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ORIGINAL PAPER

The governance of urban resilience: a valuation tool and an application to Italian provinces

Fabio Fiorillo[1] · Daniela Lena[1]

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Abstract
Urban resilience is both systemic and dynamic: it depends on interactions among local economic, social, demographic, and health-related conditions and is revealed by how urban systems absorb shocks and adjust over time. This article proposes an operational framework for assessing resilience when municipal data are rich across local units but short in time and uneven across domains, a common setting outside large metropolitan areas. The framework measures resilience through the persistence of shocks and the speed of adjustment of local outcomes. We apply it to Italy using a panel of 7442 municipalities observed over 2014–2023 and grouped into 104 province-specific systems. A province-by-province error-correction model is used to construct model-based indicators of incomplete adjustment following temporary and permanent shocks, as well as the 2020 Covid pulse. The results reveal substantial territorial heterogeneity. Entrepreneurship is the most common channel associated with economic and social adjustment, whereas healthcare provision capacity and age-related fragility are especially informative for social resilience. The Covid pulse confirms that resilience patterns are not reducible to a simple North–South divide.

JEL C33 · R11 · R58 · Q01

1 Introduction

Developing an advanced urban resilience agenda remains a significant challenge for municipalities, especially outside large metropolitan areas. One reason is the lack of operational instruments for measuring resilience with the data that local administrations can realistically access. The literature commonly defines resilience as the ability of a complex system to absorb a disturbance and recover, adapt, or move toward a new equilibrium after a perturbation or shock (Meerow et al. 2016). Its governance capa-

✉ Fabio Fiorillo
f.fiorillo@staff.univpm.it

✉ Daniela Lena
d.lena@staff.univpm.it

1 Marche Polytechnic University, Ancona, Italy

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bility is crucial for urban systems to address various risks and safety threats, including climate change, natural disasters, economic crises, migration, and the effects of globalization (Doorn et al. 2019).

What makes urban resilience capacity a problematic concept to define, develop, and measure is the intrinsic complex nature of the city system (Jabareen 2013). The components or assets of a city are usually grouped into broad physical and social spheres (Pickett et al. 2001). Physical components include the built environment, infrastructures, resources, and processes through which the city operates. Social components include individuals, institutions, collective activities, and the forms of organization through which local communities respond to change. The resilience of an urban system, therefore, cannot be reduced to the condition of a single component. It is a systemic concept because the response of the city depends on the interconnectedness and interdependence of these physical and social spheres. It can also be read as the outcome of emergent patterns generated by multidirectional feedback among human actors, physical artifacts, institutions, and their environment. It is also a dynamic concept, because resilience becomes observable only after a disturbance, through the way the system absorbs the shock and adjusts over time.

Considering the city as a bundle of interdependent components, the measurement of resilience refers to the behaviorof a complex system.[1] The performance of such a system is not simply the sum of the performance of its assets or components (Du and Jian 2024). Rather, relationships among components matter because new patterns of performance may emerge from their interaction (Doorn et al. 2019). Evaluating resilience therefore requires attention not only to the local conditions that may help a system withstand a disturbance, but also to the time profile of adjustment after the disturbance occurs. A resilient system may absorb a shock, recover previous functions, reorganize itself, or adjust toward a new equilibrium path. In this sense, resilience relies on time: it involves an initial state, a post-disturbance state, and a post-recovery or post-adjustment state (Henry and Ramirez-Marquez 2012). The speed and quality of the transition between these states are central to the system's overall resilience (Yang et al. 2022).

This article proposes an operational empirical framework for assessing urban resilience in contexts where municipal data are time-limited and unevenly available across domains. This is a common condition for many local urban systems. Municipalities are often rich in cross-sectional information, but the available series are short and do not cover all dimensions of resilience with the same degree of detail. The methodological problem is therefore not only how to select appropriate indicators, but also how to use them to recover a meaningful measure of dynamic adjustment after shocks.

Indicator-based frameworks, including the Rockefeller-ARUP City Resilience Framework, the Resilience Alliance, and the Baseline Resilience Indicator for Communities (BRIC)-type approaches, provide useful maps of the domains in which urban

[1] According to Edwards et al. (2024), a complex system is a system "with components and interconnections, interactions, or interdependencies that are difficult to describe, understand, predict, manage, design, or change." A complex system also has dynamic, static, and structural aspects, including nonlinearity, nonequilibrium dynamics, and interrelated processes that may lead to tipping points that are difficult to predict (Edwards et al. 2024).

resilience can be observed (Alliance 2010; The Rockefeller Foundation and Arup 2013; Cutter et al. 2014). In this article, they are used as conceptual and diagnostic references for selecting domains and variables. We use the frameworks to identify relevant economic, social, health care, and demographic conditions, and then measure resilience by the persistence of shocks and the speed at which local outcomes adjust over time.

We apply this approach to Italy using a panel of 7442 municipalities observed over 2014–2023 and grouped into 104 province-specific systems. This structure allows us to exploit the cross-sectional richness of municipal data while acknowledging the short time dimension available for local indicators. The empirical analysis focuses on two central outcomes, per-capita income and poverty, which capture the economic and social dimensions of local resilience. Healthcare provision capacity, entrepreneurship, high-value-added employment, and life expectancy, interpreted as a proxy for age-related fragility, enter as local conditions associated with the adjustment process.

We estimate a province-by-province error-correction model and construct model-based indicators of incomplete adjustment following temporary and permanent shocks, as well as the 2020 Covid pulse. These indicators summarize the persistence of shocks across provincial urban systems and provide a comparative measure of economic and social resilience. The empirical application reveals substantial territorial heterogeneity in both economic and social resilience. Entrepreneurial dynamics emerge as the clearest channel associated with adjustment in both dimensions, whereas healthcare provision capacity and age-related fragility are especially informative for social resilience. The geography of resilience is not reducible to a simple North–South divide: some macro-regional patterns are evident, but within-area heterogeneity remains substantial, including in responses to the Covid pulse.

The rest of the article is organized as follows. Section 2 reviews the literature on urban resilience and introduces our core contribution. Section 3 describes the data and the construction of the indicators used in the empirical analysis. Section 4 presents the empirical model and the model-based resilience metrics. Section 5 discusses the results. Section 6 concludes.

2 Urban resilience: a literature review

2.1 Definition and conceptualization

In recent years, the scientific community has devoted increasing attention to the concept of urban resilience and to the way this knowledge can inform the future development of cities. Research on urban resilience is currently progressing at a rapid pace and involves a diverse range of perspectives and scientific disciplines (Wang and Xue 2018). Although the concept of resilience has long been used in engineering, economics, and ecology, the modern theory of urban resilience can be traced back to Holling's work on ecological-system resilience in 1973. Yet, defining urban resilience remains complex because cities are intricate systems (Jabareen 2013; Navinés et al. 2023). Urban scholars and geographers have long debated the boundaries of the "urban" concept and whether the city should be understood as a limited single system (Pickett et al. 2001), a system of connected cities (Ernstson 2013), or a sophisticated networked system (Desouza and Flanery 2013). Moreover, the event or disturbance from which the city is expected to recover remains ambiguous, making the identification of a resilient city challenging. The debate concerns whether this exceptional occurrence should be understood as a specific exogenous shock or as an extraordinary event not associated with the city's assets (Simmie and Martin 2010; Sondermann 2018), a specific interference outside the control of the city governance (Welter-Enderlin and Hildenbrand 2006), a natural hazard or human-induced risk (Bosher and Coaffee 2008; Brown et al. 2012) or as a disturbance generated within socio-ecological systems (Walker 2006; Brown 2015).

The definitions of urban resilience proposed in the literature therefore come from different perspectives, with a large part of them being framed in relation to threats[2] to the urban system (Henstra 2012; Brown et al. 2012; Coaffee 2013; Lu and Stead 2013; Wamsler et al. 2013; Chang et al. 2014; Delgado-Ramos and Guibrunet 2017; Cariolet et al. 2019). In their work on defining and conceptualizing urban resilience, Meerow et al. (2016) identify twenty-five different definitions of urban resilience in the existing literature. Therefore, these authors propose their definition of urban resilience, which is based on the definition of what is an urban system, the definition of the equilibrium of this system, the perception of resilience as a favorable condition, and the centrality of the path to achieving resilience in terms of adopting behaviors and recovery times following shocks to the urban system. Moreover, considering all the political, social, ecological, and technical features of cities, as well as the complex interdependencies among cities, urban-rural connections, and the resource flows that unite them, they establish a comprehensive conceptual framework of what urban resilience means and how to define it. Similarly, Ribeiro and Gonçalves (2019) propose an analogous definition: urban resilience is the ability of a city, and of its entire urban system (socio-ecological and socio-technical networks), to absorb initial damages, to reduce the impacts of external shocks, to adapt to change and to rapidly transform systems that limit current or future adaptive capacity. This definition is particularly relevant for our purposes because it treats resilience neither as a property of a single indicator nor as a purely static condition. Rather, it emphasizes the behaviorof the urban system after a shock, that is, its capacity to absorb, adjust, and recover over time.

Furthermore, an important part of the recent literature presents urban resilience in the context of sustainability, i.e., a logic of change and transformation of systems in order to improve their ability to provide services (McPhearson et al. 2015; Mehmood 2016; Meerow et al. 2016; Spaans and Waterhout 2017; Acuti et al. 2020; Zeng et al. 2022). It is important to note a significant difference between the concepts of resilience and sustainability in the urban context. While some argue that these terms are substitutable (Saunders and Becker 2015; Suárez et al. 2016; Elmqvist et al. 2019; Chelleri and Baravikova 2021), evidence suggests that resilience should be considered a separate and distinct component of, or at least related to, sustainability. Serbanica and Constantin (2023) assert that urban resilience is primarily concerned with addressing hazards and acute shocks, such as landslides, earthquakes, droughts, and cyber-attacks,

[2] The threats concerning the urban system are those linked to natural events, that is, to modifications or alterations of the urban system due to climatic conditions and natural disasters.

that can result in significant human, material, economic, and environmental losses and impacts. Conversely, urban sustainability focuses on addressing long-term, chronic, and cumulative stresses, such as climate change (from an environmental perspective), economic inequality (from an economic perspective), and lack of cohesion (from a social perspective). Numerous studies have explored the distinctions between these two concepts, and the urban resilience agenda is commonly critiqued for not adequately addressing social equity goals (Fitzgibbons and Mitchell 2019; Muñoz-Erickson et al. 2021; Zeng et al. 2022).

It is worth emphasizing that the definition of urban resilience is still unclear, and further research should be conducted to improve collective well-being. This conceptual ambiguity does not undermine the present analysis. Rather, it motivates our focus on the elements that are most common across the literature: the systemic nature of urban resilience and its dynamic interpretation as the capacity of local systems to react to shocks and move toward recovery, adaptation, or a new equilibrium over time.

2.2 Core contributions

Within the broad literature on urban resilience, including critical review analyses (see Monteiro et al. 2012; Pandit and Crittenden 2016; Bulti et al. 2019; Diaz-Sarachaga and Jato-Espino 2020), contributions on the identification and conceptualization of urban resilience terms (see Tabibian and Movahed 2016; Yaman Galantini and Tezer 2018; Childers et al. 2019), and systematic reviews (see Sharifi and Yamagata 2016; Meerow et al. 2016; Vieira et al. 2018; Ribeiro and Gonçalves 2019; Büyüközkan et al. 2022), we identify three main strands of research: a) single-asset vulnerability, b) urban system interdependence, and c) urban performance and index development. Each approach emphasizes a distinct methodology, and they are not necessarily mutually exclusive.

The first strand is related to the presence and quality of the assets, with the analysis generally centeredon the resilience of a specific asset, for example, physical, natural, economic, institutional, and social assets (Peyroux 2015; Tyler et al. 2016; Spaans and Waterhout 2017; Klein et al. 2017; Leitner et al. 2018). Within this field of research, both physical and intangible assets shape cities' exposure and vulnerability and affect their capacity to mitigate risks, both in terms of behavior and availability of resources (Ostadtaghizadeh et al. 2015; Patel and Nosal 2016). Specifically, Lorenz and Lal (2015) focusing their analysis on urban soil carbon stocks, underscores the need to raise awareness among stakeholders about the importance of urban soil carbon stocks for climate change mitigation and ecosystem services. According to the authors, an improved understanding of processes will facilitate urban planning to enhance soil carbon stocks, promote resilience in urban ecosystems, and contribute to climate change adaptation and mitigation, ultimately benefiting human well-being. Tyler et al. (2016) describe the process of generating urban climate resilience indicator development in eight different cities, where the focus of the study was the physical and economic assets, such as water supply systems, solid waste management, public health, and flood protection systems. The authors defined essential considerations when developing a resilience framework based on their experience. Spaans and Waterhout (2017), using Rotterdam as a case study in their paper, raises questions about the selective nature of resilience planning, considering cities' diverse issues. Each city, including Rotterdam, may need to prioritize specific focus areas, such as social resilience, climate change resilience, critical infrastructures, cyber resilience, governance changes, and energy and harbor resilience. Klein et al. (2017) emphasizes the significance of good governance in establishing resilient and sustainable cities. They introduce the idea of the Responsive City, where technology empowers citizens to participate actively in urban planning processes. By identifying the critical characteristics of the city and enhancing the understanding of relationships among different components in the system, the authors aim to create a dynamic and responsive urban governance system that utilizes technology, data, and citizen engagement to improve urban living. Moreover, regarding economic, institutional, and social assets, Peyroux (2015), in his work, explores the application of the concept of resilience in shaping a more inclusive development pathway, addressing various dimensions of inclusion. The author argues that the call for increased participation and deliberation in development practices can serve as institutional mechanisms to reconcile divergent views and competing interests. The appeal of resilience to policymakers may lie in its ability to fulfill a political and symbolic function for local governments. Ziervogel et al. (2017) proposed reconceptualizing resilience that focuses on the rights of urban citizens rather than physical and ecological infrastructures. They argue that making rights and justice the target of resilience thinking can address the root causes of risks and bridge the gap between everyday and catastrophic risk management. The text outlines several entry points for a rights-oriented approach to urban resilience, including addressing financially driven risk reduction, integrating diverse interests, strengthening endogenous forms of resilience, and understanding urban resilience narratives as products of global systems. In their work, Leitner et al. (2018) emphasizes the private sector's essential contribution toward enhancing cities' resilience. They assert that this approach offers a superior urban development and governance solution. The authors cite an instance from Jakarta to underscore the significance of avoiding the commercialization of urban resilience, which should not be treated as a marketable commodity with a guaranteed return on investment.

The second strand considers the city as a system composed of interdependent systems, in which assets constitute fundamental building blocks (see Brown et al. 2012; Da Silva et al. 2012; Vieira et al. 2018; Feagan et al. 2019). Among the studies within this approach, urban resilience is not discussed only by considering the city as a single aggregate system, but also by examining the individual systems that make up the urban system (The Rockefeller Foundation and Arup 2013). In this approach, the human element is placed at the center (Wallace and Wallace 2008; Feagan et al. 2019), as are the institutions (Vieira et al. 2018). Da Silva et al. (2012) divides the urban system into three categories: institutional networks (institutions), knowledge networks (human system), and networked infrastructures (physical assets). These authors recognize the interdependence of systems and suggest a paradigm shift that considers the problem of resilience differently from the traditional "prediction and prevention" approaches typical of city risk management. In their paper, Vieira et al. (2018), they conduct a systematic review of the literature to explore the intersection of resilience in Urban Food Systems (UFS). The authors highlight the significance of diverse food sources, distribution networks, and knowledge generation for adaptive capacity and resilience.

Feagan et al. (2019) emphasizes the importance of reflexivity in the knowledge systems research community, specifically about urban resilience. They identify necessary changes in knowledge practices that can contribute to ensuring a resilient urban future.

The third strand considers urban resilience in terms of performance. Here, the performance of a city refers to its ability to perform essential functions and to serve citizens effectively. While the previous strands described resilience as a process, this one considers resilience as an outcome toward which cities tend and, therefore, examines how the fundamental functions of a city are fulfilled after an interruption in their normal operation (Da Silva et al. 2012; Suárez et al. 2016; Gaber et al. 2019; Iturriza et al. 2019; Ghouchani et al. 2021). Specifically, the Rockefeller Foundation and ARUP International created the City Resilience Index (CRI) to measure resilience as an outcome of city administration (The Rockefeller Foundation and Arup 2013). Later, Cutter et al. (2014) proposed the modified Baseline Resilience Indicator for Communities (BRIC), originally constructed around hazard-specific community resilience in the U.S. context in 2010 (see Cutter et al. 2010), with indicator selection and weighting tailored to that empirical environment. This framework encompasses 49 indices across 6 areas, is applicable at the county or municipality level worldwide, and can be readily scaled to cities with comparable data. Instead, Suárez et al. (2016) proposed a composite indicator to measure the resilience of urban ecosystems, aligning with the core concept of sustainability. The urban resilience index developed in this study is applied to Spanish provincial capitals. The findings emphasize the need for substantial efforts to enhance resilience in urban areas, calling for measures such as resource consumption reduction, promotion of local trade, citizen participation spaces, and diversification of the local economy. Gaber et al. (2019) proposed an innovative approach for resilience assessment encompassing various facets of urban resilience, such as natural, physical, social, economic, and institutional elements. Their methodology considers the current context, potential threats, and key stakeholders involved. This five-step Resilience Assessment Model outlines crucial procedures for evaluating resilience. In their study, Hernantes et al. (2019) addresses an essential need for resilience performance measurement by introducing a Resilience Maturity Model (RMM) to guide cities' efforts to enhance resilience. The RMM outlines a progression of maturity levels and corresponding policies that assist cities in evaluating their current level and determining the necessary steps to advance their resilience. Iturriza et al. (2019) has developed a comprehensive toolkit designed to assist decision-makers in their efforts to enhance city resilience. The toolkit comprises two complementary tools: the resilience maturity model (RMM) and a serious game called city resilience dynamics (CRD). The authors highlight the importance of the critical factors that have contributed to creating a practical, reliable, and flexible toolkit that decision-makers can utilize to bolster city resilience. Ghouchani et al. (2021) introduces an alternative approach involving quality indicators' interference in measuring resilience, which relies on exploratory factor analysis and comprises six general stages. It aims to identify methods and dimensions of resilience, extracting criteria and factors for each dimension. The model seeks to estimate the practical components of designing a resilient city, considering various urban crisis conditions. The authors further discuss the use of the total average distance of the optimal interval for measuring resilience, noting its high accuracy but highlighting its potential shortcomings in quality. Finally, Camacho et al. (2024) modifies the BRIC framework for the southern Korean context to measure the resilience capacity of the Korean cities after a natural hazard.

Taken together, these strands clarify the role of indicator-based frameworks in our analysis. Frameworks such as BRIC and the Rockefeller–ARUP City Resilience Framework are useful diagnostic and benchmarking tools: they help identify the domains, dimensions, and potential indicators through which urban resilience can be observed.

For this reason, the indicators considered in the paper are not combined into a static resilience score, nor is any single framework adopted as a closed empirical template. The frameworks discussed above present indicator-based approaches that primarily measure resilience-related capacities and domains rather than resilience itself, understood here as the dynamic response of a local system to shocks. By contrast, our empirical analysis focuses on the dynamic persistence of shocks and on the adjustment of local economic and social outcomes.

3 Data

Measuring urban resilience requires translating broad conceptual domains into observable variables. The literature treats a city's performance as depending on its ability to fulfill critical functions across several domains, including health and collective well-being, the economy, society, capital and infrastructure, and ecological and environmental systems (The Rockefeller Foundation and Arup 2013; Cutter et al. 2014). Using this literature as a conceptual map to identify the relevant domains of local resilience and to guide indicator selection from the available data, we focus on economic and social outcomes as the two dimensions whose adjustment can be estimated consistently across municipalities and over time. Given data availability, healthcare and longer-run local conditions enter the analysis as explanatory variables rather than as additional outcome dimensions.[3] Therefore, the variables used in the empirical analysis describe local conditions that are theoretically related to resilience and can be incorporated into a dynamic adjustment model. Resilience is then derived from the estimated responses of these urban systems to shocks.

The unit of observation is the municipality-year. However, the empirical exercise does not aim to estimate a separate resilience parameter for each municipality. Given the limited time dimension available at the municipal level, we use municipalities as the cross-sectional units of a panel within each province and estimate province-specific dynamic relationships. The resulting measures, therefore, capture the average dynamic resilience of municipalities in each province, province by province. By exploiting repeated observations for municipalities within the same province, the empirical strategy links local conditions to the average adjustment pattern of the corresponding municipal urban system.

The final estimation sample covers 104 province-specific panels and 7442 municipalities observed over the 2014–2023 period. Since the time dimension is fixed at ten

[3] Since the health and well-being domain is detailed only at the provincial level, we consider it as a regressor and not as an outcome.

Table 1 Variable definitions

Variable	Description	Domain
GDP	Per-capita taxable income, computed as total IRPEF income over population; measured in thousand euros per inhabitant	Economy and society
Poor	Share of IRPEF taxpayers with total income below 10,000 euros; measured in percentage points	Social fragility
HAV	Share of employment in high-value-added activities; measured in percentage points	Economy and society
Firms	Number of firms per 1000 inhabitants	Economy and society
Physicians	Physicians per 1000 inhabitants	Health and well-being
Mental care physicians	Physicians specializing in psychiatric activities per 1000 inhabitants	Health and well-being
Hospital beds	Ordinary hospital beds per 1000 inhabitants	Health and well-being
Life	Life expectancy at birth, measured in years	Health and well-being
HCS	Synthetic healthcare system indicator, constructed through principal component analysis on the logarithmic transformations of Physicians, Mental care physicians, and Hospital beds	Health and well-being

Variables are constructed from publicly available sources, mainly ISTAT, *A misura di comune*, ISTAT, *Health for All*, the Italian Ministry of Health, and authors' elaborations. Descriptive statistics are reported in levels, while the dynamic model uses logarithmic transformations of the variables

annual observations for each municipality, the sample includes 74,420 municipality-year observations.[4]

The dataset combines indicators that capture different dimensions of local conditions. Economic performance is measured through municipal income, while productive capacity is captured by the local presence of firms and by the sectoral composition of employment. Social fragility is measured through the share of low-income taxpayers. Health and demographic conditions are captured by life expectancy and indicators of healthcare availability. All variables are constructed from public sources, harmonized at the municipal level whenever applicable, and used in the province-specific panel estimations described in the following sections. Table 1 reports the definitions of the variables used in the empirical analysis.

Municipal socio-economic variables are taken from ISTAT, *A misura di comune*, while health-related information is mainly drawn from ISTAT, *Health for All*, complemented, when necessary, with data from the Italian Ministry of Health. Table 2 summarizes descriptive statistics for these variables in the final estimation sample.[5]

[4] Relative to the standard provincial classification, the units not included in the final estimation sample are Valle d'Aosta/Aosta, Bolzano-Bozen, and Sud Sardegna.

[5] Descriptive statistics are reported in levels. The transformations used in the empirical model are described in Sect. 4. The HCS indicator is constructed from the logarithmic transformations of the underlying healthcare variables.

Table 2 Descriptive statistics

Variable	Obs	Mean	Std. dev	Min	Max
GDP	74,420	13.292	3.584	2.321	76.827
Poor	74,420	31.431	10.480	11.538	87.255
HAV	74,420	60.135	17.853	2.721	100.000
Firms	74,420	61.617	20.630	2.238	271.210
Physicians	74,420	6.681	3.593	0.399	100.646
Mental care physicians	74,420	0.173	0.052	0.058	0.484
Hospital beds	74,420	3.131	0.703	1.337	5.887
Life	74,420	82.661	0.870	79.765	84.700
HCS	1,040	0.000	1.282	−3.554	4.801

HCS is a synthetic province-year healthcare system indicator constructed through principal component analysis. All variables except HCS are observed at the municipality-year level; HCS is constructed at the province-year level over 104 provinces and 10 years

3.1 Construction of the HCS indicator

The HCS indicator is constructed at the province-year level, because the underlying healthcare variables are available at that territorial scale. Specifically, we collapse Physicians, Mental care physicians, and Hospital beds at the province-year level and apply principal component analysis to their logarithmic transformations. HCS is defined as the score of the first principal component.

The use of a single component is appropriate for our purpose. The first component has an eigenvalue above one and explains 54.8% of the total variance. Its loadings are positive and similar in magnitude across the three underlying variables, supporting the interpretation of HCS as a synthetic indicator of healthcare availability. The overall Kaiser–Meyer–Olkin statistic is 0.5956, indicating a moderate degree of common variation among the three variables. This is consistent with the intended use of HCS as a parsimonious synthetic indicator, rather than as a complex latent scale (Table 3).

For the panel estimations, the province-year value of HCS is assigned to all municipalities belonging to the corresponding province and year.

4 Methods

In this paper, resilience is understood as a dynamic property of the local system. The object of interest is not the static level of a single indicator, but the speed with which shocks to local economic and social outcomes are reabsorbed as the system moves back toward its underlying equilibrium path. In principle, the ideal empirical framework for studying such a concept would be a structural vector autoregression, since that setting would allow one to identify shocks and trace their dynamic transmission across indicators. In practice, however, the short time dimension of the available municipal panel makes a full structural approach infeasible. We therefore adopt a province-by-province panel model in error-correction form. This choice follows the methodological

Table 3 Principal component analysis for the HCS indicator

Component	Eigenvalue	Proportion	Cumulative
Panel A. Eigenvalues and explained variance			
Comp1	1.6429	0.5476	0.5476
Comp2	0.7917	0.2639	0.8115
Comp3	0.5654	0.1885	1.0000
Panel B. Loadings			
Variable	Comp1	Comp2	Comp3
Physicians	0.5480	−0.7004	0.4573
Mental care physicians	0.6351	−0.0074	−0.7724
Hospital beds	0.5444	0.7137	0.4407
Panel C. Kaiser–Meyer–Olkin measure			
Variable	KMO		
Physicians	0.6173		
Mental care physicians	0.5677		
Hospital beds	0.6205		
Overall	0.5956		

HCS is the score of the first principal component. Since only the first component is retained, no rotation is applied

suggestion that ECM representations can remain informative even without formal pre-testing of the order of integration or cointegrating rank, and can still recover an appropriate linear combination of the underlying long-run relations in the data-generating process (Smeekes and Wijler 2021). The resulting dynamics are interpreted as a model-based descriptive measure of resilience rather than as a fully identified structural representation.

4.1 Empirical setting and dynamic specification

The observational unit is municipality i in year t, within province p. All models are estimated separately for each province, so that the adjustment parameters are province-specific. Municipality fixed effects absorb time-invariant local heterogeneity within each province, while standard errors are clustered at the municipal level. All continuous variables are entered in logarithms. Accordingly, the estimated coefficients can be read as elasticities.[6] For each province, moreover, both equations are estimated on the same final sample of municipalities, so that cross-equation comparisons are not driven by differences in sample composition.

Within this framework, per-capita income (GDP) and the poverty indicator ($Poor$) are treated as the two central outcome variables, representing the economic and social dimensions of local resilience. The starting point of the empirical model is the province-specific GDP–poverty relation, estimated within each province as

[6] For the Covid dummy, the corresponding coefficient captures the direct impact of the pulse intervention in log points.

$$Poor_{it}^{p} = \alpha_i^{p} + \kappa^{p} GDP_{it}^{p} + e_{it}^{p}, \tag{1}$$

where α_i^p denotes municipality fixed effects and e_{it}^p is the deviation from the province-specific GDP–poverty relation. The lagged residual

$$ECT_{i,t-1}^{p} = \widehat{e}_{i,t-1}^{p} \tag{2}$$

is then used as the disequilibrium term in the dynamic system.[7] Intuitively, $ECT_{i,t-1}^{p}$ measures whether, in a given municipality and year, the observed poverty level is above or below the level associated with local income in the underlying province-specific GDP-poverty relation. The residual is used as a parsimonious and economically meaningful measure of disequilibrium, rather than as the outcome of a formal cointegration exercise (Smeekes and Wijler 2021). For transparency, Appendix B reports a Harris and Tzavalis (1999) panel unit-root test on the residual, which is the most suitable diagnostic for our setting, given the short time dimension and the panel structure of the data.

The empirical model is written in first differences. This reflects both the short time dimension of the panel and the desire to focus on short-run adjustment around a province-specific equilibrium relation rather than on level stationarity. The structural regressors are treated as predetermined and enter with one lag. This is intended to attenuate contemporaneous simultaneity while preserving a parsimonious specification. For each structural covariate x_{it}, we estimate the projection

$$x_{it} = a_x + b_x C_t + v_{it}, \tag{3}$$

where C_t is a dummy equal to one in 2020 and zero otherwise. We then define the decovidized covariate as

$$\widetilde{x}_{it} \equiv \widehat{v}_{it}. \tag{4}$$

The projection in (3) is estimated on the pooled sample, so that decovidization removes the common national 2020 Covid pulse from the predetermined structural regressors. This preserves province-specific heterogeneity in 2020 exposure and in the subsequent local adjustment, which is left to the province-by-province structural estimates. Its purpose is not to eliminate every possible consequence of Covid from the data, but to separate the common 2020 pulse from the slower local adjustment of the system.

The synthetic healthcare indicator HCS is constructed in the Data section. In the empirical specification, the relevant regressor is $resHCS$, namely the component of HCS orthogonal to province-level average per-capita income (M_GDP). As with the other structural regressors, the variable enters the ECM through its lagged decovidized value.

The baseline specification reported in the main text includes an explicit Covid pulse in both equations. As a robustness check, we also estimate a variant without that pulse

[7] Writing the long-run relation with *Poor* on the left-hand side is a normalization used to construct a common disequilibrium term; it is not intended to impose a one-way causal restriction from GDP to poverty.

term, while keeping the structural regressors decovidized; the robustness results are reported in Appendix D.

The final empirical specification is

$$\Delta GDP_{it}^{p} = \lambda_{GDP}^{p} ECT_{i,t-1}^{p} + \theta_{GDP,F}^{p} \widetilde{Firms}_{i,t-1}^{p} + \theta_{GDP,HAV}^{p} \widetilde{HAV}_{i,t-1}^{p} + \theta_{GDP,HCS}^{p} \widetilde{resHCS}_{i,t-1}^{p} + \theta_{GDP,L}^{p} \widetilde{life}_{i,t-1}^{p} + \delta_{GDP}^{p} C_t + u_{it}^{GDP,p}, \tag{5}$$

$$\Delta Poor_{it}^{p} = \lambda_{Poor}^{p} ECT_{i,t-1}^{p} + \theta_{Poor,F}^{p} \widetilde{Firms}_{i,t-1}^{p} + \theta_{Poor,HAV}^{p} \widetilde{HAV}_{i,t-1}^{p} + \theta_{Poor,HCS}^{p} \widetilde{resHCS}_{i,t-1}^{p} + \theta_{Poor,L}^{p} \widetilde{life}_{i,t-1}^{p} + \delta_{Poor}^{p} C_t + u_{it}^{Poor,p}. \tag{6}$$

Finally, the Covid dummy is modeled as a pulse intervention. This reflects the nature of the 2020 shock in our setting: a common, abrupt, and exceptional event hitting all municipalities on the same date. In (5)–(6), δ_{GDP}^{p} and δ_{Poor}^{p} therefore capture the direct common impact of the Covid pulse on the two outcome variables, while the lagged disequilibrium term and the predetermined structural regressors describe the subsequent local adjustment.

4.2 Model-based resilience metrics

Within the error-correction specification, resilience is evaluated by means of model-based metrics of incomplete adjustment. For temporary shocks, including the Covid pulse intervention, these metrics measure the share of the initial effect that is still not reabsorbed after n periods. For permanent shocks, they measure the share of the adjustment toward the new long-run equilibrium that is still missing after n periods. Accordingly, higher values correspond to slower adjustment and therefore to lower resilience.[8] To avoid an excessively heavy notation, province superscripts are omitted throughout this subsection; all coefficients and resilience metrics remain province-specific.

Combining (1), (5), and (6), let $\theta_{GDP,m}$ and $\theta_{Poor,m}$ denote the coefficients of predetermined variable m in the two dynamic equations. To simplify notation, define the following composite quantities, all constructed from the estimated coefficients of the two equations: $\phi \equiv 1 + \lambda_{Poor} - \kappa\lambda_{GDP}$, which measures the persistence of the GDP–poverty disequilibrium; $\psi_m \equiv \theta_{Poor,m} - \kappa\theta_{GDP,m}$, which measures the net loading of predetermined variable m on the disequilibrium; and $\chi \equiv \delta_{Poor} - \kappa\delta_{GDP}$, which measures the net loading of the Covid pulse on the disequilibrium. The implied law of motion of the disequilibrium is then

$$ECT_{it} = \phi\, ECT_{i,t-1} + \sum_{m} \psi_m \widetilde{x}_{i,t-1}^{(m)} + \chi C_t + \nu_{it}, \tag{7}$$

[8] The main algebraic steps used to derive the resilience metrics from the error-correction specification are reported in Appendix A.

where ν_{it} denotes the composite disturbance term implied by the two dynamic equations (see Appendix A). The parameter ϕ summarizes the persistence of the disequilibrium term, while $1 - |\phi|$ is used as a diagnostic measure of the distance from the stability boundary $|\phi| = 1$, rather than as a resilience metric. More generally, $|\phi| < 1$ is the condition under which the disequilibrium is mean reverting: temporary shocks are eventually reabsorbed, whereas permanent shocks lead the system to converge to a new long-run disequilibrium level.

At a given horizon n, the resilience metrics used in the empirical analysis are constructed from the responses of ΔGDP and $\Delta Poor$ implied by the disequilibrium dynamics after a shock to a predetermined variable or to the Covid pulse. We assume that the system is initially on its estimated province-specific GDP–poverty relation, so that $ECT_{i,t-1} = 0$, and use the implied path of the disequilibrium term as an intermediate object in deriving the equation-specific metrics. Two cases must be distinguished. If the shock is temporary, the long-run disequilibrium does not change, and the metrics measure the share of the initial effect that is still not reabsorbed after n periods. If the shock is permanent, the system converges to a new long-run disequilibrium level,

$$\widehat{ECT}_m = \frac{\psi_m}{1-\phi}\Delta x, \tag{8}$$

and the metrics measure the share of the adjustment toward this new long-run equilibrium that is still missing after n periods. The Covid intervention is treated as a temporary common pulse and is therefore analyzed within the first case.

Consider first a temporary shock to predetermined variable m. The corresponding resilience metrics are constructed from the responses of the two dynamic equations. The persistence parameter ϕ governs the evolution of the disequilibrium term, while λ_{GDP} and λ_{Poor} determine how that adjustment is transmitted to the GDP and poverty equations. The corresponding residual elasticities are

$$R_{n,m}^{T,GDP} \equiv \left|\frac{\Delta GDP_{i,t+n}}{\Delta x}\right| = |\lambda_{GDP}\phi^{n-1}\psi_m|, \quad n \geq 1, \tag{9}$$

$$R_{n,m}^{T,Poor} \equiv \left|\frac{\Delta Poor_{i,t+n}}{\Delta x}\right| = |\lambda_{Poor}\phi^{n-1}\psi_m|, \quad n \geq 1. \tag{10}$$

These metrics measure the residual elasticities of the GDP and poverty equations after a temporary shock. Larger values imply slower reabsorption and hence lower resilience. Under $|\phi| < 1$, both residual elasticities converge to zero as n increases.

The Covid intervention is treated as a temporary common pulse. The relevant resilience metrics are therefore the remaining shares of the initial pulse intervention in the GDP and poverty equations:

$$R_{n}^{C,GDP} \equiv \left|\frac{\Delta GDP_{i,t+n}}{\delta_{GDP}}\right| = \left|\frac{\lambda_{GDP}\phi^{n-1}\chi}{\delta_{GDP}}\right|, \quad n \geq 1, \tag{11}$$

$$R_{n}^{C,Poor} \equiv \left|\frac{\Delta Poor_{i,t+n}}{\delta_{Poor}}\right| = \left|\frac{\lambda_{Poor}\phi^{n-1}\chi}{\delta_{Poor}}\right|, \quad n \geq 1. \tag{12}$$

Under $|\phi| < 1$, these equation-specific Covid metrics also converge to zero as n increases.

We now turn to the case of a permanent shock to predetermined variable m. Since the shock is persistent, the system converges to the new long-run disequilibrium level $\widehat{ECT}_m$ defined above. For the GDP and poverty equations, let

$$\widehat{\Delta GDP}_m = \left(\theta_{GDP,m} + \lambda_{GDP} \frac{\psi_m}{1-\phi} \right) \Delta x, \tag{13}$$

$$\widehat{\Delta Poor}_m = \left(\theta_{Poor,m} + \lambda_{Poor} \frac{\psi_m}{1-\phi} \right) \Delta x. \tag{14}$$

These are the long-run responses of the two equations implied by a permanent shock to predetermined variable m. The corresponding equation-specific resilience metrics are therefore

$$R^{P,GDP}_{n,m} \equiv \left| \frac{\Delta GDP_{i,t+n} - \widehat{\Delta GDP}_m}{\widehat{\Delta GDP}_m} \right|, \quad n \geq 1, \tag{15}$$

$$R^{P,Poor}_{n,m} \equiv \left| \frac{\Delta Poor_{i,t+n} - \widehat{\Delta Poor}_m}{\widehat{\Delta Poor}_m} \right|, \quad n \geq 1. \tag{16}$$

We refer to these as the remaining long-run elasticity shares of the two equations. Under $|\phi| < 1$, these missing shares also converge to zero as the two equations adjust toward their new long-run responses.

Taken together, the retained metrics quantify the speed with which the economic and social dimensions of the provincial system reabsorb the effects of temporary shocks, permanent shocks, and the Covid pulse. In all cases, larger residual values indicate slower reabsorption and therefore lower resilience. In the empirical analysis below, these metrics are evaluated at fixed horizons to compare resilience across provinces and specifications.

5 Results

Figure 1 reports the spatial distribution of $1 - |\phi|$, that is, the distance of each provincial system from the critical boundary $|\phi| = 1$. Since this distance is positive for all provinces, the estimated systems remain within the stability region. The relevant territorial variation therefore lies in how close provinces are to the boundary: smaller values of $1 - |\phi|$ indicate slower convergence and greater persistence of disequilibrium. All maps are divided into quartiles. In Fig. 1, lighter shades correspond to smaller values of $1 - |\phi|$, hence to provinces closer to the stability boundary. In the resilience

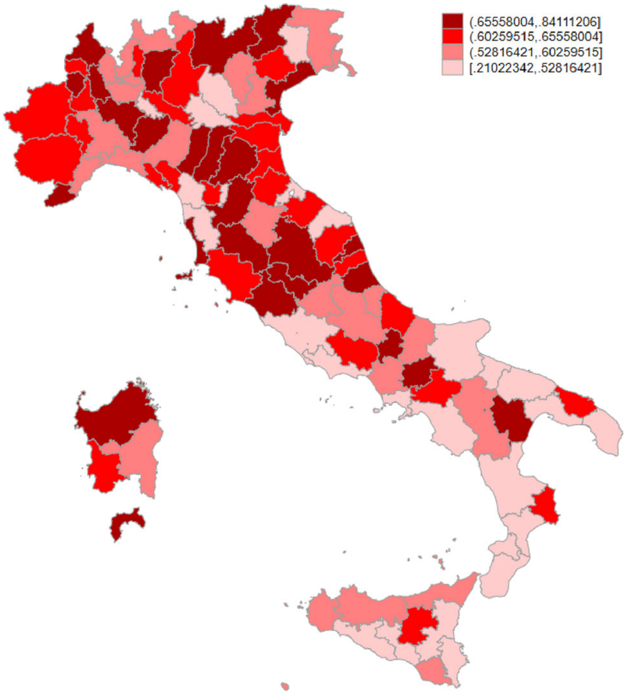


Fig. 1 Distance from the stability boundary

maps that follow, darker shades correspond to higher values of the relevant metric and therefore to higher persistence and slower adjustment.[9]

Table 4 summarizes the estimated effects of the main explanatory variables on the two dimensions considered in the analysis: the economic dimension, captured by GDP, and the social dimension, captured by $Poor$. For each coefficient, the table reports the median value across provinces, the number of positive and negative estimates, and the corresponding number of statistically significant coefficients. The table should therefore be read not only in terms of median effects, but also in terms of the regularity of the sign across space.

Three results stand out. First, $\widetilde{F}$ is the only variable that displays a clear and regular association with both dimensions of resilience. Its estimated effect is predominantly positive in the GDP equation and predominantly negative in the $Poor$ equation, suggesting that stronger entrepreneurial dynamics are generally associated with a more favorable adjustment of both income and poverty. Second, $\widetilde{HAV}$ appears, at most, as a secondary determinant of the economic dimension: its sign in the GDP

[9] This map-based evidence is broadly consistent with the Harris–Tzavalis panel unit-root diagnostic on the disequilibrium residual reported in Appendix B. The null of a unit root is not rejected in 7 provinces out of 104. The two diagnostics are not equivalent: the Harris–Tzavalis test bears on the stochastic properties of the estimated residual, whereas $1 - |\phi|$ measures the distance from the model-implied stability boundary. Still, the overlap is not negligible: five of the seven provinces in which the unit-root null is not rejected are also among the provinces closest to the stability boundary.

Table 4 Estimated effects of the explanatory variables on resilience

Coefficient	Median	Positive	of which signif	Negative	of which signif
$\theta_{GDP,F}$	0.035	77	37	27	4
$\theta_{GDP,HAV}$	0.008	66	13	38	5
$\theta_{GDP,HCS}$	0.008	71	52	33	21
$\theta_{GDP,L}$	0.493	62	53	42	31
$\theta_{Poor,F}$	−0.064	18	5	86	47
$\theta_{Poor,HAV}$	−0.006	44	5	60	13
$\theta_{Poor,HCS}$	−0.014	25	17	79	62
$\theta_{Poor,L}$	0.966	79	59	25	16
δ_{GDP}	−0.038	1	0	103	98
δ_{Poor}	0.047	103	93	1	0

equation is broadly coherent, but its magnitude is small, and it does not display an equally clear role in the social dimension. Third, $\widetilde{HCS}$ and $\widetilde{L}$ are especially informative for the social dimension. The effect of $\widetilde{HCS}$ in the $Poor$ equation is predominantly negative, consistently with the idea that stronger local healthcare provision capacity may reduce social fragility. By contrast, $\widetilde{L}$, interpreted as a slow-moving proxy for age-related fragility, has a predominantly positive effect in the $Poor$ equation.[10]

The correlation structure across the resilience metrics, reported in Appendix Table 6, further clarifies which maps add substantive information. A first result is that no relevant negative correlations emerge, so territorial vulnerabilities tend to cumulate rather than offset one another. A second result is that the Covid pulse metric in the social dimension is strongly associated with the temporary-shock metric for $\widetilde{L}$ in the same dimension. This is coherent with the interpretation of temporary shocks to $\widetilde{L}$ as localized demographic disturbances, including exceptional epidemiological episodes. The territories that are more resilient to temporary age-related fragility also tend to be more resilient to the Covid pulse. In the economic dimension, the temporary-shock metrics are strongly and positively correlated across determinants, indicating that they largely trace a common geography of short-run economic resilience. Finally, the comparison between temporary and permanent metrics is especially informative for $\widetilde{F}$, whose territorial ranking changes markedly across the two types of shocks.[11]

[10] Appendix D reports the corresponding robustness exercise without isolating the 2020 Covid pulse. This comparison verifies whether the determinants identified in the baseline specification retain the same broad territorial pattern when the common Covid shock is not modeled separately, but is instead absorbed by the structural coefficients. The main channels remain broadly recognizable. At the same time, the coefficients associated with age-related fragility are more sensitive to the specification, especially in the GDP equation, where the effect is less conclusive, whereas in the $Poor$ equation it becomes stronger. This is consistent with the idea that, when the Covid pulse is not isolated separately, the coefficient on $\widetilde{L}$ may absorb a larger fragility-related component.

[11] A similarly weak correlation between temporary and permanent metrics also emerges for $\widetilde{L}$, but this is less informative because temporary shocks to $\widetilde{L}$ are already captured, to a large extent, by their overlap with the Covid pulse. By contrast, the correlation is stronger for $\widetilde{HCS}$, but there the permanent metric is the more meaningful one because healthcare provision capacity is best read as a slow-moving local condition. The same correlation is also strong for $\widetilde{HAV}$, which nevertheless remains a secondary determinant of resilience.

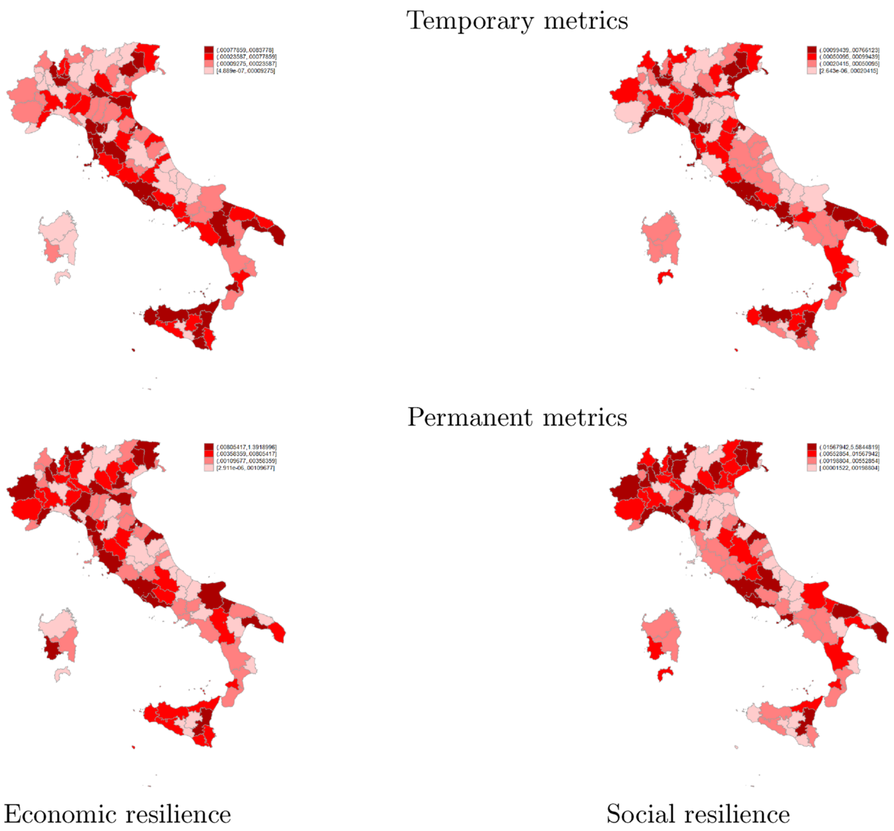
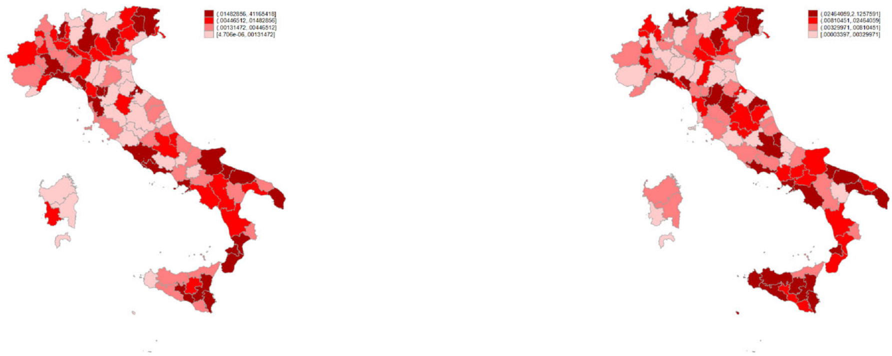


Fig. 2 Resilience metrics associated with $\widetilde{F}$

Figure 2 reports the resilience metrics associated with the entrepreneurship variable $\widetilde{F}$. The upper panels report the temporary-shock metrics for GDP and $Poor$, that is, the residual elasticity after a temporary shock. The lower panels report the corresponding permanent-shock metrics, that is, the remaining long-run elasticity share after five periods.

Under temporary shocks, persistence is higher in several provinces of the Centre and the South, especially in parts of Tuscany, Lazio, Apulia, and Sicily. Lower values, and therefore faster adjustment, are more common in several provinces of the North-East, in the Adriatic Centre, and in parts of Liguria and Molise. In the social dimension, the same broad contrast remains, but it becomes sharper in parts of the Mezzogiorno, especially in Apulia and Sicily. Under permanent shocks, however, the territorial ordering is not simply an intensification of the temporary-shock pattern. Some provinces that absorb temporary disturbances relatively quickly remain more exposed when the shock has permanent effects, while other provinces display the opposite pattern.

The maps also show that substantial differences may arise even between neighboring provinces. In Central Italy, for instance, Firenze and Prato are neighboring



$\widetilde{HCS}$ $\widetilde{L}$

Fig. 3 Permanent social resilience metrics associated with $\widetilde{HCS}$ and $\widetilde{L}$

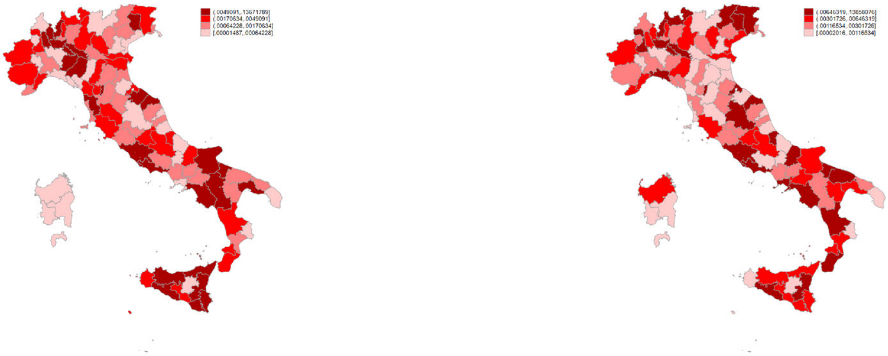
provinces in Tuscany, yet they lie at opposite ends of the temporary-shock distribution: Firenze adjusts rapidly, whereas Prato is among the slowest cases. A possible interpretation is that the effect of entrepreneurship is mediated by local productive structure: in a more diversified system such as Firenze, the loss of firms is more easily absorbed across sectors, whereas in a more specialized system such as Prato the same shock may weigh more heavily on the local economy and social conditions. More generally, the geography of resilience depends not only on the entrepreneurship variable itself, but also on productive specialization and on how open or closed the local system is.

Figure 3 turns to the two variables that are most informative for the social dimension of resilience, namely $\widetilde{HCS}$ and $\widetilde{L}$. In both cases, the figure reports the permanent-shock metric in the $Poor$ equation. This is the most natural representation for both variables, since they capture slow-moving local conditions rather than short-lived disturbances. Temporary shocks to healthcare provision capacity are possible, for instance after earthquakes or landslides that temporarily disrupt a hospital, but they are relatively infrequent. For $\widetilde{L}$, temporary shocks are even less natural to interpret, except in exceptional cases such as highly localized epidemics.[12]

The two maps show that the social geography of resilience is not driven by a single mechanism. For $\widetilde{HCS}$, the remaining long-run elasticity share is spatially scattered. High-persistence provinces are not confined to the South and the Islands, but also appear in parts of the North and the Centre. Conversely, lower-persistence cases are found in several areas of the Adriatic Centre and Emilia-Romagna, as well as in other scattered provinces. This pattern indicates that healthcare provision capacity does not produce a simple North–South geography of social resilience.

For $\widetilde{L}$, the map displays a clearer territorial gradient: higher persistence is more frequent in the South and the Islands, while lower persistence is more common in the Centre-North. At the same time, the pattern is not mechanically regional. The map still displays substantial within-area heterogeneity, suggesting that age-related

[12] The corresponding temporary-shock metrics are reported in Appendix E.



Economic resilience Social resilience

Fig. 4 Resilience metrics associated with the Covid pulse

fragility interacts with local social structures in ways that cannot be reduced to a uniform North–South divide.

The territorial heterogeneity is particularly visible in Campania, a region in Southern Italy. For $\widetilde{HCS}$, Napoli and Benevento display very different remaining long-run elasticity shares, with markedly slower social adjustment in Napoli. A possible interpretation is that, in a regional hub such as Napoli, a persistent change in local healthcare provision capacity may matter not only because of its direct effect on social fragility, but also because of the broader local relevance of the health sector itself. This example also illustrates why the social maps should be read as evidence of local mechanisms rather than as a simple macro-regional ordering.

Figure 4 reports the resilience metrics associated with the Covid pulse intervention in the GDP and $Poor$ equations. Unlike the previous figures, these maps do not describe the propagation of a local determinant, but the absorption of a common shock. In both dimensions, the relevant metric is the remaining share of the initial pulse intervention, so higher values indicate that a larger portion of the initial Covid impact is still present after five periods.

A mild territorial gradient emerges, with median values somewhat higher in the South and the Islands. Yet the geography of the Covid pulse is far from a mechanical North–South divide: high-persistence cases are also found in several Northern and Central provinces, and within-macro-area heterogeneity remains substantial. This heterogeneity is especially informative in the social dimension, where the Covid pulse map closely resembles the temporary-shock map for $\widetilde{L}$ in the $Poor$ equation. This echoes the high correlation between the two metrics discussed above and suggests that the territories in which the social effects of the Covid pulse are more persistent are also those where temporary shocks to age-related fragility are absorbed more slowly.

In this sense, the Covid maps complement the previous evidence: provincial systems differ not only in the way they absorb shocks operating through entrepreneurship, healthcare provision capacity, or age-related fragility, but also in the way they reabsorb an exceptional common disturbance.

6 Conclusion

Urban resilience is a complex and multidimensional concept, but it is also an empirical problem. This article has addressed how urban resilience can be operationalized in a context in which municipal data are limited in time and unevenly available across domains. This is a common condition for many local urban systems, especially outside large metropolitan areas, where the need for resilience assessment is strong but the data required for fully structural dynamic models are rarely available.

The analysis also shows the trade-off faced by empirical work on urban resilience. A broad conceptual framework is needed to recognize the multidimensional nature of resilience, but only a subset of domains can usually be observed with sufficient temporal consistency and territorial coverage. For this reason, the article gives priority to a dynamic and comparable measure of adjustment, while leaving the extension to a broader set of urban domains to future research.

Operationally, the article uses a province-by-province ECM framework to measure incomplete adjustment after temporary shocks, permanent shocks, and the Covid pulse. The resulting metrics are comparative and descriptive: They summarize how persistent shocks remain across provincial urban systems. In this sense, the article does not construct a static resilience score. Rather, it uses the available indicators to measure the speed with which local economic and social outcomes absorb disturbances and move back toward an equilibrium path, or adjust toward a new one.

The empirical application to Italian municipalities reveals substantial territorial heterogeneity in both economic and social resilience. Entrepreneurial dynamics emerge as the most regular channel associated with adjustment in both dimensions: provinces differ markedly in the extent to which shocks operating through the local firm structure are reabsorbed over time. Healthcare provision capacity and age-related fragility are especially informative for social resilience, confirming that social adjustment cannot be read only through standard economic conditions. The Covid pulse provides an additional benchmark because it captures the absorption of a common exceptional shock. Its geography is not reducible to a simple North–South divide: some macro-regional patterns are visible, but within-area heterogeneity remains substantial.

These findings have implications for territorial policy. If local systems differ in the persistence of shocks and in the speed of adjustment, then uniform national interventions may generate different dynamic effects across territories. This is relevant for large national investment programs, including Italy's National Recovery and Resilience Plan (*Piano Nazionale di Ripresa e Resilienza*, PNRR). The same policy impulse may be absorbed at different speeds depending on local productive structure, healthcare provision capacity, demographic fragility, and the broader ability of the local system to reorganize resources after a disturbance. From this perspective, resilience metrics can help identify not only where needs are larger, but also where adjustment may require more time and complementary support.

The same data constraints that motivate the empirical strategy also define the scope and limits of the results. First, because the available municipal series are short, the empirical strategy exploits municipalities as repeated observations within each province and recovers province-specific average adjustment patterns. The resulting indicators should therefore be read as measures of the resilience of provincial urban systems, rather than as direct measures of the resilience of each individual municipality or city. Second, the analysis is necessarily limited to the domains that can be observed with sufficient temporal continuity and territorial coverage in public secondary data. A further issue concerns the identification of the relationships among local variables. With short annual panels and publicly available secondary data, the analysis cannot fully disentangle all simultaneity and endogeneity channels among economic, social, demographic, and health-related conditions. The lag structure adopted in the empirical model mitigates the most immediate simultaneity concerns and is consistent with the descriptive objective of the article.

Future research could move beyond these limitations by combining comparable public secondary data with administrative information collected within individual cities or networks of cities. Such data would make it possible to measure resilience more directly at the city level, to include a richer set of urban outcomes, and to specify a more complete system of relationships among economic, social, demographic, healthcare, infrastructural, and institutional variables. More granular administrative data could also help address endogeneity and simultaneity concerns more directly, for example, by providing more precise timing, richer information on local policies and institutional conditions, and city-specific shocks or interventions. At the same time, this research agenda would require moving beyond readily available public sources. Building long and comparable time series from city-level administrative data is itself a demanding task, because access, definitions, coverage, digitization, and data-governance arrangements may differ substantially across municipalities.

Appendix A: Derivation of the model-based resilience metrics

After estimating (1), the disequilibrium term is constructed from the estimated long-run relation as

$$ECT_{it} \equiv Poor_{it} - \widehat{\alpha}_i - \widehat{\kappa} GDP_{it}.$$

It then follows that

$$ECT_{it} - ECT_{i,t-1} = \Delta Poor_{it} - \widehat{\kappa}\, \Delta GDP_{it}.$$

Substituting (5) and (6), and recalling the definitions of ϕ, ψ_m, and χ, yields (7), where

$$\nu_{it} = u_{it}^{Poor} - \widehat{\kappa}\, u_{it}^{GDP}$$

is the composite disturbance term implied by the two dynamic equations.

Let the system be initially on its estimated province-specific GDP–poverty relation, so that $ECT_{i,t-1} = 0$, and let predetermined variable $\widetilde{x}^{(m)}$ initially be at its baseline level x^*. Since the ECM uses lagged structural regressors, suppose that the shock first affects the system through

$$\widetilde{x}_{i,t-1}^{(m)} = x^* + \Delta x.$$

The shock is *temporary* if

$$\widetilde{x}_{i,\tau}^{(m)} = x^* \quad \forall \tau \geq t,$$

and *permanent* if

$$\widetilde{x}_{i,\tau}^{(m)} = x^* + \Delta x \quad \forall \tau \geq t.$$

For a temporary shock, the long-run disequilibrium does not change. At impact,

$$ECT_{it} = \psi_m \Delta x.$$

For $n \geq 0$, repeated substitution into (7) gives

$$ECT_{i,t+n} = \phi^n \psi_m \Delta x.$$

At impact, the temporary shock enters the two dynamic equations through their direct coefficients:

$$\Delta GDP_{it} = \theta_{GDP,m} \Delta x, \quad \Delta Poor_{it} = \theta_{Poor,m} \Delta x.$$

For $n \geq 1$, the subsequent responses are driven by the adjustment of the disequilibrium term:

$$\begin{aligned} \Delta GDP_{i,t+n} &= \lambda_{GDP} ECT_{i,t+n-1} = \lambda_{GDP} \phi^{n-1} \psi_m \Delta x, \\ \Delta Poor_{i,t+n} &= \lambda_{Poor} ECT_{i,t+n-1} = \lambda_{Poor} \phi^{n-1} \psi_m \Delta x, \end{aligned}$$

which give (9) and (10). Under $|\phi| < 1$, both residual elasticities converge to zero.

The Covid intervention is treated as a temporary common pulse, so that

$$C_t = 1 \quad \text{only in 2020}, \quad C_\tau = 0 \quad \text{otherwise.}$$

At impact, the disequilibrium response is

$$ECT_{it} = \chi.$$

For $n \geq 0$,

$$ECT_{i,t+n} = \phi^n \chi.$$

At impact, the Covid pulse enters directly as

$$\Delta GDP_{it} = \delta_{GDP}, \quad \Delta Poor_{it} = \delta_{Poor}.$$

For $n \geq 1$, the subsequent responses again operate through the disequilibrium term:

$$\begin{aligned}\Delta GDP_{i,t+n} &= \lambda_{GDP} ECT_{i,t+n-1} = \lambda_{GDP} \phi^{n-1} \chi, \\ \Delta Poor_{i,t+n} &= \lambda_{Poor} ECT_{i,t+n-1} = \lambda_{Poor} \phi^{n-1} \chi,\end{aligned}$$

which give (11) and (12). Under $|\phi| < 1$, these equation-specific Covid metrics also converge to zero.

For a permanent shock, the system no longer returns to the original disequilibrium level. Instead, it converges to a new long-run disequilibrium level. With

$$\widetilde{x}_{i,\tau}^{(m)} = x^* + \Delta x \quad \forall \tau \geq t-1,$$

repeated substitution yields

$$ECT_{i,t+n} = \psi_m \Delta x \sum_{j=0}^{n} \phi^j = \psi_m \Delta x \frac{1-\phi^{n+1}}{1-\phi}, \quad n \geq 0,$$

provided $|\phi| < 1$. Letting $n \to \infty$, we obtain the new long-run disequilibrium level (8).

For a permanent shock, equations (5) and (6) imply, for $n \geq 1$,

$$\begin{aligned}\Delta GDP_{i,t+n} &= \theta_{GDP,m} \Delta x + \lambda_{GDP} ECT_{i,t+n-1}, \\ \Delta Poor_{i,t+n} &= \theta_{Poor,m} \Delta x + \lambda_{Poor} ECT_{i,t+n-1}.\end{aligned}$$

Substituting the permanent-shock path for ECT gives

$$\begin{aligned}\Delta GDP_{i,t+n} &= \left(\theta_{GDP,m} + \lambda_{GDP} \psi_m \frac{1-\phi^n}{1-\phi}\right) \Delta x, \\ \Delta Poor_{i,t+n} &= \left(\theta_{Poor,m} + \lambda_{Poor} \psi_m \frac{1-\phi^n}{1-\phi}\right) \Delta x.\end{aligned}$$

Letting $n \to \infty$, the corresponding long-run responses are (13) and (14). The permanent-shock metrics are (15) and (16). Under $|\phi| < 1$, both missing shares converge to zero as the GDP and poverty equations adjust toward their new long-run responses.

Appendix B: Unit-root diagnostic on the disequilibrium residual

We report a Harris–Tzavalis panel unit-root test on the disequilibrium residual. The key reason for using this diagnostic is that, within each province, the residual is observed for many municipalities over only a few years. A standard time-series unit-root test would require collapsing this information into a single aggregated provincial series, whereas the Harris–Tzavalis approach preserves the panel nature of the residual and

Table 5 Harris–Tzavalis panel unit-root test on the disequilibrium residual by province

Province	N	HT statistic	p-value
Torino	307	−18.486	0.0000
Vercelli	79	−9.756	0.0000
Novara	86	−10.320	0.0000
Cuneo	246	−16.586	0.0000
Asti	116	−12.285	0.0000
Alessandria	182	−13.233	0.0000
Imperia	65	−8.936	0.0000
Savona	69	−7.003	0.0000
Genova	67	−6.744	0.0000
La Spezia	32	−5.076	0.0000
Varese	134	−10.538	0.0000
Como	143	−9.965	0.0000
Sondrio	76	−7.922	0.0000
Milano	132	−8.256	0.0000
Bergamo	242	−20.045	0.0000
Brescia	205	−12.466	0.0000
Pavia	183	−18.368	0.0000
Cremona	112	−10.267	0.0000
Mantova	62	−4.101	0.0000
Trento	144	−19.775	0.0000
Verona	98	−7.823	0.0000
Vicenza	107	−8.018	0.0000
Belluno	56	−8.285	0.0000
Treviso	93	−5.546	0.0000
Venezia	44	−5.343	0.0000
Padova	99	−5.433	0.0000
Rovigo	50	−6.551	0.0000
Udine	131	−10.501	0.0000
Gorizia	25	−4.200	0.0000
Trieste	6	−1.763	0.0390
Piacenza	44	−6.260	0.0000
Parma	42	−3.649	0.0001
Reggio nell’Emilia	41	−7.396	0.0000
Modena	47	−7.530	0.0000
Bologna	54	−7.779	0.0000
Ferrara	18	−4.525	0.0000
Ravenna	18	−4.974	0.0000
Forlì-Cesena	30	−5.264	0.0000
Pesaro e Urbino	47	−8.484	0.0000
Ancona	47	−4.420	0.0000
Macerata	54	−8.254	0.0000

Table 5 continued

Province	N	HT statistic	p-value
Ascoli Piceno	33	−5.088	0.0000
Massa-Carrara	17	−2.885	0.0020
Lucca	33	−5.595	0.0000
Pistoia	18	−4.394	0.0000
Firenze	40	−5.004	0.0000
Livorno	18	−2.409	0.0080
Pisa	37	−0.514	**0.3037**
Arezzo	35	−4.584	0.0000
Siena	34	−5.172	0.0000
Grosseto	28	−3.082	0.0010
Perugia	59	−12.155	0.0000
Terni	33	−7.336	0.0000
Viterbo	60	−6.457	0.0000
Rieti	73	−7.600	0.0000
Roma	121	−6.911	0.0000
Latina	33	−0.530	**0.2980**
Frosinone	91	−9.173	0.0000
Caserta	104	−7.913	0.0000
Benevento	78	−11.168	0.0000
Napoli	92	−2.920	0.0018
Avellino	118	−10.419	0.0000
Salerno	158	−7.105	0.0000
L'Aquila	107	−9.085	0.0000
Teramo	47	−8.809	0.0000
Pescara	46	−5.630	0.0000
Chieti	102	−11.573	0.0000
Campobasso	84	−8.845	0.0000
Foggia	61	−5.397	0.0000
Bari	41	−2.689	0.0036
Taranto	29	−1.812	0.0350
Brindisi	20	−1.320	**0.0934**
Lecce	95	−2.401	0.0082
Potenza	100	−8.022	0.0000
Matera	31	−7.722	0.0000
Cosenza	148	−7.590	0.0000
Catanzaro	80	−4.922	0.0000
Reggio Calabria	97	−5.777	0.0000
Trapani	24	−4.053	0.0000
Palermo	82	−9.822	0.0000
Messina	108	−8.723	0.0000
Agrigento	43	−4.723	0.0000

Table 5 continued

Province	N	HT statistic	p-value
Caltanissetta	22	−3.559	0.0002
Enna	20	−4.609	0.0000
Catania	58	−1.162	**0.1226**
Ragusa	12	−2.328	0.0100
Siracusa	21	−1.135	**0.1282**
Sassari	66	−8.981	0.0000
Nuoro	52	−7.205	0.0000
Cagliari	17	−1.268	**0.1024**
Pordenone	50	−5.551	0.0000
Isernia	52	−8.707	0.0000
Oristano	87	−9.964	0.0000
Biella	70	−9.251	0.0000
Lecco	81	−7.731	0.0000
Lodi	58	−3.507	0.0002
Rimini	24	−4.146	0.0000
Prato	7	−3.674	0.0001
Crotone	27	−4.914	0.0000
Vibo Valentia	50	−4.532	0.0000
Verbano-Cusio-Ossola	72	−9.737	0.0000
Monza e della Brianza	55	−4.960	0.0000
Fermo	40	−11.761	0.0000
Barletta-Andria-Trani	10	−1.515	**0.0649**

N is the number of municipalities in the provincial panel. The time dimension is fixed at $T = 10$ for all provinces. Boldface p-values indicate failure to reject the null hypothesis of a unit root at the 5% level

is specifically designed for settings with many cross-sectional units and a short, fixed time dimension (Harris and Tzavalis 1999). The null hypothesis is that the residual contains a unit root. The time dimension is fixed at $T = 10$ for all provinces. This test therefore provides a natural diagnostic for the mean-reversion properties of the estimated disequilibrium term.

Table 5 shows that the null hypothesis of a unit root is not rejected at the 5% level in 7 provinces out of 104. Thus, for most provinces, the Harris–Tzavalis diagnostic is consistent with a mean-reverting disequilibrium residual.

Appendix C: Correlation among metrics

See the Table 6.

Table 6 Pairwise correlations across resilience metrics

	T-GDP-F	T-GDP-HAV	T-GDP-HCS	T-GDP-L	T-Poor-F	T-Poor-HAV	T-Poor-HCS	T-Poor-L	P-GDP-F	P-GDP-HAV	P-GDP-HCS	P-GDP-L	P-Poor-F	P-Poor-HAV	P-Poor-HCS	P-Poor-L	C-GDP	C-Poor
T-GDP-F	1.000																	
T-GDP-HAV	**0.598**	1.000																
T-GDP-HCS	**0.838**	**0.609**	1.000															
T-GDP-L	**0.833**	**0.596**	**0.782**	1.000														
T-Poor-F	**0.442**	*0.223*	*0.222*	*0.254*	1.000													
T-Poor-HAV	*0.349*	**0.863**	*0.346*	*0.348*	*0.317*	1.000												
T-Poor-HCS	*0.246*	*0.241*	**0.513**	*0.208*	*0.279*	*0.210*	1.000											
T-Poor-L	**0.445**	*0.389*	*0.341*	**0.599**	**0.657**	**0.456**	*0.274*	1.000										
P-GDP-F	**0.459**	*0.219*	**0.440**	**0.630**	0.162	0.113	0.142	**0.410**	1.000									
P-GDP-HAV	**0.534**	**0.547**	**0.531**	**0.498**	0.178	**0.460**	0.194	*0.283*	*0.274*	1.000								
P-GDP-HCS	**0.617**	**0.721**	**0.647**	**0.632**	*0.206*	**0.576**	*0.269*	*0.379*	*0.261*	**0.522**	1.000							
P-GDP-L	**0.465**	*0.263*	**0.446**	**0.550**	0.149	0.132	0.184	*0.361*	*0.364*	*0.259*	*0.276*	1.000						
P-Poor-F	−0.006	−0.012	−0.017	0.019	0.020	0.027	−0.016	0.093	**0.672**	−0.010	−0.028	−0.006	1.000					
P-Poor-HAV	0.111	*0.235*	0.112	0.085	0.123	*0.355*	0.119	0.152	0.046	**0.698**	*0.310*	0.034	0.027	1.000				
P-Poor-HCS	0.097	*0.256*	0.132	0.098	0.182	*0.298*	*0.248*	0.194	−0.007	*0.243*	**0.707**	0.014	−0.033	*0.322*	1.000			
P-Poor-L	0.044	0.023	0.064	0.070	0.086	0.061	0.089	0.153	0.026	0.013	0.017	**0.749**	−0.016	−0.001	0.002	1.000		
C-GDP	*0.380*	*0.248*	*0.400*	**0.417**	0.059	0.112	0.079	0.152	*0.239*	*0.283*	*0.318*	*0.243*	−0.006	0.132	0.061	0.025	1.000	
C-Poor	*0.215*	*0.296*	0.162	*0.297*	*0.222*	*0.337*	0.143	**0.507**	0.108	*0.337*	*0.241*	0.167	0.010	*0.304*	0.139	0.071	0.174	1.000

Appendix D: Robustness to omitting the Covid pulse

This appendix assesses the robustness of the main results to omitting the Covid pulse from the baseline specification. The comparison focuses on whether the key coefficients preserve their sign, remain significant conditional on sign preservation, display similar provincial distributions, and retain a similar territorial ranking across the two specifications. Table 7 first summarizes the comparison across all estimated parameters in the two specifications.[13]

Table 7 shows that omitting the Covid pulse does not overturn the qualitative interpretation of the results, but it does modify the magnitude of some parameters. The dynamic coefficients remain negative in both specifications and preserve a very similar territorial ordering, although the comparison also suggests slightly faster adjustment in the GDP equation and slightly slower adjustment in the $Poor$ equation when the pulse is omitted. Among the slope coefficients, the clearest quantitative differences concern $\theta_{GDP,F}$, $\theta_{Poor,F}$, and the coefficients associated with $\widetilde{L}$. In particular, $\theta_{Poor,L}$ becomes markedly larger in absolute magnitude in the specification without the pulse, while $\theta_{GDP,L}$ becomes less conclusive. This pattern suggests that, when the common Covid shock is not isolated explicitly, part of its effect is absorbed by the structural channels, above all by age-related fragility. By contrast, $\theta_{GDP,HAV}$, $\theta_{Poor,HAV}$, $\theta_{GDP,HCS}$, and $\theta_{Poor,HCS}$ are much more stable across specifications. Taken together, these results indicate that the main mechanisms identified in the baseline model survive the alternative specification, even though the omission of the Covid pulse partly redistributes the quantitative weight of some channels.

[13] The corresponding province-level estimates for the GDP and $Poor$ equations from which the summary results are derived can be requested from the authors.

Table 7 Robustness summary: with and without Covid pulse

Coefficient	Q1 (pulse)	Q1 (no pulse)	Median (pulse)	Median (no pulse)	Q3 (pulse)	Q3 (no pulse)	Share same sign	Share among significant same-sign provinces (pulse)	Share among significant same-sign provinces (no pulse)	Spearman corr
λ_{GDP}	−0.285	−0.325	−0.211	−0.225	−0.145	−0.163	0.981	0.892	0.931	0.930
λ_{Poor}	−0.471	−0.446	−0.360	−0.348	−0.265	−0.218	1.000	0.904	0.856	0.966
$\theta_{GDP,F}$	−0.003	0.033	0.035	0.092	0.107	0.177	0.827	0.465	0.640	0.661
$\theta_{Poor,F}$	−0.172	−0.241	−0.064	−0.138	−0.016	−0.068	0.885	0.554	0.685	0.749
$\theta_{GDP,HAV}$	−0.014	−0.018	0.008	0.006	0.023	0.024	0.885	0.196	0.261	0.876
$\theta_{Poor,HAV}$	−0.040	−0.034	−0.006	−0.004	0.026	0.025	0.942	0.184	0.143	0.921
$\theta_{GDP,HCS}$	−0.003	−0.006	0.008	0.006	0.019	0.018	0.904	0.745	0.766	0.869
$\theta_{Poor,HCS}$	−0.041	−0.042	−0.014	−0.010	−0.000	0.001	0.942	0.796	0.735	0.943
$\theta_{GDP,L}$	−1.022	−2.095	0.493	−0.481	2.468	0.602	0.798	0.831	0.795	0.855
$\theta_{Poor,L}$	0.074	1.199	0.966	2.396	2.260	3.174	0.885	0.739	0.859	0.804

Appendix E: Additional maps not reported in the main text

See the Figs. 5, 6 and 7.

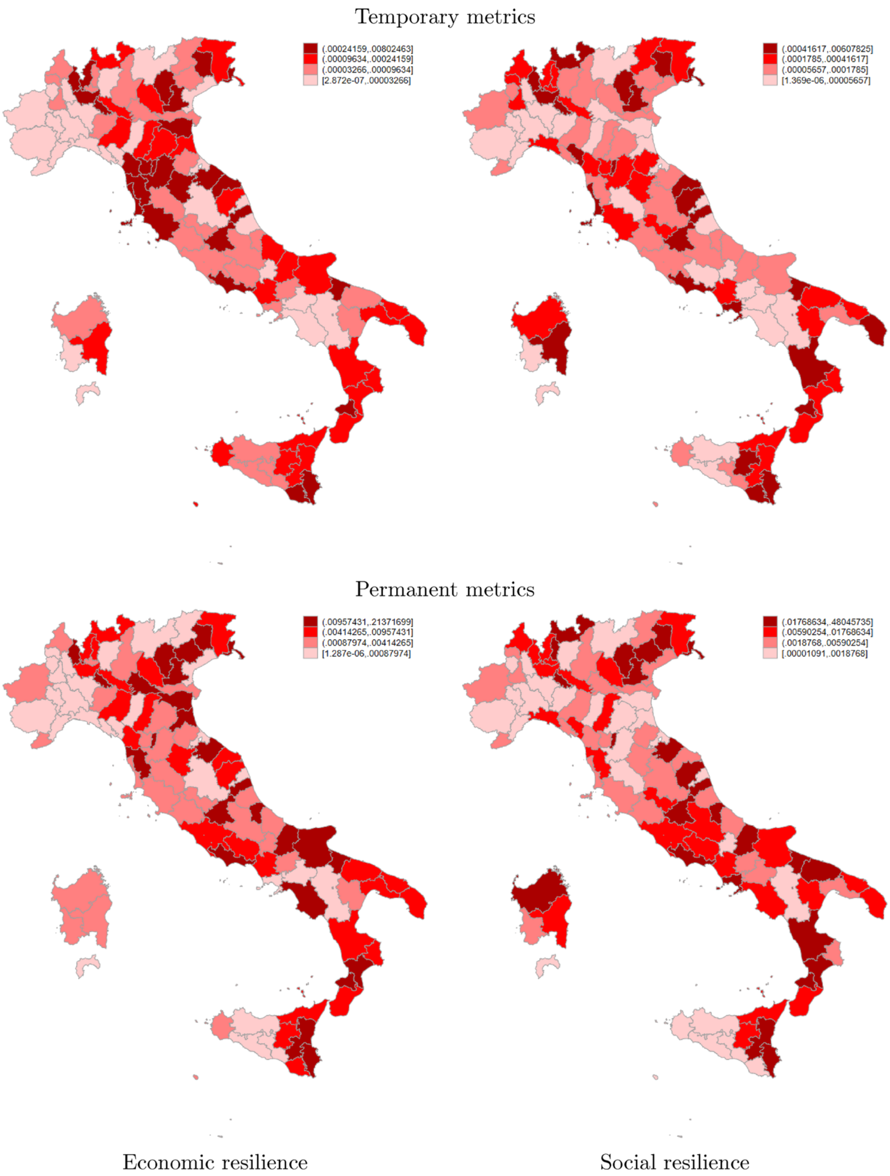


Fig. 5 HAV's metrics

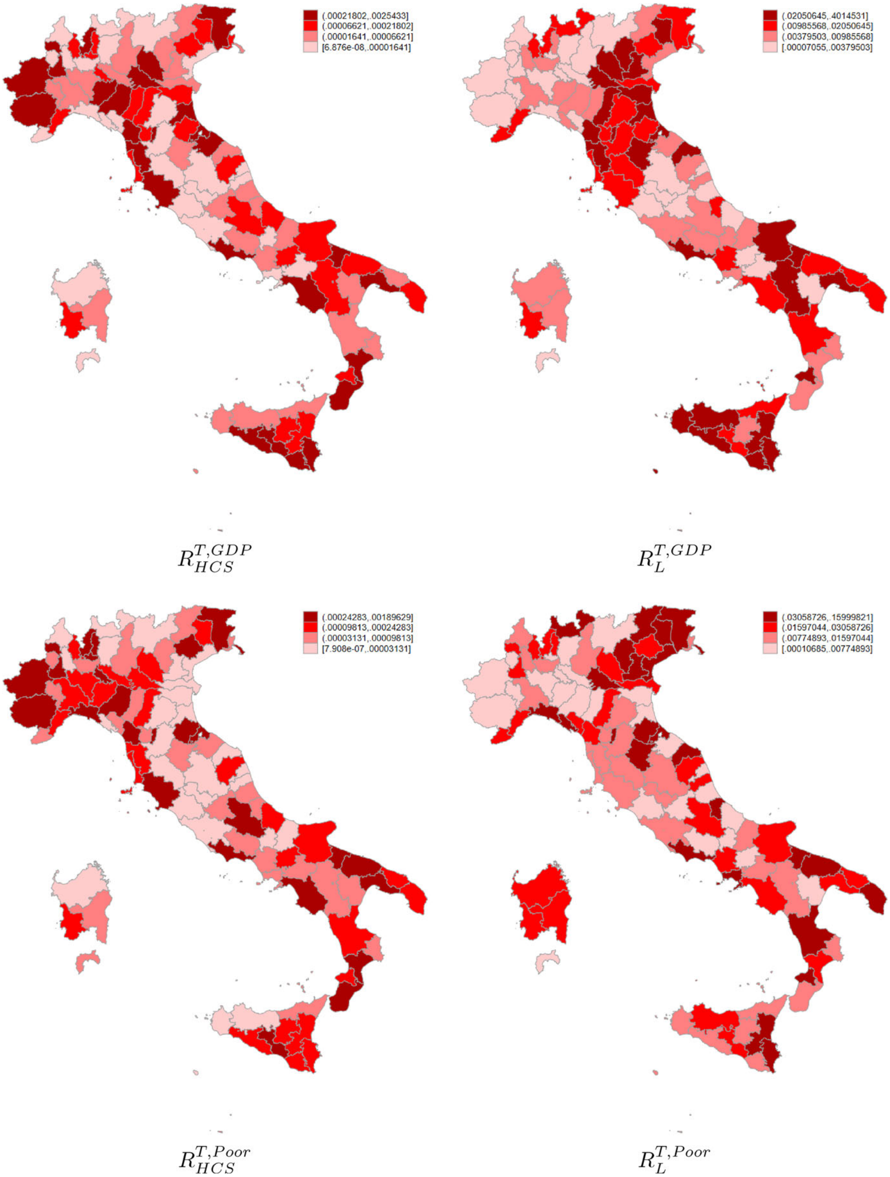
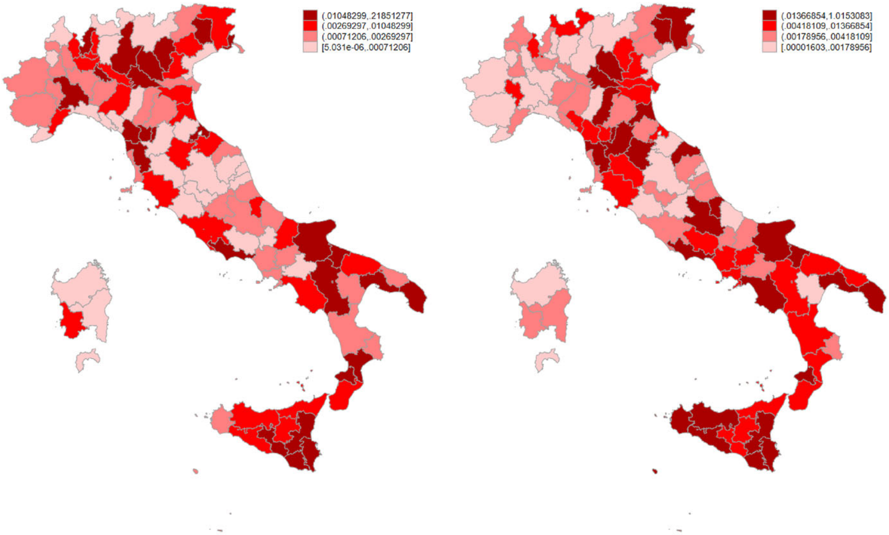


Fig. 6 Remaining temporary metrics



$R_{HCS}^{P,GDP}$ $R_{L}^{P,GDP}$

Fig. 7 Remaining permanent metrics

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Declarations

Conflict of interest The authors declare no conflict of interest.

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