863)		(0.0886)	(0.0915)	(0.0888)
σ^2	0.0006***	0.0006***	0.0006***	0.0006***	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
λ		0.7498***			
		(0.0895)			
Spatial ECI			-0.0024		
			(0.0169)		
Spatial ECI X North				0.0596**	0.0594**
				(0.0242)	(0.0245)
Spatial ECI X South				-0.0789***	-0.0794***
				(0.0252)	(0.0235)
ECI X South					0.0011
					(0.0020)
Observations	2060	2060	2060	2060	2060
R-squared	0.5314	0.2400	0.5311	0.5220	0.5202
Provinces Dummy	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES
Sample	Full	Full	Full	Full	Full

Notes: The table depicts the result of the main spatial estimations. Column (1) and (2) present estimations of SAR and SEM Column (3) present estimations of SDM model. Column (4) present estimations of SDM model interacting the spatial term with macro–area variable.Column (5) present estimations of SDM model interacting direct ECI and the spatial term with macro–area variable. Driscoll–Kraay robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Overall, these findings underscore the relevance of considering spatial interactions and territorial heterogeneity when analysing the link between complexity and development. Complexity capacity to foster productivity depends on the broader territorial environment—networks, institutions, and infrastructures. While in the North, more integrated productive networks and richer infrastructures enhance capabilities diffusion and spatial spillover, resulting in productivity advancements across provinces, in the South, more isolated economies and less integrated production processes seem not to assure agglomerative externalities. These asymmetries highlight the importance of considering spatial interactions and structural context when designing complexity-informed development strategies.

5.3 Simultaneity

In order to model the bidirectional and looping relationship between regional productivity and economic complexity, Additionally, Table 13 provides a further specification that employs bootstrapped robust standard errors with 1,200 repetitions. Furthermore, Table 14 includes institutional controls in its analysis.

This econometric approach allows us to model the endogenous interplay between territorial structural capabilities and economic performance, capturing the cumulative and path-dependent dynamics that underpin regional uneven development. Rooted in the classical and post-Keynesian tradition of growth theory (Kaldor, 1961), this perspective underlines the agglomerative feedback loops between demand-side and supply-side forces that shape territorial uneven development (Hirschman, 1958).

In the first equation, regional productivity (*Lab. Productivity (ln)*) is positively and significantly associated with the ECI, consistent with the claim that territorial productivity is strongly shaped by the structure and diversification of local capabilities. This supports the idea that structural local complexity contributes to regional economic performances, aligning with the recent contributions in evolutionary geography (Pinheiro et al., 2025).

In the second equation, complexity is modelled as a function of regional productivity and other covariates. Here, productivity enters positively and significantly (*Lab. Productivity (ln)*, coefficient: 0.7585, $p<0.05$), suggesting that more productive territories are better positioned to expand into higher-value, more sophisticated activities (Pinheiro et al., 2025). These findings support the circular and cumulative causation mechanisms articulated in the regional development and in post-Keynesian frameworks (Myrdal, 1957, Pianta, 2018), which emphasise a self-reinforcing growth-circle in which productivity growth fuels structural upgrading, learning-by-doing, and innovation-driven diversification (Hirschman, 1958). Within this framework, more advanced regions, benefitting from dense productive networks, knowledge externalities and functional complementarities, improve their structural complexity and reinforce virtuous development trajectories (Pinheiro et al., 2025). In contrast, less productive regions, typically marked by initially lower levels of complexity, tend to remain locked into stagnating traditional activities with limited access to innovation ecosystems and dynamic learning channels, increasing the risk of being trapped in low-value-added sectors with limited opportunities (Balland and Boschma, 2024).

Table 6: Three-Stage Least Squares Estimation Results

Variable	Productivity Equation	Complexity Equation
L.ECI	0.0038**	
	(0.0015)	
L.GFCF per capita (ln)	0.0032	
	(0.0080)	
L.Hrs worked per capita (ln)l	0.4527***	
	(0.0647)	
L.Openess (ln)	0.0033	
	(0.0023)	
L.Patent per c. (ln)	0.0004	
	(0.0014)	
L.Density (ln)	-0.2652***	1.2448***
	(0.0269)	(0.3316)
L.Female Share	0.2441**	-3.3687**
	(0.0873)	(1.2281)
L.Young Share	-0.5177***	6.8629***
	(0.1102)	(1.4997)
L.VA per c. (ln)	0.2168***	
	(0.0182)	
L.ICT Empl Share	-1.3052***	
	(0.2676)	
L.Manuf. Empl. Share	-0.0002	
	(0.0006)	
L.Hrs compensation (ln)	0.4855***	
	(0.0317)	
L. Infrastructure Density (ln)	0.1946***	
	(0.0236)	
L.Gradueted Share	-0.0424	
	(0.0410)	
L.Lab. Productivity (ln)		0.7585**
		(0.2829)
Constant	6.1355***	-15.1106***
	(0.6222)	(3.6252)
Observations	2,021	
R-squared	0.9656	0.8748

Notes: Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Year and province dummies were included in the estimation but omitted from the table.

Overall, the simultaneous modelling strategy corroborates the idea that economic complexity and productivity evolve through mutually reinforcing feedback loops, consistent with models of circular and cumulative causation (Dosi et al., 1988). This feedback mechanism may reinforce regional divergence over time, especially in the absence of institutional counterweights capable of redistributing capabilities or stimulating catch-up dynamics in lagging areas.

5.4 Discussion

The composite empirical approach proposed witnessed the simultaneous and endogenous nature and the spatially embedded dimension of the link between complexity and productivity. This enables us to assess and quantify the bias that arises from using different econometric specifications, which are able to capture only partially these different patterns. Therefore, single-FE estimates are compared to specifications that explicitly address reverse feedback and spatial dependence, including the 3SLS, which allows productivity and complexity to be jointly determined; the SLX specification that augments the FE baseline with spatially lagged explanatory variables; and the SDM to capture comprehensively spatial spillovers.

Using the FE estimate as a descriptive starting point (0.0051), Table 7 reports the point estimates of the effect from each specification and provides a quantification of absolute and relative bias. Formally, for a focal estimator $\hat{\beta}_{\text{FE}}$ and any reference estimator $\hat{\beta}_{\text{ref}}$ we report

$$\text{Absolute bias} = \hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{ref}}, \qquad \text{Relative bias}(\%) = 100 \times \frac{\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{ref}}}{\hat{\beta}_{\text{ref}}}.$$

Two insights emerge. First, correcting for simultaneity via 3SLS lowers the local effect appreciably (3SLS = 0.0038), implying an absolute difference of 0.0013 and a relative upward bias of about +34.2% of the FE coefficient. This pattern indicates that part of the observed ECI—Productivity correlation reflects reverse feedback; higher productivity accelerates capability accumulation, so that FE estimates overstate the effect of complexity when feedback is ignored.

Second, introducing spatial dynamics through SLX leaves the local point estimate almost unchanged (SLX = 0.0050), producing a negligible absolute bias (0.0001, +2.0%). The SDM direct effect (0.0046) lies between SLX and 3SLS: FE overstates this direct effect by 0.0005, or about +10.9%. SDM tends to capture both direct and indirect spillovers, accounting also for possible spatial shocks in the error term and outcome variable.

From a substantive perspective, these results point to a mixed mechanism. A non-trivial share of the FE association is driven by cumulative mechanisms, which 3SLS corrects for. At the same time, spatial dynamics matter, so that regional networks, supply-chain linkages, and knowledge diffusion amplify or dampen the locally measured returns to ECI. In practice, embracing both simultaneous and spatial specifications should be preferred; 3SLS for the identification of the local effect under simultaneity, and SDM to decompose direct vs indirect (spillover) effects. Ideally, a more exhaustive approach would integrate panel dimension, endogeneity and spatial patterns.

Table 7 reports these diagnostics for the estimated direct effect of lagged ECI on productivity. The FE estimate (0.0051) is compared to the 3SLS simultaneous estimate (0.0038), the SLX estimate (0.0050) and the SDM direct effect (0.00460).

Table 7: Bias diagnostics– FE vs simultaneous and spatial specifications

Reference model	Estimate (ECI $\rightarrow$ Productivity)	Absolute bias (FE $-$ ref)	Relative bias (%)
FE	0.00510	—	—
3SLS	0.00380	0.00130	+34.21%
SLX	0.00500	0.00010	+2.00%
SDM	0.00460	0.00050	+10.87%

Notes: Point estimates are the reported coefficients of ECI on productivity. Absolute bias and relative bias are computed using the FE estimate as a benchmark.

6 Conclusions

This paper has sought to unpack the structural roots of regional productivity disparities across Italian provinces by leveraging a subnational measure of economic complexity. Grounded in the conceptual framework of capability accumulation and evolutionary economic geography, and enriched with a rigorous multi-model empirical strategy, this study offers robust evidence that economic complexity is a powerful predictor of productivity performance across territories. Notably, this paper provides evidence for the first time of the cumulative link at the root of regional development, encompassing a reinforcing loop between complexity and productivity.

Our analysis, covering over two decades (2000–2021) and 103 Italian NUTS-3 provinces, yields several compelling insights. First, economic complexity emerges as a consistent and statistically significant determinant of regional labour productivity, even when controlling for a wide set of structural, demographic, and institutional factors. This confirms that what a territory produces—and its position in the hierarchy of technological and organisational sophistication—matters deeply for its economic outcomes.

Second, we find that the strength of this relationship varies markedly across Italy. In the Northern macro-region, complexity delivers stronger productivity gains and generates positive spatial spillovers. In contrast, such spillovers are largely absent in the South, where institutional weakness and economic fragmentation inhibit these externalities. This geographical asymmetry in the returns to complexity represents a novel and critical contribution to the economic geography of development.

Furthermore, by implementing a simultaneous equation model using 3SLS estimation, we introduce the first integrated and systematic empirical analysis of the cumulative, bidirectional relationship between complexity and productivity. We show that productivity growth reinforces complexity by enabling territories to diversify into more sophisticated activities, while rising complexity in turn boosts productivity by facilitating innovation, efficiency, and upgrading. This dynamic embodies the circular causation models long discussed in classical development theory (Hausmann et al., 2014, Myrdal, 1957), but still rarely explored in the contemporary regional studies and economic complexity approach. This paper thus serves as a pivotal bridge between the structural change tradition and the emerging paradigm of economic complexity, providing a cohesive explanation of how territorial divergence is driven by feedback mechanisms embedded in the structure of local economies.

These findings carry significant policy implications. Uniform, sector-neutral, or place-blind interventions are unlikely to yield transformative outcomes in structurally lagging regions. Instead, there is a pressing need for territorially tailored, complexity-informed development strategies that build on local capabilities while addressing the institutional and infrastructural barriers to diversification. Northern regions may benefit from policies aimed at deepening complexity—such as promoting high-value services, advanced manufacturing, and scale-ups—while the South requires foundational investments in human capital, innovation ecosystems, and public investments to unlock its productive potential.

Despite these contributions, the paper faces several limitations. A primary limitation concerns data availability. While our analysis benefits from rich temporal and spatial granularity, it relies on export data to construct the ECI. Ideally, a more granular sectoral decomposition of employment or value-added data—particularly within services or knowledge-intensive domains—would allow for a multi-dimensional complexity index that captures both tradable and non-tradable sectors. Unfortunately, such disaggregated employment data at the provincial level is not publicly available or systematically collected in Italy over the study period. Similarly, it would be useful to have a more detailed province–level control variables to address for spatial heterogeneity in local human-capital endowments, labour market composition, innovation dynamics, intangible asset accumulation, and social capital, which are still unavailable.

Due to current constraints in subnational statistics, we construct the ECI using export data, which may overlook complexity in service-based or domestically oriented sectors. Ideally, a multi-dimensional complexity index would include sectoral employment and value-added data to better reflect non-tradable capabilities. However, such disaggregated data are not publicly available at the NUTS-3 level in Italy over the 2000–2021 period.

That said, extensive literature demonstrates that export-based ECI is not limited to explaining trade performance alone. Rather, it captures a deeper layer of productive knowledge and structural sophistication, correlating strongly with outcomes such as wage growth, innovation, resilience, and institutional strength (Antonietti and Burlina, 2023, Basile and Cicerone, 2022, D'Ingiullo et al., 2024, Hidalgo, 2021). In this regard, export-derived ECI serves as a valid and widely accepted proxy for regional economic capabilities.

A second limitation pertains to the identification strategy. While we mitigate endogeneity concerns through lag structures, IV-GMM techniques, and simultaneous equation modelling, the challenge of fully disentangling causality in structural economic processes remains demanding. Future work may build on this foundation by incorporating historical instruments, sectoral shocks, or quasi-experimental designs that allow for cleaner identification of causal pathways.

Third, while the Italian case provides a compelling empirical setting—marked by persistent dualism, intra-regional divergence, and long-run stagnation—the generalizability of our findings would benefit from comparative cross-country analyses. Applying a similar framework to other European nations or OECD countries would allow for the identification of common mechanisms and context-specific nuances. However, still, data limitations prevent the construction of multi-country or European-level economic complexity comparable indicators at the sub-national level (Diodato et al., 2024). Future research should seek to enhance the geographical coverage of such measures and bridge the macro-micro divide by integrating firm-level datasets with territorial complexity indicators and expand econometric specification to further understand complementary mechanisms at the roots of the productivity-complexity puzzle.

References

Antonelli, C., Crespi, F., Mongeau Ospina, C. A., and Scellato, G. (2017). Knowledge composition, jacobs externalities and innovation performance in european regions. *Regional Studies*, 51(11):1708–1720.

Antonelli, C., Crespi, F., and Quatraro, F. (2022). Knowledge complexity and the mechanisms of knowledge generation and exploitation: The european evidence. *Research Policy*, 51(8):104081.

Antonietti, R. and Burlina, C. (2023). Exploring the entropy-complexity nexus. evidence from italy. *Economia Politica*, 40(1):257–283.

Audretsch, D. B. and Feldman, M. P. (1996). R&d spillovers and the geography of innovation and production. *The American economic review*, 86(3):630–640.

Balland, P.-A. and Boschma, R. (2024). *An evolutionary approach to regional development traps in European regions*. Utrecht University, Human Geography and Planning.

Balland, P.-A., Boschma, R., Crespo, J., and Rigby, D. L. (2019). Smart specialization policy in the european union: relatedness, knowledge complexity and regional diversification. *Regional studies*, 53(9):1252–1268.

Balland, P.-A., Jara-Figueroa, C., Petralia, S. G., Steijn, M. P., Rigby, D. L., and Hidalgo, C. A. (2020). Complex economic activities concentrate in large cities. *Nature Human Behaviour*, 4(3):248–254.

Basile, R. and Cicerone, G. (2022). Economic complexity and productivity polarization: Evidence from italian provinces. *German Economic Review*, 23(4):567–594.

Bathelt, H., Buchholz, M., and Storper, M. (2024). The nature, causes, and consequences of inter-regional inequality. *Journal of Economic Geography*, 24(3):353–374.

Boschma, R. and Lambooy, J. (1999). Evolutionary economics and economic geography. *Journal of Evolutionary Economics*, 9(4):411–429.

Capriati, M., Cirillo, V., and Divella, M. (2024). Productivity slowdown across european regions: does non-standard work matter? *Regional Studies*, 58(9):1687–1709.

Capriati, M., Cirillo, V., Divella, M., and Simone, G. (2025). Più complesse, più disuguali: dove vanno le province italiane? *Menabò di Etica ed Economia*.

Carboni, O. A. and Medda, G. (2020). Linkages between r&d, innovation, investment and export performance: evidence from european manufacturing firms. *Technology Analysis & Strategic Management*, 32(12):1379–1392.

Ciccone, A. and Hall, R. E. (1996). Productivity and the Density of Economic Activity. *American Economic Review*, 86(1):54–70.

Çınar, I. T., Korkmaz, I., and Baycan, T. (2022). Regions' economic fitness and sectoral labor productivity: Evidence from turkey. *Regional Science Policy & Practice*, 14(3):575–599.

Dijkstra, L., Garcilazo, E., and McCann, P. (2015). The effects of the global financial crisis on european regions and cities. *Journal of Economic Geography*, 15(5):935–949.

Diodato, D., Napolitano, L., Pugliese, E., and Tacchella, A. (2024). *Handbook of Economic Complexity for Policy*. Publications Office of the European Union.

Dosi, G., Freeman, C., Nelson, R., Silverberg, G., Soete, L., et al. (1988). *Technical change and economic theory*, volume 988. Pinter London.

D'Ingiullo, D., Odoardi, I., Quaglione, D., and Di Berardino, C. (2024). Exploring the nexus between exports' economic complexity and institutional quality: insights from italian provinces. *Regional Studies, Regional Science*, 11(1):667–695.

Elhorst, J. P. et al. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*, volume 479. Springer.

Feldman, M., Guy, F., and Iammarino, S. (2021). Regional income disparities, monopoly and finance. *Cambridge Journal of Regions, Economy and Society*, 14(1):25–49.

Fiorentino, S. and Phelps, N. A. (2025). The fourth italy: a contemporary account of the italian economic geography. *Journal of Economic Geography*, page lbaf032.

Florida, R. (2017). *The new urban crisis: How our cities are increasing inequality, deepening segregation, and failing the middle class-and what we can do about it*. Basic Books.

Fritz, B. S. and Manduca, R. A. (2021). The economic complexity of us metropolitan areas. *Regional Studies*, 55(7):1299–1310.

Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., Chung, S., Jimenez, J., Simoes, A., and Yildirim, M. (2014). *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. MIT Press, Cambridge, MA.

Hidalgo, C. A. (2021). Economic complexity theory and applications. *Nature Reviews Physics*, 3(2):92–113.

Hidalgo, C. A. and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the national academy of sciences*, 106(26):10570–10575.

Hirschman, A. O. (1958). *The strategy of economic development*. New Haven, Conn.: Yale University,.

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The stata journal*, 7(3):281–312.

Iammarino, S., Rodriguez-Pose, A., and Storper, M. (2018). Regional inequality in europe: evidence, theory and policy implications. *Journal of Economic Geography*, 19(2):273–298.

Kaldor, N. (1961). Capital accumulation and economic growth. In *The Theory of capital: proceedings of a conference held by the International Economic Association*, pages 177–222. Springer.

Kemeny, T. and Storper, M. (2024). The changing shape of spatial income disparities in the united states. *Economic Geography*, 100(1):1–30.

Kemp-Benedict, E. (2014). An interpretation and critique of the method of reflections. *Science and Public Policy*, 41(5):597–612.

Mealy, P., Farmer, J. D., and Teytelboym, A. (2019). Interpreting economic complexity. *Science Advances*, 5(1):eaau1705.

Mewes, L. and Broekel, T. (2022). Technological complexity and economic growth of regions. *Research Policy*, 51(8):104156.

Moretti, E. (2012). *The new geography of jobs*. Houghton Mifflin Harcourt.

Myrdal, G. (1957). *Economic theory and underdeveloped regions*.

Nifo, A. and Vecchione, G. (2015). Measuring institutional quality in italy. *Rivista economica del Mezzogiorno*, 29(1-2):157–182.

OECD (2024). *OECD, OECD Regions and Cities at a Glance*. OECD Publishing, Paris. DOI: https://doi.org/10.1787/f42db3bf-en.

OECD (2025). Strengthening regional policy for resilient places: Key issues and policy considerations. Technical Report No. 148, OECD Publishing, Paris.

OECD/EC (2020). *A new perspective on urbanisation*. OECD Publishing.

Pianta, M. (2018). Technology and employment: twelve stylised facts for the digital age. *The Indian Journal of Labour Economics*, 61(2):189–225.

Pinheiro, F. L., Balland, P.-A., Boschma, R., and Hartmann, D. (2025). The dark side of the geography of innovation: relatedness, complexity and regional inequality in europe. *Regional Studies*, 59(1):2106362.

Pintar, N. and Scherngell, T. (2022). The complex nature of regional knowledge production: Evidence on european regions. *Research Policy*, 51(8):104170.

Reynolds, E., Ubaldi, B., and Lorenz, E. (2018). Knowledge spaces and the economic complexity of cities. *OECD Local Economic and Employment Development (LEED) Papers*, (2018/06).

Rodríguez-Pose, A. (2025). Discontent is europe's main threat. *Intereconomics*.

Sassen, S. (2018). *Cities in a world economy*. Sage Publications.

Sbardella, A., Perruchas, F., Napolitano, L., Barbieri, N., and Consoli, D. (2018). Green technology fitness. *Entropy*, 20(10):776.

Simone, G. (2025). The polarisation of italian metropolitan areas, 2000–2018: structural change, technology and growth. *Cambridge Journal of Regions, Economy and Society*, 18(1):131–156.

Simone, G., Evangelista, R., and Pianta, M. (2024). Profits, innovation, investment. exploring the virtuous circle. *Italian Economic Journal*, pages 1–26.

Velthuis, S., Royer, J., Le Petit-Guerin, M., Cauchi-Duval, N., Franklin, R., Leibert, T., MacKinnon, D., and Pike, A. (2025). Regional varieties of 'left-behindness' in the eu15. *Regional Studies*, 59(1):2417704.

Viesti, G. (2021). *Centri e periferie: Europa, Italia, Mezzogiorno dal XX al XXI secolo*. Gius. Laterza & Figli Spa.

Appendix

6.1 Appendix A: Tables

Table 8: FE specifications with current regressors

	(1) FE-Core_Controls	(2) FE-Core_Controls	(3) FE-Structural	(4) FE-Demand	(5) FE-Full	(6) FE-Institutional
ECI	0.0045*** (0.0016)	0.0043*** (0.0012)	0.0039*** (0.0013)	0.0059*** (0.0017)	0.0064*** (0.0014)	0.0072*** (0.0019)
GFCF per capita (ln)		0.0666*** (0.0161)	0.0761*** (0.0132)	-0.0237*** (0.0083)	-0.0202** (0.0091)	-0.0160 (0.0120)
Hrs worked per capita (ln)		0.1237 (0.1057)	0.1647 (0.1144)	0.5778*** (0.1261)	0.5900*** (0.1252)	0.7239*** (0.1409)
Density (ln)			0.1354** (0.0492)	-0.2385*** (0.0509)	-0.2693*** (0.0494)	-0.2661*** (0.0268)
Openess (ln)			0.0091*** (0.0021)	0.0057** (0.0023)	0.0060** (0.0023)	0.0072*** (0.0024)
Female Share			0.3069*** (0.0979)	0.3353*** (0.0462)	0.3435*** (0.0502)	-1.0816 (0.6797)
Young Share			-0.3744** (0.1769)	-0.5496*** (0.0943)	-0.6099*** (0.0905)	-0.6239*** (0.1525)
ICT. Empl. Share			-0.0922 (0.3087)	-2.1729*** (0.2604)	-2.2232*** (0.2999)	-2.0327*** (0.4742)
Manuf. Empl. Share			0.0030*** (0.0005)	-0.0008 (0.0006)	-0.0008 (0.0008)	-0.0013 (0.0014)
ln_patent_pop				-10.0955** (4.3183)	-12.7978*** (3.4965)	-10.9638*** (3.2451)
VA per c. (ln)				0.3842*** (0.0273)	0.3930*** (0.0261)	0.4078*** (0.0271)
Hrs compensation (ln)				0.5491*** (0.0577)	0.5624*** (0.0681)	0.5328*** (0.0734)
Infrastructure Density (ln)					0.0198*** (0.0041)	0.0173*** (0.0038)
share_high_degree					-0.0025 (0.0284)	-0.0318 (0.0307)
Corruption						-0.0120 (0.0116)
Constant	11.1277*** (0)	11.4014*** (0.8022)	10.3384*** (0.9498)	2.3467** (1.0468)	2.3088** (1.0283)	2.0599 (1.4782)
Observations	2,266	2,266	2,266	2,266	2,163	1,648
Pseudo R^2	0.593	0.612	0.741	0.745	0.741	0.711
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	D-K	D-K	D-K	D-K	D-K	D-K

Notes: The table depicts the estimations of the stepwise procedure. In each model, a more comprehensive set of control variables is included. Driscoll–Kraay robust standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Province codes by macro-area

Centre–North (1)									
TO	VC	NO	CN	AT	AL	AO	IM	SV	GE
SP	VA	CO	SO	MI	BG	BS	PV	CR	MN
BZ	TN	VR	VI	BL	TV	VE	PD	RO	UD
GO	TS	PC	PR	RE	MO	BO	FE	RA	FC
PU	AN	MC	AP	MS	LU	PT	FI	LI	PI
AR	SI	GR	PG	TR	VT	RI	RM	LT	FR
PN	BI	LC	LO	RN	PO	VB			
Centre–South (2)									
CE	BN	NA	AV	SA	AQ	TE	PE	CH	CB
FG	BA	TA	BR	LE	PZ	MT	CS	CZ	RC
TP	PA	ME	AG	CL	EN	CT	RG	SR	SS
NU	CA	IS	OR	KR	VV				

*Note:*The table lists province codes grouped by macro-area.

Table 10: Spatially lagged Estimation: Institutional quality

	(1) North	(2) South	(3) Interaction	(4) SLX	(5) SLX-N	(6) SLX-S
L.ECI	0.0095***	0.0028	0.0089***	0.0042**	0.0091***	0.0035
	(0.0019)	(0.0027)	(0.0028)	(0.0017)	(0.0023)	(0.0026)
L.GFCF per capita (ln)	-0.0713***	-0.0011	-0.0144	-0.0116	-0.0644**	0.0009
	(0.0229)	(0.0192)	(0.0104)	(0.0102)	(0.0221)	(0.0193)
L.Hrs worked per capita (ln)	0.6154***	0.3603**	0.5848***	0.5512***	0.5834***	0.2882
	(0.1704)	(0.1532)	(0.1567)	(0.1674)	(0.1698)	(0.1768)
L.Openess (ln)	0.0066	0.0065*	0.0090**	0.0092**	0.0070	0.0072**
	(0.0066)	(0.0033)	(0.0035)	(0.0036)	(0.0067)	(0.0030)
L.Patent per c. (ln)	-0.0024	-0.0013	-0.0014	-0.0011	-0.0022	-0.0010
	(0.0017)	(0.0030)	(0.0015)	(0.0014)	(0.0017)	(0.0029)
L.Density (ln)	-0.1157**	-0.3944***	-0.2006***	-0.2047***	-0.1142**	-0.3881***
	(0.0436)	(0.1055)	(0.0339)	(0.0320)	(0.0432)	(0.1089)
L.Female Share	-2.7553**	0.6152	-1.2371	-1.3786	-2.4064*	0.5323
	(1.2481)	(1.4074)	(0.7563)	(0.8228)	(1.2039)	(1.4161)
L.Young Share	-1.0331***	0.4329	-0.5414***	-0.5802***	-1.0546***	0.4366
	(0.2388)	(0.3139)	(0.1780)	(0.1790)	(0.2343)	(0.2953)
L.VA per c. (ln)	0.2819***	0.3028***	0.2586***	0.2530***	0.2718***	0.3054***
	(0.0487)	(0.0631)	(0.0308)	(0.0292)	(0.0459)	(0.0657)
LICT Empl Share	-1.3072*	-0.9384	-1.2841**	-1.1926**	-1.2079	-0.9194
	(0.7064)	(0.6098)	(0.4910)	(0.4992)	(0.6993)	(0.6372)
L.Manuf. Empl. Share	-0.0008	-0.0015	-0.0011	-0.0009	-0.0003	-0.0019
	(0.0016)	(0.0014)	(0.0012)	(0.0012)	(0.0015)	(0.0015)
L.Hrs compensation (ln)	0.5128***	0.3877***	0.5163***	0.5105***	0.5175***	0.3964***
	(0.0422)	(0.0994)	(0.0601)	(0.0655)	(0.0427)	(0.1059)
L.Corruption	0.0894***	-0.0157	-0.0051	-0.0146	0.0754***	-0.0245
	(0.0131)	(0.0244)	(0.0143)	(0.0160)	(0.0155)	(0.0256)
L.Infrastructure Density (ln)	0.0029	-0.0049	0.0071	0.0079	0.0097*	-0.0144
	(0.0040)	(0.0098)	(0.0065)	(0.0068)	(0.0047)	(0.0107)
L.Graduated Share	0.0651	-0.0083	0.0143	-0.0079	0.0322	-0.0139
	(0.0608)	(0.1409)	(0.0562)	(0.0537)	(0.0608)	(0.1422)
ECI X South			-0.0082*			
			(0.0039)			
Spatial ECI				0.045**	0.1019***	0.0951**
				(0.0187)	(0.0212)	(0.0371)
_cons	/	5.8666**	4.1671**	4.6517**	/	6.4089**
	/	(2.2798)	(1.5713)	(1.6563)	/	(2.4152)
Observations	1072	576	1648	1648	1072	576
R-squared	0.2679	0.2728	0.2751	0.2240	0.2748	0.2754
Provinces Dummy	YES	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES	YES

Notes: The table depicts the result of the spatial baseline estimations. Columns (1) and (2) are estimated using macro–areas subsamples. In column (3), ECI is interacted with macro–area variable. In column (4), the spatial lagged ECI is introduced. Models (4) and (5) includethe SLX term and are estimated using macro–areas subsamples. Driscoll–Kraay robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Spatial regression results– alternative spatial matrix

	(1) SAR	(2) SAR	(3) SEM	(4) SEM	(5) SDM	(6) SDM	(7) SDM
L.ECI	0.0046**	0.0050***	0.0038**	0.0046***	0.0045**	0.0044**	0.0051***
	(0.0019)	(0.0019)	(0.0016)	(0.0017)	(0.0019)	(0.0019)	(0.0019)
L.GFCF per capita (ln)	-0.0057	-0.0050	0.0023	-0.0033	-0.0057	-0.0060	-0.0043
	(0.0096)	(0.0109)	(0.0121)	(0.0119)	(0.0098)	(0.0098)	(0.0113)
L.Hrs worked per capita (ln)	0.3429***	0.4092***	0.3455***	0.4294***	0.3314***	0.3442***	0.4177***
	(0.1083)	(0.1121)	(0.1144)	(0.1248)	(0.1143)	(0.1173)	(0.1200)
L.Openess (ln)	0.0048	0.0049	0.0046	0.0039	0.0049	0.0047	0.0049
	(0.0033)	(0.0031)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0030)
L.Patent per c. (ln)	-0.0004	-0.0001	-0.0009	-0.0005	-0.0002	-0.0002	0.0000
	(0.0018)	(0.0017)	(0.0017)	(0.0016)	(0.0018)	(0.0018)	(0.0016)
L.Density (ln)	-0.2304***	-0.2124***	-0.2167***	-0.2176***	-0.2330***	-0.2332***	-0.2143***
	(0.0423)	(0.0438)	(0.0437)	(0.0451)	(0.0444)	(0.0446)	(0.0457)
L.Female Share	0.2792***	0.3273***	0.2504***	0.3072***	0.2895***	0.2850***	0.3206***
	(0.0654)	(0.0792)	(0.0643)	(0.0778)	(0.0590)	(0.0567)	(0.0730)
L.Young Share	-0.5002***	-0.5748***	-0.4403***	-0.5373***	-0.5212***	-0.5079***	-0.5553***
	(0.1095)	(0.1362)	(0.1127)	(0.1351)	(0.0958)	(0.0929)	(0.1249)
L.VA per c. (ln)	0.2267***	0.2275***	0.2287***	0.2317***	0.2274***	0.2273***	0.2281***
	(0.0170)	(0.0186)	(0.0171)	(0.0192)	(0.0173)	(0.0177)	(0.0189)
L.ICT. Empl. Share	-1.2581***	-1.3310***	-1.2047***	-1.2843***	-1.2474***	-1.2294***	-1.3362***
	(0.3770)	(0.3922)	(0.3546)	(0.3909)	(0.3770)	(0.3772)	(0.3957)
L.Manuf. Empl. Share	-0.0002	-0.0003	-0.0003	-0.0005	-0.0001	-0.0001	-0.0003
	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0007)	(0.0008)
L.Hrs compensation (ln)	0.4918***	0.5265***	0.5751***	0.5669***	0.4911***	0.4961***	0.5293***
	(0.0536)	(0.0573)	(0.0611)	(0.0603)	(0.0540)	(0.0541)	(0.0575)
L.Infrastructure Density (ln)	0.0181***	0.0178***	0.0193***	0.0209***	0.0180***	0.0188***	0.0186***
	(0.0050)	(0.0057)	(0.0062)	(0.0066)	(0.0051)	(0.0052)	(0.0058)
L.Graduates Share	0.0074	-0.0065	0.0034	-0.0118	0.0060	0.0083	-0.0056
	(0.0420)	(0.0429)	(0.0393)	(0.0450)	(0.0415)	(0.0420)	(0.0427)
ρ	0.3196***	0.1540***			0.3178***	0.3135***	0.1530***
	(0.0470)	(0.0191)			(0.0482)	(0.0486)	(0.0195)
σ^2	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
λ			0.3677***	0.1549***			
			(0.0520)	(0.0225)			
Spatial ECI					0.0033		
					(0.0027)		
Spatial ECI X North						0.0095***	0.0028*
						(0.0037)	(0.0017)
Spatial ECI X South						-0.0010	-0.0027**
						(0.0033)	(0.0013)
Observations	2060	2060	2060	2060	2060	2060	2060
R-squared	0.2679	0.2728	0.2751	0.2240	0.2748	0.2754	0.2687
Matrix	K6nn	Econ	K6nn	Econ	K6nn	K6nn	Econ
Provinces Dummy	YES	YES	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES	YES	YES
Sample	Full	Full	Full	Full	Full	Full	Full

Notes: The table depicts the result of the alternative spatial estimations. Columns (1) and (2) present estimations of SAR models using nearest neighbours and economic–distance matrix. Columns (3) and (4) present estimations of the SEM model using nearest neighbours and economic-distance matrices. Column (5) presents estimations of the SDM model using the nearest neighbours matrix. Column (6) presents estimations of the SDM model interacting the spatial term with macro–area variable using the nearest neighbours matrix. Column (7) presents estimations of the SDM model interacting the spatial term with macro–area variable using economic–distance matrix. Economic–distance matrix is computed based on the province's internationalisation (Openness). Driscoll–Kraay robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Spatial regression results–Institutional controls

	(1) SAR	(2) SEM	(3) SDM	(4) SDM	(5) SDM
L.ECI	0.0036**	0.0034**	0.0034**	0.0033*	0.0039**
	(0.0015)	(0.0016)	(0.0016)	(0.0017)	(0.0017)
L.GFCF per capita (ln)	-0.0128	-0.0122	-0.0116	-0.0134	-0.0102
	(0.0109)	(0.0113)	(0.0108)	(0.0114)	(0.0107)
L.Hrs worked per capita (ln)	0.4564***	0.4675***	0.4421***	0.4619***	0.4440***
	(0.1448)	(0.1470)	(0.1513)	(0.1556)	(0.1348)
L.Openess (ln)	0.0104***	0.0092**	0.0102***	0.0095**	0.0091**
	(0.0036)	(0.0038)	(0.0035)	(0.0038)	(0.0037)
L.Patent per c. (ln)	-0.0014	-0.0012	-0.0012	-0.0013	-0.0011
	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0019)
L.Density (ln)	-0.1954***	-0.2105***	-0.1973***	-0.2023***	-0.2147***
	(0.0370)	(0.0400)	(0.0362)	(0.0370)	(0.0401)
L.Female Share	-1.1966	-1.1269	-1.1851	-1.0153	-0.9476
	(0.8990)	(0.9414)	(0.9022)	(0.9548)	(0.8823)
L.Young Share	-0.4634***	-0.5379***	-0.4857***	-0.4585***	-0.5449***
	(0.1636)	(0.1618)	(0.1633)	(0.1666)	(0.1464)
L.VA per c. (ln)	0.2574***	0.2547***	0.2552***	0.2546***	0.2367***
	(0.0289)	(0.0287)	(0.0287)	(0.0288)	(0.0242)
L.ICT. Empl. Share	-1.1826**	-1.0856**	-1.1371**	-1.0586**	-0.9991**
	(0.5410)	(0.5172)	(0.5573)	(0.5128)	(0.4775)
L.Manuf. Empl. Share	-0.0009	-0.0003	-0.0008	-0.0005	-0.0001
	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0010)
L.Hrs compensation (ln)	0.5031***	0.4890***	0.4974***	0.4926***	0.4562***
	(0.0357)	(0.0330)	(0.0392)	(0.0391)	(0.0244)
L.Infrastructure Density (ln)	0.0071	0.0078	0.0084	0.0114	0.0097
	(0.0064)	(0.0067)	(0.0064)	(0.0073)	(0.0071)
L.share_upperhcl	-0.0072	-0.0102	-0.0126	-0.0096	-0.0030
	(0.0505)	(0.0545)	(0.0512)	(0.0516)	(0.0513)
L.corruption	-0.0102	-0.0071	-0.0161	-0.0110	-0.0084
	(0.0124)	(0.0128)	(0.0146)	(0.0168)	(0.0132)
ρ	0.4433***		0.4318***	0.4607***	0.1348***
	(0.1450)		(0.1569)	(0.1640)	(0.0210)
σ^2	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
λ		0.5988***			
		(0.1820)			
Spatial ECI			0.0311*		
			(0.0180)		
Spatial ECI X North				0.0882***	0.0029**
				(0.0227)	(0.0015)
Spatial ECI X South				-0.0421	-0.0007
				(0.0534)	(0.0018)
Observations	1648	1648	1648	1648	1648
R-squared	0.5461	0.2096	0.5500	0.5412	0.2300
Matrix	Idist	Idist	Idist	Idist	Econ
Provinces Dummy	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES
Sample	Full	Full	Full	Full	Full

Notes: The table depicts the result of the alternative spatial estimations, including the institutional variable. Columns (1) and (2) present estimations of SAR and SEM models. Column (3) presents estimations of the SDM model. Column (4) presents estimations of the SDM model interacting the spatial term with macro–area variable. Column (5) presents estimations of the SDM model interacting the direct ECI and the spatial term with macro–area variable using economic–distance matrix is computed based on province internationalisation (Openness). Driscoll–Kraay robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Three-Stage Least Squares Estimation Results

Variable	**Productivity Equation**	**Complexity Equation**
L.ECI	0.0038*	
	(0.0020)	
L.GFCF per capita (ln)	0.0032	
	(0.0093)	
L.Hrs worked per capita (ln)l	0.4527***	
	(0.0761)	
L.Openess (ln)	0.0033	
	(0.0029)	
L.Patent per c. (ln)	0.0004	
	(0.0015)	
L.Density (ln)	-0.2652***	1.2448***
	(0.0340)	(0.3914)
L.Female Share	0.2441	-3.3687
	(0.1757)	(2.6846)
L.Young Share	-0.5177***	6.8629***
	(0.1299)	(2.2711)
L.VA per c. (ln)	0.2168***	
	(0.0210)	
LICT Empl Share	-1.3052***	
	(0.2772)	
L.Manuf. Empl. Share	-0.0002	
	(0.0007)	
L.Hrs compensation (ln)	0.4855***	
	(0.0359)	
L.ln_infra_density_short	0.1946***	
	(0.0249)	
L.Gradueted Share	-0.0424	
	(0.0522)	
L.Lab. Productivity (ln)		0.7585*
		(0.4371)
Constant	6.1355***	-15.1106***
	(0.7385)	(5.3733)
Observations	2,021	
R-squared	0.9656	0.8748

Notes: The table depict the result 3SLS with 1200 Bootstrap standard errors reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

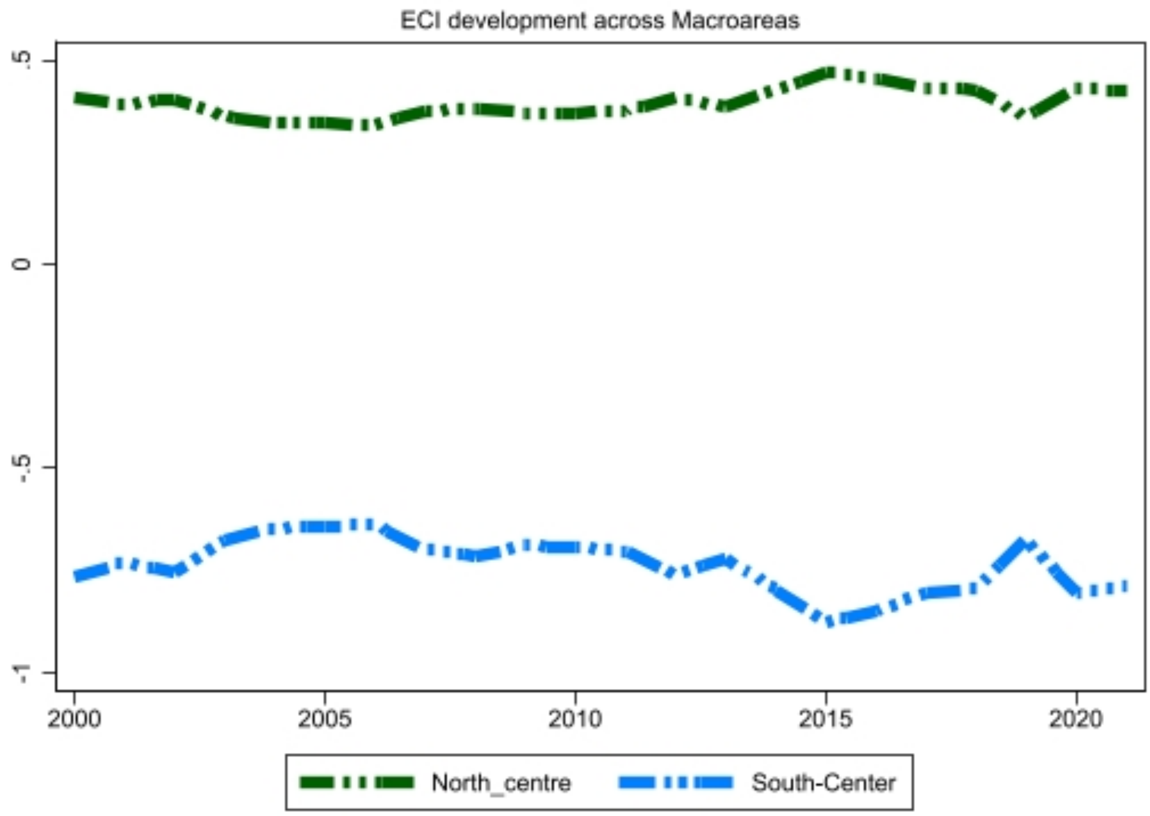
Table 14: Three-Stage Least Squares Estimation – Institutional Quality Included

Variable	(1) Productivity Equation	(2) Complexity Equation
L.ECI	0.0028*	
	(0.0016)	
L.GFCF per capita (ln)	-0.0051	
	(0.0085)	
L.Hrs worked per capita (ln)	0.5142***	
	(0.0768)	
L.Openess (ln)	0.0084***	
	(0.0025)	
L.Patent per c. (ln)	-0.0013	
	(0.0014)	
L.Density (ln)	-0.2289***	1.3976***
	(0.0315)	(0.4346)
L.Female Share	-1.5448***	-20.4228**
	(0.4743)	(7.3049)
L.Young Share	-0.5385***	4.3363**
	(0.1452)	(2.1199)
L.VA per c. (ln)	0.2392***	
	(0.0197)	
LICT Empl Share	-1.2021***	
	(0.2965)	
L.Manuf. Empl. Share	-0.0007	
	(0.0007)	
L.Hrs compensation (ln)	0.4538***	
	(0.0379)	
L.Corruption (institutional)	-0.0085	
	(0.0104)	
L.Infrastructure Density (ln)	0.1330***	
	(0.0313)	
L.Graduated Share	-0.0243	
	(0.0531)	
L.Lab. Productivity (ln)		0.9040***
		(0.3362)
Constant	5.8129***	-8.1226
	(0.8045)	(5.5768)
Observations	1,648	
R-squared	0.9703	0.8776

Notes: The table depict the result 3SLS with institutional control. Standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6.2 Appendix B: Figures

Figure 3: The complexity development across macro–areas



Source: Author's elaboration.