Journal Pre-proof

Better politicians, fewer deaths? Local resilience in overcoming the pandemic crisis in Italy

Stefania Fontana, Calogero Guccio, Giacomo Pignataro, Francesco Vidoli

PII: S0277-9536(26)00274-1
DOI: https://doi.org/10.1016/j.socscimed.2026.119198
Reference: SSM 119198

To appear in: *Social Science & Medicine*

Received date : 31 July 2025
Revised date : 11 March 2026
Accepted date : 15 March 2026

Please cite this article as: S. Fontana, C. Guccio, G. Pignataro et al., Better politicians, fewer deaths? Local resilience in overcoming the pandemic crisis in Italy. *Social Science & Medicine* (2026), doi: https://doi.org/10.1016/j.socscimed.2026.119198.

Better Politicians, Fewer Deaths? Local Resilience in Overcoming the Pandemic Crisis in Italy

Abstract

The quality of institutions is widely recognized as a key determinant of public sector performance across various levels of governance. This paper investigates how institutional quality shaped the resilience of Italian Labour Market Areas during the COVID-19 pandemic. To this end, we introduce a localized, non-parametric Interrupted Time Series (ITS) approach, using long-run mortality data (2004-2023), to construct a data-driven, local-level resilience index. This index captures deviations from counterfactual mortality trajectories, reflecting the ability of local areas to withstand and recover from the pandemic. We then assess the determinants of this resilience index, with a particular focus on institutional quality. Our findings show that higher institutional quality - particularly the quality of local politicians - emerges as the most significant factor driving differences in performance at the local level. Multiple robustness checks, including alternative model specifications and pre-pandemic forecast accuracy benchmarks, confirm the reliability of our results.

Keywords: Institutional quality, Health sector resilience, Resilience indices, Interrupted time series, Extreme Gradient Boosting
JEL: I18; C43; C53

1. Introduction

The COVID-19 pandemic has presented a profound and unprecedented test for institutions around the world, exposing stark differences in the capacity of governments, especially at the local level, to respond effectively to large-scale shocks, as exemplified by the significant spatial heterogeneity observed in Italy (Benedetti et al., 2020; ISTAT and ISS, 2020, 2022). While much attention has focused on national policies and healthcare infrastructures, the crisis also highlighted the critical role of local governance and institutions in mitigating adverse outcomes. Subnational governments were on the frontline of crisis management, playing a pivotal role in implementing nationally designed policies and ensuring the continuity of essential public services (OECD, 2021; de Mello and Ter-Minassian, 2022). At the local level, preparedness for shocks, administrative and coordination capacities, and adaptability emerged as key determinants of effective crisis management (Previtali and Salvati, 2023). In Italy, one of the earliest and most severely affected countries, qualitative and descriptive evidence highlights the operational importance of local institutions in mitigating negative outcomes, coordinating central and regional authorities with local communities, addressing social-assistance needs, and maintaining essential local services (Garavaglia et al., 2021).

Building on this premise, the study investigates how the institutional quality of local governments affected the health resilience of local communities in Italy. Resilience is empirically evaluated during the COVID-19 pandemic using Local Market Areas (LMAs) - clusters of municipalities defined by commuting flows - as the relevant spatial unit of analysis, thereby capturing both local health-system capacity and population exposure within integrated labour and mobility markets. Italy provides a particularly informative setting for this analysis. It was among the first European countries to experience a severe COVID-19 outbreak and is characterized by substantial subnational heterogeneity in institutional quality. Long-standing historical differences - such as those between areas shaped by medieval republican institutions and those governed by more autocratic regimes - continue to influence contemporary patterns of local governance quality (Diliberto and Sideri, 2015; Guiso et al., 2016). This institutional diversity offers a valuable opportunity to assess how deep-rooted governance characteristics condition population responses to large-scale health shocks.

Although resilience - both in general and in its health dimension, understood as the capacity to absorb, adapt to, and recover from a crisis - is inherently difficult to operationalize empirically, we focus on a concrete and policy-relevant outcome: all-cause mortality in the general population following the initial COVID-19 shock and over the subsequent recovery period. Our empirical results indicate that institutional quality played a significant role in shaping local health resilience to the pandemic. Among the various dimensions of institutional quality, the competence of political leadership emerges as the most influential factor. These findings are robust across alternative model specifications and forecasting benchmarks, supporting the conclusion that effective local governance substantially mitigated the mortality burden associated with the COVID-19 crisis.

This paper makes two contributions to the literature. First, we introduce a novel, data-driven methodology to measure resilience in Italian LMAs using a geographically localized, non-parametric Interrupted Time Series (ITS) approach. Leveraging monthly all-cause mortality data from 2004 to 2023, we generate LMA-specific counterfactual trajectories to estimate excess mortality. Unlike traditional ITS models that rely on linear trends or parametric assumptions (Bernal et al., 2017; Schaffer et al., 2021), we enhance this framework with Extreme Gradient Boosting (XGBoost), a machine learning technique capable of capturing complex, non-linear temporal patterns. Methodologically, our approach relates to recent work that employs machine learning techniques to estimate counterfactual mortality trajectories, in particular Cerqua et al. (2021). While this study focuses on predictive performance across a range of algorithms and shows how these methods improve excess mortality estimates, we rely on XGBoost to construct a dynamic, counterfactual-based indicator and examine how institutional quality is associated with local mortality outcomes during the pandemic.

Second, we explore the determinants of local resilience, focusing on the role of institutional quality. Specifically, we ask whether LMAs with stronger institutions-particularly in terms of political leadership-were more effective in managing the pandemic. To do so, we employ the Municipal Administration Quality Index (MAQI) developed by Cerqua et al. (2025a), which measures local government performance across bureaucratic efficiency, fiscal soundness, and the competence of political leaders. Our results reveal that the positive impact of institutional quality on resilience is driven almost exclusively by the quality of local politicians (Pillar II). Conversely, bureaucratic efficiency and financial stability do not appear to be statistically significant determinants in the context of the pandemic crisis.

Our analysis is situated within a broader literature on how institutions respond to and are shaped by systemic shocks. Scholars such as Alesina and Giuliano (2015) and Nunn (2020) emphasize that major disruptions can have lasting effects on institutional structures and cultural norms, particularly in relation to trust. Trust, in turn, plays a foundational role in supporting economic performance by fostering innovation, financial intermediation, and labour market participation (Algan and Cahuc, 2013). However, trust is unevenly distributed across and within countries (Tabellini, 2010), and can erode during crises, especially when governments are perceived as ineffective (Algan et al., 2017; Kroknes et al., 2015; Aksoy et al., 2020). This erosion undermines the legitimacy of public institutions and their capacity to manage future shocks (Funke et al., 2020; Acemoglu et al., 2013; Bottasso et al., 2022; Li et al., 2021; Cannonier and Burke, 2025).

More specifically, our work relates to recent studies that examine the role of trust in local institutions as a potential driver of community resilience in the context of public health shocks such as pandemics, highlighting its relevance for compliance with public health measures and local pandemic outcomes (Fraser and Aldrich, 2021; Fraser et al., 2022; Busic-Sontic and Schubert, 2024). In emphasizing the role of local institutional quality, our work complements Rodríguez-Pose and Burlina (2021), who show that weak national government effectiveness was correlated with higher excess mortality during the first half of 2020 across European regions. Our work is also closely related to Alfano and Ercolano (2021), who investigate the role of institutional quality and social capital in mediating the effectiveness of lockdown measures across Italian provinces. They find that both factors, particularly institutional quality, are associated with larger reductions in new COVID-19 cases and argue that stronger institutions promote higher compliance with containment measures.

In sum, this paper contributes to both the theoretical and empirical understanding of institutional resilience. By combining a novel methodological framework with a rich institutional dataset, we provide evidence that effective local governance - particularly through competent political leadership - can mitigate the human cost of crises. These findings offer valuable insights for policymakers seeking to strengthen institutional capacity and build more resilient communities in anticipation of future shocks.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on resilience and ITS methodologies. Section 3 presents the results. Section 4 discusses policy implications. Section 5 concludes.

2. Literature Review

2.1. Resilience: conceptualization and measurement

Resilience is a multifaceted concept that has been conceptualized across disciplines - ranging from physics and philosophy to the social sciences. In economics, resilience is commonly understood as an economy's capacity to withstand, absorb, and recover from external shocks, such as financial crises, natural disasters, or pandemics. This notion encompasses both the robustness of systems in resisting initial impacts and their adaptability in managing the recovery process.

Empirically measuring resilience, however, poses significant challenges. It requires not only identifying the effects of a shock but also evaluating the process of recovery. The key challenge lies in capturing how rapidly and effectively a system returns to equilibrium-or establishes a new one-following a disruption.

Initial attempts to measure economic resilience emerged from regional economics, where scholars studied how different territories responded to macroeconomic shocks. One class of approaches, termed *capacity-based*, constructs composite indicators based on presumed drivers of resilience-such as infrastructure, labour market flexibility, and innovation potential (Briguglio et al., 2009; Rizzi et al., 2018). While useful in assessing ex-ante preparedness, these indicators rely heavily on theoretical assumptions and risk conflating resilience *drivers* with *outcomes* (Sensier et al., 2016).

An alternative is the *revealed resilience* approach (Alessi et al., 2020), which evaluates post-shock outcomes using observable economic indicators like GDP or employment. This approach captures both the *resistance* (initial impact) and *recovery* (return to baseline) dimensions of resilience. One prominent example is the sensitivity/recovery framework developed by Martin (2012), which compares the performance of a region during and after a shock to national averages or peer group benchmarks (Fingleton et al., 2012; Lagravinese, 2015; Di Caro and Fratesi, 2018; Faggian et al., 2018).

However, relative measures such as these depend heavily on the choice of benchmark, which may be problematic in cases where shocks vary spatially in timing or severity-as occurred during the staggered COVID-19 waves across Italian regions. To address these limitations, some scholars propose *absolute* measures that rely on historical baselines or counterfactual trajectories for each unit (Sensier et al., 2016; Fratesi and Perucca, 2018; Alessi et al., 2020).

In this study, we adopt a strictly outcome-based definition of resilience, operationalized as the capacity of a local system to minimize deviations from its expected mortality trajectory following a health shock. While resilience is a multidimensional construct involving social and economic adaptation, we focus specifically on excess mortality as the primary revealed indicator of system performance. This choice allows us to empirically test whether higher institutional quality translates into a concrete ability to protect public health and mitigate the biological impact of the crisis.

Finally, from a methodological point of view, we adopt a localized ITS framework that compares observed mortality to a model-estimated counterfactual, producing a single, comprehensive measure of resilience. This method retains the advantages of revealed outcome measures while avoiding arbitrary benchmarking, enabling us to assess each LMA relative to its own historical trend. Moreover, this approach captures both short-term shocks and long-term recovery trajectories within a common modelling framework.

2.2. Interrupted Time Series Analysis in the Health Domain

Interrupted time series (ITS) analysis is widely regarded as one of the most robust quasi-experimental designs for evaluating the effects of interventions when randomized controlled trials are not feasible (Bernal et al., 2018b). ITS leverages longitudinal data collected at regular intervals before and after an intervention (or shock) to estimate its causal effect by extrapolating pre-intervention trends into the post-intervention period (Bernal et al., 2017; Jandoc et al., 2015). This technique is particularly valuable in settings where control groups are unavailable, and it reduces bias relative to simple pre-post comparisons by accounting for underlying secular trends (Penfold and Zhang, 2013).[1]

ITS has been extensively applied in health economics and public health research to assess the impacts of vaccination programs (Bernal et al., 2019), tobacco control policies (Barone-Adesi et al., 2011), road safety initiatives (Grundy et al., 2009; Dennis et al., 2013), drug regulation (Jandoc et al., 2015), and unanticipated shocks such as financial crises (Bernal et al., 2013) and the COVID-19 pandemic (Li et al., 2023).

[1]ITS can also be extended to multiple-group designs, where the inclusion of a comparable control group strengthens internal validity (Linden and Adams, 2011; Linden, 2018; Bernal et al., 2018a).

The most common ITS model is segmented regression, which estimates both level and trend changes associated with an intervention (Wagner et al., 2002; Kontopantelis et al., 2015; Bernal et al., 2017). For more complex time series, autoregressive integrated moving average (ARIMA) models are often used to explicitly account for autocorrelation, seasonality, and nonstationarity (Box and Jenkins, 1970; Schaffer et al., 2021). Recent literature has proposed sophisticated enhancements to the traditional ITS design, for instance by combining counterfactual outcomes with ARIMA models to improve forecasting accuracy (Menchetti et al., 2023). However, in the context of local mortality data characterized by high noise and non-linear dynamics, parametric assumptions may still be too restrictive. This data-driven approach, furthermore, aligns with recent methodological shifts in regional policy evaluation (*e.g.*, Cerqua et al., 2021), which demonstrate that non-parametric techniques can generate more accurate counterfactuals in contexts characterized by high heterogeneity and structural volatility.

This study advances the ITS framework in two key ways. First, in addition to ARIMA, we incorporate a machine learning algorithm - Extreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016; Hastie et al., 2009) - to generate robust, non-parametric counterfactuals.
More in depth, XGBoost is a high-performance machine learning algorithm that combines decision trees in an additive, sequential manner to improve predictive accuracy through gradient-based optimisation. It is particularly suited to large and complex datasets, as it efficiently models non-linear relationships and interactions across multiple predictors while maintaining computational efficiency.
Formally, XGBoost minimises a differentiable loss function $L(y, \hat{y})$ through an additive model expansion. The general objective function is:

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} L(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \Omega(f_k), \tag{1}$$

where $\hat{y}_i^{(t)}$ denotes the prediction for observation i at iteration t, f_k represents the k-th decision tree, and $\Omega(f)$ is a regularisation term controlling model complexity to avoid overfitting.
To optimise this function, XGBoost applies a second-order Taylor expansion:

$$\mathcal{L}^{(t)} \approx \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t), \tag{2}$$

where $g_i = \frac{\partial L(y_i, \hat{y}_i^{(t-1)})}{\partial \hat{y}_i^{(t-1)}}$ and $h_i = \frac{\partial^2 L(y_i, \hat{y}_i^{(t-1)})}{\partial \hat{y}_i^{(t-1)2}}$ are the first- and second-order derivatives of the loss function. The algorithm incrementally adds trees by maximising the gain from each split, thereby refining model accuracy. The regularisation term $\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$ constrains both the number of leaves T and their associated weights w_j, ensuring stability and interpretability of results.

Second, unlike traditional ITS studies that estimate a global average effect, we employ a localized design at the Labour Market Area (LMA) level. This enables us to capture spatial heterogeneity and context-specific dynamics that would be lost in aggregate models, yet are potentially crucial in explaining uneven resilience outcomes (Bosque-Mercader et al., 2025). Importantly, this localized approach also allows us to examine how institutional contexts shape resilience across the Italian territory.

Table 1 summarises the main conceptual and methodological differences between the conventional ITS framework and the enhanced approach proposed in this study. The resulting framework not only improves predictive performance but also strengthens the analytical foundation for assessing territorial resilience and policy effectiveness in the face of systemic shocks.

Analytical dimension	**Traditional ITS framework**	**Extended ITS with XGBoost**
Modelling approach	Parametric segmented regression or ARIMA models assuming linear relationships between variables.	Non-parametric machine learning model (XGBoost) capable of capturing non-linear, high-dimensional relationships without strict parametric assumptions.
Counterfactual construction	Based on extrapolation of pre-intervention linear trend.	Based on data-driven estimation using multiple predictors and temporal interactions, generating robust and adaptive counterfactual trajectories.
Treatment of autocorrelation and seasonality	Explicitly modelled through ARIMA structure or included as covariates.	Implicitly handled by the learning algorithm through iterative optimisation and feature selection.
Spatial design	Typically estimated at national or regional aggregate level, assuming homogeneous effects across units.	Fully localised estimation at Labour Market Area (LMA) level, allowing for heterogeneous responses and local contextual interpretation.
Interpretation of results	Focused on average level and slope changes following the intervention.	Focused on unit-specific deviations from counterfactuals, quantifying both magnitude and persistence of the shock across territories.
Resilience analysis	Indirectly inferred through trend recovery analysis.	Explicitly measured via post-shock convergence toward the counterfactual series, enabling a dynamic assessment of recovery capacity.
Policy relevance	Provides general insights into national intervention effects.	Offers granular evidence on local performance and vulnerability, supporting differentiated and place-based policy responses.

Table 1: Comparison between traditional and extended Interrupted Time Series (ITS) approaches

3. Local Resilience in the Face of the COVID-19 Crisis in Italy

3.1. Data sources, model specifications, and analytical techniques

The dataset employed in this study comprises monthly mortality data at the municipal level, spanning the period from January 2003 to August 2023. The primary source is the Italian National Institute of Statistics (ISTAT), which provides a comprehensive record of mortality across the entire national territory. The dataset consists of approximately 1.5 million observations, ensuring a robust empirical foundation for the analysis. All-cause mortality is widely used in the literature as a proxy for evaluating health system performance and resilience (Wang et al., 2022; Borsati et al., 2023; Papanicolas and Ledesma, 2025). Unlike infection rates or reported COVID-19 deaths, it is not subject to measurement errors or endogeneity arising from uneven testing coverage, diagnostic capacity, or inconsistencies in death classification (Modi et al., 2021). Moreover, it captures both direct and indirect effects of the pandemic, including possible excess deaths linked to unmet medical needs resulting from disruptions in regular healthcare provision (Glasbey et al., 2021; Santi et al., 2021). Finally, its consistent measurement over long time periods makes it suitable for constructing credible counterfactual benchmarks through ITS analysis. For these reasons, we treat mortality as an appropriate proxy for constructing a transparent, outcome-based and empirically tractable measure of revealed resilience, capturing how local areas absorbed and recovered from an extreme and unexpected health shock. Importantly, deviations from expected mortality are not intended to provide an exhaustive definition of resilience, but rather to proxy its most salient and observable manifestation during a pandemic.

To facilitate a more meaningful spatial aggregation and mitigate the fragmentation inherent in municipality-level data, the original dataset was restructured according to Local Labour Market Areas (LMAs). This choice is dictated by statistical necessity: monthly mortality time series for individual small municipalities are highly unstable and sparse (characterized by frequent zero counts), making it impossible to estimate reliable counterfactuals using ITS techniques. LMAs are defined based on commuting flows, specifically daily home-to-work travel patterns, allowing for the construction of a more functionally cohesive territorial grid. In other terms, LMAs, being functional areas based on commuting patterns, provide both the statistical stability required for time-series modelling and a more accurate representation of the spatial propagation of the virus. It is important to note that LMAs are de-

fined as clusters of municipalities; therefore, the boundaries of the former are perfectly aligned with the sum of the boundaries of the latter, ensuring full spatial consistency. Through this process, the initial dataset covering 7,890 municipalities was consolidated into a more manageable framework consisting of 583 LMAs. This approach is not only methodologically sound, but also aligns with the stylized fact that the virus primarily spread through direct contact between individuals within work and social environments, reinforcing the relevance of labour market areas as a spatial unit for analysis. Finally, we note that the administrative boundary changes (*e.g.*, mergers) occurring during the 2003-2023 period do not bias our analysis, as they took place entirely within the same Labour Market Area.
The 583 LMAs included in our analysis cover the entire Italian territory, ensuring a representative picture of the country's geographical and socio-economic heterogeneity. The sample spans three distinct macro-regions with different pandemic experiences: the North, which acts as the country's economic engine and was the epicentre of the first wave; the Centre, characterized by a mix of medium-sized cities and rural landscapes; and the South and Islands, which faced the emergency with a historically more fragile healthcare infrastructure but lower initial infection rates. Furthermore, the use of LMAs allows us to capture the functional diversity of the territory, ranging from large Metropolitan Areas (such as Milan, Rome, and Naples) to the so-called 'Inner Areas' - peripheral zones characterized by lower population density and greater distance from essential services.

The analysis has been structured into four distinct temporal phases, each serving a specific methodological purpose:

- Training Period (January 2003 - September 2018): this phase was utilised to train predictive models, specifically leveraging the XGBoost algorithm and ARIMA models. These methodologies were selected to capture both non-linear dependencies and temporal trends in mortality dynamics.

- Pre-Pandemic Period (referred to as Period PRE, see *e.g.* Figure 1, October 2018 - January 2020): the primary objective of this period was to evaluate forecast accuracy by assessing model performance under normal conditions. The forecast error estimated during this phase provided a benchmark against which deviations observed in subsequent periods could be measured. Later measurements will then be proposed with and without the correction derived from the estimate of accuracy in that time period.

- Pandemic Period (referred to as Period A, February 2020 - March 2022): this phase corresponds to the onset and progression of the COVID-19 pandemic and has been identified based on Decree-Law No. 6 of February 23, 2020, marking its beginning, and Decree-Law No. 24 of March 24, 2022, establishing its conclusion. Mortality trends during this interval were analysed to quantify excess mortality and evaluate deviations from expected trends based on pre-pandemic model projections.

- Post-Pandemic Period (referred to as Period B, April 2022 - August 2023): this final phase encompasses the period following the acute phase of the pandemic. The analysis of mortality trends in this stage aims to assess long-term effects, potential stabilization patterns, and whether mortality levels returned to pre-pandemic expectations.

The identification strategy of our approach relies on the assumption that, in the absence of the COVID-19 pandemic, the mortality trends in each LMA would have continued to follow the complex, non-linear patterns learned by the XGBoost algorithm during the calibration period (2003-2019). Under this assumption, the predicted counterfactual serves as a valid proxy for the 'business-as-usual' scenario. Consequently, any systematic and significant deviation of the observed mortality from this generated baseline after February 2020 can be causally attributed to the pandemic shock and the area's specific resilience capacity, rather than to pre-existing seasonality or trend components.

For the second-stage analysis, as referenced in Section 4, data from multiple sources were utilized to provide a comprehensive evaluation of various municipal characteristics at the LMA level. In particular, the focus of our analysis is on investigating whether higher institutional quality is associated with greater local resilience during the COVID-19 pandemic. The importance of institutional quality in driving economic development is well-established (*e.g.*, Rodrik et al., 2004; Acemoglu et al., 2005), prompting the creation of various indicators at different administrative levels. These range from perception-based assessments to objective, administrative metrics. Among the most widely used are the Worldwide Governance Indicators (WGI) at the national level (Kaufmann et al., 2011), the European Quality of Government

Index (EQI) at the regional level (Charron et al., 2014), and the Institutional Quality Index (IQI) at the provincial level (Nifo and Vecchione, 2014).
Yet, at the municipal level, systematic measures of institutional quality have remained scarce. Existing indicators tend to be fragmented, temporally inconsistent, or limited in geographical coverage (see Suzuki et al., 2022; Albanese and Gentili, 2021). This lack of granularity risks overlooking substantial governance heterogeneity across municipalities, masking important variation in institutional effectiveness.
To overcome these limitations, we utilize the Municipal Administration Quality Index (MAQI) developed by Cerqua et al. (2025a). MAQI provides a consistent, comprehensive measure of institutional quality at the municipal level across the 2001-2021 period. Covering nearly all municipalities over the 2001-2021 period, MAQI evaluates bureaucratic efficiency, fiscal performance, and the valence attributes of political leadership (for a detailed description of the elementary indicators, their polarity, and the data sources used to construct the three pillars of the MAQI, please refer to Table B.2 in Appendix B). MAQI offers a comparative assessment of the technical, bureaucratic, economic, and political dimensions of Italian municipalities by means of 3 pillars: "Pillar I - Local Bureaucracy" which aims to estimate the quality and capacity of the municipal bureaucracy, "Pillar II - Local Politicians" which covers the training aspects and personal characteristics of leading municipal politicians and finally "Pillar III - Local Government" which summarises the economic performance and fiscal efficiency of the municipality. By offering a granular, consistent measure of administrative quality, MAQI enables researchers to assess how local institutions influence a wide range of outcomes, including resilience. Additionally, data from ISTAT were employed to analyse mobility patterns derived from commuting flows, while air quality information was sourced from ISPRA. Notably, pollutant levels of PM2.5 at the LMA level were estimated using kriging procedure, ensuring a refined spatial interpolation of air quality data.
Finally, as we stated, while the MAQI index is originally measured at the municipal level, our empirical analysis is conducted at the LMA level. To ensure consistency, municipal-level variables were aggregated to the LMA level computing the population-weighted average of the municipalities for the institutional and socio-economic variables and employing area kriging spatial interpolation to estimate the average exposure levels across the LMA territory.
Aggregating MAQI at the LMA level, furthermore, can be considered the-

oretically sound because LMAs represent functionally integrated economic systems. In such interconnected areas, the administrative capacity of the main pole (the 'hub' municipality, which carries the highest weight in our aggregation) generates significant institutional spillovers. The efficiency of the hub in managing public services, healthcare coordination, and emergency responses likely influences the resilience of the peripheral municipalities whose workforce commutes daily to the hub. Therefore, the population-weighted MAQI can be interpreted as a proxy for the 'institutional governance' of the entire functional area.

Finally, in Appendix C we have included a detailed description of all variables used in the analysis (Table C.3), reporting for each variable the definition, the data source, and its specific role within our two-stage identification strategy together with the main statistics (Table C.4 and Figures C.1 and C.2).

3.2. Results

To accurately capture the distinctive features of each territory in a unique and tailored manner, the training process, along with all subsequent analytical phases, has been conducted independently for each LMA. In other terms, the counterfactual mortality series (*Emort*) estimated using the XGBoost model has been derived separately for each LMA, employing a distinct training dataset specific to the characteristics of that particular area. This approach ensures that the estimations reflect the localised dynamics of mortality with greater precision.

To validate the suitability of our non-parametric approach, we assessed the goodness of fit of both models across two distinct periods (see Table A.1 for full results). In-sample, during the pre-pandemic calibration period (January 2003 – September 2018), the XGBoost model achieves a MAPE of 0.61% compared to 19.73% for the ARIMA specification. Out-of-sample, over the PRE period (October 2018 - January 2020), the two models perform comparably (MAPE: 20.97% and 18.30%, respectively). The sharp deterioration in XGBoost's out-of-sample accuracy relative to its in-sample fit might, at first glance, raise concerns about overfitting or data leakage (Babii et al., 2024; Cerqua et al., 2025b). However, in our ITS framework this pattern is not only expected but intentional: unlike standard forecasting exercises where out-of-sample generalization is the primary goal, here the counterfactual serves to reconstruct each LMA's historical mortality trajectory as faithfully as possible. A model that closely tracks the complex non-linearities and idiosyncrasies of the pre-pandemic period is therefore preferable, as it

minimizes the risk of attributing pre-existing structural volatility to the pandemic shock rather than to genuine excess mortality.
We further note that the risk of the model projecting spurious historical fluctuations into the pandemic period is structurally limited by our design. XGBoost is trained on a single observation per (month, year) combination within each LMA, so the model learns a smooth function of seasonal and trend components rather than memorizing idiosyncratic noise. Model complexity is further constrained through the regularization term $\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_j w_j^2$ already embedded in our objective function (eq. 1 as defined following eq. 2), which penalizes both tree size and leaf weights, and through cross-validated selection of key hyperparameters. The resulting counterfactual trajectories are, therefore, smooth extrapolations of pre-pandemic trends rather than arbitrary projections of past fluctuations.
As a representative case study, the results for the district of Bergamo, a region profoundly impacted during the initial phase of the pandemic, are presented in Figure 1. Analysing the training period, the model exhibits an almost perfect alignment with the observed data, demonstrating its robustness and reliability in capturing historical trends. During the PRE period, the model continues to perform well, with a minimal margin of error. However, a stark deviation emerges in the first two months of 2020 (referred to as period A), where a significant misalignment is observed between the predicted values and the actual recorded data, highlighting the disruptive effects of the pandemic's onset. Subsequently, in period B, the data show a moderate reversion toward the expected average values, suggesting a partial stabilization following the initial shock.

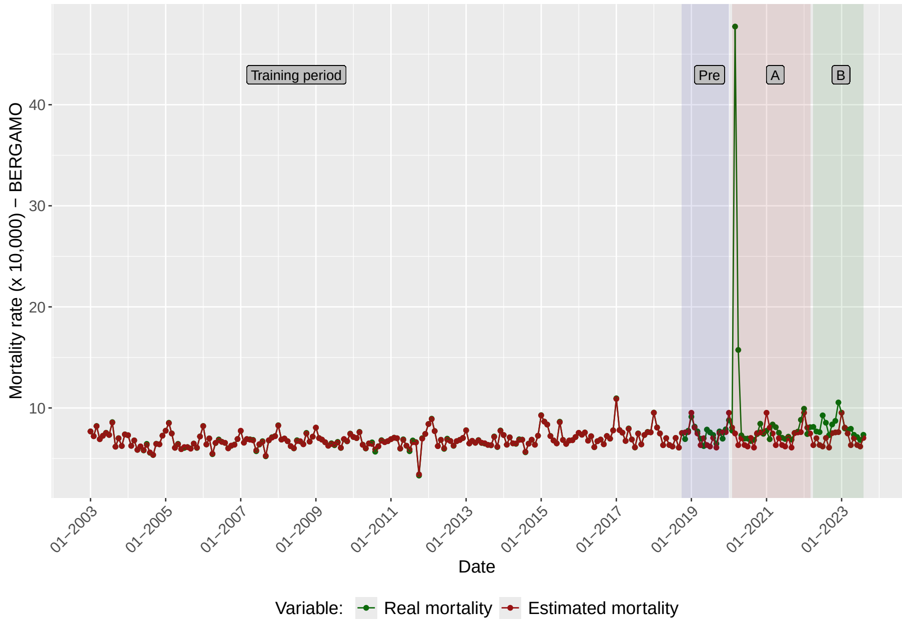

Figure 1: Real and estimated mortality for the different periods, Bergamo LMA, years 2003-2023

Using the counterfactual mortality series, two indicators have been computed to compare the pandemic period (A) with the estimated series for each LMA: the average mortality excess pandemic period (EX_A, eq. 3) and the Corrected average mortality excess pandemic period (CEX_A, eq. 4) using the pre-pandemic period (PRE) mortality excess, too.

$$EX_A = \sum_{t_A} (mort_A - Emort_A)^+ / t_A \tag{3}$$

$$\begin{aligned} CEX_A = &\sum_{t_A} (mort_A - Emort_A)^+ / t_A - \\ &\sum_{t_{PRE}} (mort_{PRE} - Emort_{PRE})^+ / t_{PRE} \end{aligned} \tag{4}$$

Methodologically, we calculate the resilience index by aggregating exclusively positive deviations (excess mortality marked with a +), without offsetting them against periods of lower-than-expected mortality and normalising

for periods (t) in which deviations were positive. This choice is grounded in a specific normative definition of resilience: the capacity of a local system to minimize irreversible damage during a shock. From a policy perspective, we adopt an asymmetric loss function approach: an excess death represents a definitive welfare loss and a system failure that cannot be theoretically "compensated" or cancelled out by a subsequent drop in mortality (often merely a mechanical consequence of the harvesting effect). Consequently, by isolating positive deviations, our indicator strictly measures the accumulated stress on the local system and the magnitude of the crisis managed by the administration, independent of subsequent demographic adjustments.
The same measures have also been calculated for the post-pandemic period (B) (EX_B and CEX_B), measures which are shown in Figure 2.

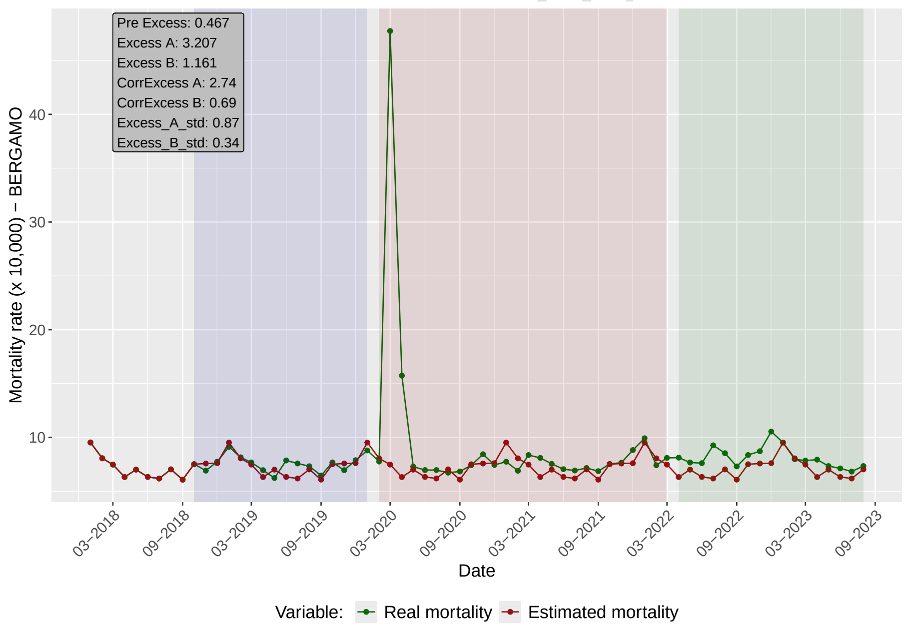

Figure 2: Real and estimated mortality for the different periods with EX_A, CEX_A, EX_B and CEX_B measures, Bergamo LMA, years 2018-2023

Finally, all excess measures from periods A and B have been standardised to ensure the comparability of estimated measurements across each LMA.

4. Assessing the Determinants of Local Resilience to COVID-19

What underlying factors might explain the observed excess mortality, once local characteristics and the expected mortality for each specific area have been duly accounted for? Furthermore, considering a given level of excess mortality during period A (CEX_A), what additional elements contributed to a more rapid return to normal conditions in period B (CEX_B)? To address these complex questions, we will proceed systematically. First, we will examine the key determinants that contributed to higher mortality excess in certain areas in period A, drawing upon the extensive body of literature developed in recent years. This initial analysis will provide a foundation for understanding the broader dynamics at play before moving on to the factors that influenced the speed of recovery in the subsequent period B.

Regarding the excess mortality during the Covid period (CEX_A) in Italy, the literature has proposed multiple determinants. Once local healthcare system characteristics are accounted for - as we do by estimating the counterfactual trend by homogeneous LMA areas - these determinants are primarily linked to exogenous factors, such as environmental conditions (*e.g.*, air pollution; Coker et al., 2020; Fattorini and Regoli, 2020) and social interaction measures, notably human mobility (Cartenì et al., 2020; Bonaccorsi et al., 2020).

Using ISTAT mobility data derived from commuting flows calculated at the LMA level, along with air pollution measurements (PM2.5 - particles with a diameter of 2.5 microns or less) from ISPRA, we can establish a preliminary first stage in analysing the relationship between excess mortality in period A and these determinants (see Table 2).

CEX_A	Coefficient	Std. err.	t	P>t	[95% conf.	interval]
Mobility	2.0103	0.7995	2.5100	0.0120	0.4400	3.5806
PM2.5	0.0455	0.0124	3.6700	0.0000	0.0212	0.0698
Constant	-0.2471	0.3501	-0.7100	0.4810	-0.9349	0.4406

Table 2: First-stage results from the OLS regression

We can now address the second question: which exogenous factors, while accounting for the varying local impact of the epidemic, explain the different recovery trajectories of the territories? Formally, which elements of X_B

drive the variation in CEX_B, conditional on CEX_A being instrumented by differences in mobility and pollution? So, in this second-stage analysis, we focus on CEX_B (Recovery Phase) as the main dependent variable conditional to the acute phase (CEX_A) reflecting the structural capacity of local institutions to reorganize services and mitigate long-term impacts.

$$\begin{cases} CEX_B = \beta_0 + \beta_1 CEX_A + \sum_{j=1} \beta_2 X_B + \epsilon \\ CEX_A = f(IV) \end{cases} \tag{5}$$

Equation 5 has been estimated with the two-step efficient Generalized Method of Moments (GMM) using the initial set of moment conditions to obtain a consistent first-step estimator and where the parameters are re-estimated with an optimal weighting matrix that is heteroskedasticity and autocorrelation consistent.

The results presented in Table 3 highlight several key aspects. Firstly, the negative and significant effect of CEX_A underscores the remarkable resilience of areas severely affected by the epidemic, which responded more effectively than those less impacted (it is worth recalling that a lower CEX_B indicates a better outcome). As a second point, the findings on local political determinants suggest that, all else being equal, only the average quality of local politicians played a role in mitigating excess mortality in period B.

The results, furthermore, suggest that the instruments are generally valid and relevant. The underidentification test (Kleibergen-Paap LM statistic = 14.057, p = 0.0009) confirms that the instruments are appropriately correlated with the endogenous variables. While the Kleibergen-Paap Wald F statistic (7.751) is slightly below the critical value for the 10% maximal IV bias threshold, it is still within a reasonable range, indicating that the instruments are not extremely weak. Additionally, the Hansen J statistic (0.785, p = 0.375) suggests no issue with over-identification, supporting the validity of the instruments used.

A final step is, however, still necessary to validate the obtained results. In a setting based on cross-sectional data, in fact, it is not possible to generally control for the local "hidden confounders" hypothesis, the presence of unobserved variables that influence both the independent and dependent variables but are not included in the model. These hidden confounders can introduce bias in the estimates of the causal relationship between the observed variables, potentially leading to incorrect or misleading conclusions. Therefore, as defined in equation (6), a spatial delay in the error term $\widehat{u}$ has

	Coefficient	Robust std. err.	z	P>z	[95% conf.	interval]
CEX_A	-0.7195	0.2718	-2.6500	0.0080	-1.2522	-0.1867
Pillar I - Local Bureaucracy	0.0113	0.0276	0.4100	0.6810	-0.0427	0.0653
Pillar II - Local Politicians	-0.0405	0.0140	-2.8900	0.0040	-0.0680	-0.0130
Pillar III - Local Government	0.0153	0.0261	0.5900	0.5580	-0.0359	0.0664
Income	-0.0077	0.0043	-1.7800	0.0750	-0.0162	0.0008
Constant	3.5633	3.2645	1.0900	0.2750	-2.8350	9.9616
Underidentification test (Kleibergen-Paap rk LM statistic):						14.057
Chi-sq(2) P-val =						0.0009
Weak identification test (Cragg-Donald Wald F statistic):						12.963
(Kleibergen-Paap rk Wald F statistic):						7.751
Stock-Yogo weak ID test critical values: 10% maximal IV size						19.93
15% maximal IV size						11.59
20% maximal IV size						8.75
25% maximal IV size						7.25
Hansen J statistic (over-identification test of all instruments):						0.785
Chi-sq(1) P-val =						0.3757

Table 3: Two-step GMM with robust SEs

been incorporated by introducing a neighbourhood matrix W. This term is introduced to capture the spatial interdependencies among observations, allowing for the correction of potential hidden confounders that may influence both the independent and dependent variables. By explicitly considering the spatial structure of the data through the matrix W, we can capture the interaction between neighbouring units that could otherwise lead to omitted variable bias problem.

$$\begin{cases} CEX_B = \beta_0 + \beta_1 CEX_A + \sum_{j=1} \beta_2 X_B + \widehat{u} \\ CEX_A = f(IV) \\ \widehat{u} = \rho W u + \epsilon \end{cases} \tag{6}$$

Finally, for the sake of robustness, the specification in eq. (6) has been expanded to also account for a potential autoregressive term on the dependent variable.

$$\begin{cases} CEX_B = \phi W CEX_B + \epsilon + \beta_0 + \beta_1 CEX_A + \sum_{j=1} \beta_2 X_B + \widehat{u} \\ CEX_A = f(IV) \\ \widehat{u} = \rho W u + \epsilon \end{cases} \tag{7}$$

It is worth noting that we do not include regional fixed effects in the Spatial Durbin Model specification. Given the strong spatial clustering of Italian regions, the spatial lag terms ($\rho W y$ and $W x$) effectively capture the influence of shared regional characteristics and policies. This approach allows us to exploit the significant within-region heterogeneity in mortality outcomes, focusing the identification on the specific contribution of municipal administrative quality net of broader territorial trends.

Table 4 presents the results of the different models, highlighting both overarching patterns and model-specific findings. One of the key results is the clear and consistent effect of high-quality local politicians in reducing excess mortality during period B, an effect that remains stable and significant across all models, regardless of specification. Additionally, the autoregressive error parameter (ρ) underscores the necessity of the specification outlined in eq. (6), while the most comprehensive specification (column 4) confirms the robustness of the simplest models (columns 2 and 3) without adding too much (ϕ not significant).

	GMM (1)	Sp.GMM1 (2)	Sp.GMM2 (3)	Sp.GMM3 (4)
CEX_A	-0.6604***	-0.1710	-0.1975*	-0.1203
	[0.243]	[0.124]	[0.108]	[0.090]
Pillar I - Local Bureaucracy	0.0107	0.0195	0.0092	0.0100
	[0.027]	[0.019]	[0.018]	[0.018]
Pillar II - Local Politicians	-0.0331***	-0.0242***	-0.0197**	-0.0187**
	[0.012]	[0.008]	[0.008]	[0.007]
Pillar III - Local Government	0.0046	-0.0020	-0.0040	-0.0055
	[0.024]	[0.017]	[0.016]	[0.016]
Income	-0.0137**	-0.0084	-0.0041	-0.0034
	[0.006]	[0.009]	[0.009]	[0.008]
Distance from general practitioners	0.0049**	0.0006	-0.0004	-0.0008
	[0.002]	[0.002]	[0.002]	[0.002]
% of elderly population			6.5261***	6.2573***
			[1.376]	[1.331]
Constant	3.7259	2.2152	1.2852	1.2432
	[3.146]	[2.631]	[2.519]	[2.440]
ρ		0.3529***	0.3349**	0.3711**
		[0.071]	[0.134]	[0.152]
ϕ				-0.0164
				[0.191]
Observations	583	583	583	583

Robust standard errors in brackets: *** p<0.01, ** p<0.05, * p<0.1

Table 4: Two-step GMM models with and without spatial lag, robust SEs in parentheses

Finally, it is worth noting that the estimated effect of political quality is not merely a proxy for the municipality's scale or resources. By incorporating mobility patterns in the construction of the resilience index and including spatial lags in the econometric model, we effectively isolate the specific contribution of administrative capacity from structural confounders related to size and density.

5. Final remarks

This paper proposes a novel, data-driven methodology to assess the resilience of local areas during the COVID-19 pandemic, introducing the first counterfactual-based resilience index for Italian Local Market Areas (LMAs). By leveraging a non-parametric geographically-adapted ITS approach on long-run mortality data, we construct a robust and context-sensitive measure that captures how local communities absorbed and responded to an unprecedented public health shock.

The resilience index allows for systematic, comparative analysis of local responses across space and time, moving beyond aggregate national indicators and enabling fine-grained insights into local variation. It also provides a scalable framework that can be replicated in other decentralized contexts and applied to future crises.

Building on this index, we explore the role of institutional quality - measured using the newly developed MAQI index as a key explanatory factor. We find consistent evidence that local areas with higher MAQI scores, particularly in the dimension of quality of local politicians, were better able to navigate the pandemic. This reinforces the broader insight that resilient outcomes are closely tied not only to structural factors but also to the institutional quality of local administrations.

Our findings regarding the pivotal role of local political quality can be read in light of the broader literature on community resilience during the COVID-19 pandemic. While a large share of existing studies focuses on the role of social capital in shaping resilience outcomes (Kuchler et al., 2022; Fraser and Aldrich, 2021), a smaller set of studies has drawn attention to the role of formal institutions and their interaction with local communities. In this respect, our findings are consistent with contributions showing that the effectiveness and credibility of local administrations shape resilience outcomes by strengthening citizens' confidence in collective action and facilitating compliance with public health measures (Busic-Sontic and Schubert, 2024). Similarly, evidence on the role of vertical trust between citizens and authorities suggests that institutional relationships are a relevant channel through which local pandemic outcomes are determined, although results remain heterogeneous across settings (Fraser et al., 2022; Fraser and Aldrich, 2021).

Our results also speak to empirical evidence linking institutional quality to pandemic outcomes across different geographical scales. Rodríguez-Pose and Burlina (2021) document a strong association between weak government effectiveness and higher excess mortality across European regions during the first wave of the pandemic. Focusing on Italy, Alfano and Ercolano (2021) provide suggestive evidence that institutional quality plays a particularly important role in the effectiveness of lockdown measures, by enhancing compliance and thereby reducing new infections.

Relative to these contributions, our study advances the literature by adopting a quantitative and explicitly counterfactual-based approach to the measurement of community resilience, grounded in all-cause excess mortality at a local level, and by identifying the role of local political quality in shaping communities' ability to absorb and recover from an unprecedented shock.

Several avenues remain open for future research. First, incorporating additional outcome variables beyond excess mortality, such as indicators of healthcare supply at hospital level, could provide a more comprehensive and precise picture of resilience across multiple dimensions. Second, conducting comparative analyses across countries or regions that exhibit similar institutional heterogeneity would allow for testing the generalizability of our findings and contribute to a broader discourse on governance quality and crisis management in decentralized contexts.

References

Acemoglu, D., Johnson, S., Robinson, J. A., 2005. *Institutions as a Fundamental Cause of Long-Run Growth.* Handbook of Economic Growth 1, 385–472.

Acemoglu, D., Robinson, J. A., Verdier, T., 2013. *Choosing Our Own Fate: Unintended Consequences of Electoral Rule Reform.* American Economic Review 103 (3), 62–68.

Aksoy, C. G., Eichengreen, B., Saka, O., 2020. *The Political Scar of Epidemics.* NBER Working Paper No. 27401Available at SSRN: https://ssrn.com/abstract=3666900.

Albanese, G., Gentili, E., 2021. *Indicatori territoriali di qualità delle istituzioni: un aggiornamento.* Regional Economy 5 (3), 43–58.

Alesina, A., Giuliano, P., 2015. *Culture and Institutions.* Journal of Economic Literature 53 (4), 898–944.

Alessi, L., Benczur, P., Campolongo, F., Cariboni, J., Manca, A. R., Menyhert, B., Pagano, A., 2020. *The resilience of EU member states to the financial and economic crisis.* Social Indicators Research 148, 569–598.

Alfano, V., Ercolano, S., 2021. *Social capital, quality of institutions and lockdown. Evidence from Italian provinces.* Structural Change and Economic Dynamics 59, 31–41.

Algan, Y., Cahuc, P., 2013. *Trust and Growth.* Annual Review of Economics 5, 521–549.

Algan, Y., Guriev, S., Papaioannou, E., Passari, E., 2017. *The European Trust Crisis and the Rise of Populism.* Brookings Papers on Economic Activity 2017 (2), 309–400.

Babii, A., Ball, R. T., Ghysels, E., Striaukas, J., 2024. *Panel Data Nowcasting: The Case of Price-Earnings Ratios.* Journal of Applied Econometrics 39 (2), 292–307.

Barone-Adesi, F., Gasparrini, A., Vizzini, L., Merletti, F., Richiardi, L., 2011. *Effects of Italian smoking regulation on rates of hospital admission for acute coronary events: a country-wide study*. PloS one 6 (3), e17419.

Benedetti, R., Piersimoni, F., Pignataro, G., Vidoli, F., 2020. *Identification of spatially constrained homogeneous clusters of COVID-19 transmission in Italy*. Regional Science Policy & Practice 12 (6), 1169–1188.

Bernal, J. L., Andrews, N., Amirthalingam, G., 2019. *The use of quasi-experimental designs for vaccine evaluation*. Clinical Infectious Diseases 68 (10), 1769–1776.

Bernal, J. L., Cummins, S., Gasparrini, A., 2017. *Interrupted time series regression for the evaluation of public health interventions: a tutorial*. International journal of epidemiology 46 (1), 348–355.

Bernal, J. L., Cummins, S., Gasparrini, A., 2018a. *The use of controls in interrupted time series studies of public health interventions*. International journal of epidemiology 47 (6), 2082–2093.

Bernal, J. L., Gasparrini, A., Artundo, C. M., McKee, M., 2013. *The effect of the late 2000s financial crisis on suicides in Spain: an interrupted time-series analysis*. The European Journal of Public Health 23 (5), 732–736.

Bernal, J. L., Soumerai, S., Gasparrini, A., 2018b. *A methodological framework for model selection in interrupted time series studies*. Journal of clinical epidemiology 103, 82–91.

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., Schmidt, A. L., Valensise, C. M., Scala, A., Quattrociocchi, W., et al., 2020. *Economic and social consequences of human mobility restrictions under COVID-19*. Proceedings of the national academy of sciences 117 (27), 15530–15535.

Borsati, M., Cascarano, M., Percoco, M., 2023. *Resilience to health shocks and the spatial extent of local labour markets: evidence from the COVID-19 outbreak in Italy*. Regional Studies 57 (12), 2503–2520.

Bosque-Mercader, L., Conroy, S., Lasserson, D., Mannion, R., Nicodemo, C., Wittenberg, R., 2025. *Resilience of the acute sector in recovery from COVID-19 pressures*. Social Science & Medicine 375, 118062.

Bottasso, A., Cerruti, G., Conti, M., 2022. *Institutions matter: The impact of the COVID-19 pandemic on the political trust of young Europeans*. Journal of Regional Science 62 (4), 1122–1148.

Box, G. E., Jenkins, G. M., 1970. Time Series Analysis: Forecasting and Control. Holden-Day, San Francisco.

Briguglio, L., Cordina, G., Farrugia, N., Vella, S., 2009. *Economic Vulnerability and Resilience: Concepts and Measurements*. Oxford Development Studies 37 (3), 229–247.

Busic-Sontic, A., Schubert, R., 2024. *Social resilience indicators for pandemic crises.* Disasters 48 (2), e12610.

Cannonier, C., Burke, M. G., 2025. *Trust during troubled times: Evidence from Sierra Leone's Ebola epidemic.* Economic Modelling 144, 107004.

Cartenì, A., Di Francesco, L., Martino, M., 2020. *How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study.* Science of the Total Environment 741, 140489.

Cerqua, A., Di Stefano, R., Letta, M., Miccoli, S., 2021. *Local mortality estimates during the COVID-19 pandemic in Italy.* Journal of Population Economics 34 (4), 1189–1217.

Cerqua, A., Giannantoni, C., Zampollo, F., Mazziotta, M., Mar 2025a. *The Municipal Administration Quality Index: The Italian Case.* Social Indicators Research 177 (1), 345–378.

Cerqua, A., Letta, M., Pinto, G., 2025b. *On the (Mis)Use of Machine Learning With Panel Data.* Oxford Bulletin of Economics and Statistics 70019, 1–13.

Charron, N., Dijkstra, L., Lapuente, V., 2014. *Regional Governance Matters: Quality of Government within European Union Member States.* Regional Studies 48 (1), 68–90.

Chen, T., Guestrin, C., 2016. *XGBoost: A Scalable Tree Boosting System.* In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 785–794.

Coker, E. S., Cavalli, L., Fabrizi, E., Guastella, G., Lippo, E., Parisi, M. L., Pontarollo, N., Rizzati, M., Varacca, A., Vergalli, S., 2020. *The effects of air pollution on COVID-19 related mortality in northern Italy.* Environmental and Resource Economics 76, 611–634.

de Mello, L., Ter-Minassian, T., 2022. *Improving subnational governments' resilience in the wake of the COVID-19 pandemic.* OECD Working Papers on Fiscal Federalism 37, OECD, Paris.

Dennis, J., Ramsay, T., Turgeon, A. F., Zarychanski, R., 2013. *Helmet legislation and admissions to hospital for cycling related head injuries in Canadian provinces and territories: interrupted time series analysis.* Bmj 346.

Di Caro, P., Fratesi, U., 2018. *Regional determinants of economic resilience.* The Annals of Regional Science 60, 235–240.

Diliberto, O., Sideri, M., 2015. *Historical Institutions and Human Capital Formation: Evidence from Italy.* Regional Studies 49 (8), 1395–1411.

Faggian, A., Gemmiti, R., Jaquet, T., Santini, I., 2018. *Regional economic resilience: The experience of the Italian local labor systems.* The Annals of Regional Science 60, 393–410.

Fattorini, D., Regoli, F., 2020. *Role of the chronic air pollution levels in the Covid-19 outbreak risk in Italy*. Environmental pollution 264, 114732.

Fingleton, B., Garretsen, H., Martin, R., 2012. *Recessionary shocks and regional employment: evidence on the resilience of UK regions*. Journal of regional science 52 (1), 109–133.

Fraser, T., Aldrich, D. P., 2021. *The dual effect of social ties on COVID-19 spread in Japan*. Scientific reports 11 (1), 1596.

Fraser, T., Page-Tan, C., Aldrich, D. P., 2022. *Social capital's impact on COVID-19 outcomes at local levels*. Scientific reports 12 (1), 6566.

Fratesi, U., Perucca, G., 2018. *Territorial capital and the resilience of European regions*. The Annals of Regional Science 60 (2), 241–264.

Funke, M., Schularick, M., Trebesch, C., 2020. *Populist Leaders and the Economy*. American Economic Review: Insights 2 (3), 362–379.

Garavaglia, C., Sancino, A., Trivellato, B., 2021. *Italian mayors and the management of COVID-19: adaptive leadership for organizing local governance*. Eurasian geography and economics 62 (1), 76–92.

Glasbey, J., Ademuyiwa, A., Adisa, A., AlAmeer, E., Arnaud, A. P., Ayasra, F., Azevedo, J., Minaya-Bravo, A., Costas-Chavarri, A., Edwards, J., et al., 2021. *Effect of COVID-19 pandemic lockdowns on planned cancer surgery for 15 tumour types in 61 countries: an international, prospective, cohort study*. The Lancet Oncology 22 (11), 1507–1517.

Grundy, C., Steinbach, R., Edwards, P., Green, J., Armstrong, B., Wilkinson, P., 2009. *Effect of 20 mph traffic speed zones on road injuries in London, 1986-2006: controlled interrupted time series analysis*. Bmj 339.

Guiso, L., Sapienza, P., Zingales, L., 2016. *Long-Term Persistence*. Journal of the European Economic Association 14 (6), 1401–1436.

Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd Edition. Springer.

ISTAT, ISS, May 2020. *Impatto dell'epidemia COVID-19 sulla mortalità totale della popolazione residente - Primo trimestre 2020*. Tech. rep., Istituto Nazionale di Statistica and Istituto Superiore di Sanità.
URL https://www.istat.it/it/files//2020/05/Rapporto_Istat_Iss.pdf

ISTAT, ISS, 2022. *Impatto dell'epidemia COVID-19 sulla mortalità totale della popolazione residente - Anni 2020-2021 e Gennaio 2022*. Tech. rep., Istituto Nazionale di Statistica and Istituto Superiore di Sanità.
URL https://www.istat.it/wp-content/uploads/2022/03/Report_ISS_ISTAT_2022_tab3.pdf

Jandoc, R., Burden, A. M., Mamdani, M., Levesque, L. E., Cadarette, S. M., 2015. *Interrupted time series analysis in drug utilization research is increasing: systematic review and recommendations.* Journal of clinical epidemiology 68 (8), 950–956.

Kaufmann, D., Kraay, A., Mastruzzi, M., 2011. *The worldwide governance indicators: methodology and analytical issues1.* Hague journal on the rule of law 3 (2), 220–246.

Kontopantelis, E., Doran, T., Springate, D. A., Buchan, I., Reeves, D., 2015. *Regression based quasi-experimental approach when randomisation is not an option: interrupted time series analysis.* BMJ 350, h2750.

Kroknes, V. F., Jakobsen, T. G., Grønning, L. R., 2015. *Economic Performance and Political Trust: The Impact of the Financial Crisis on European Citizens.* European Societies 17 (5), 700–723.

Kuchler, T., Russel, D., Stroebel, J., 2022. *JUE Insight: The geographic spread of COVID-19 correlates with the structure of social networks as measured by Facebook.* Journal of urban economics 127, 103314.

Lagravinese, R., 2015. *Economic crisis and rising gaps North–South: evidence from the Italian regions.* Cambridge journal of regions, economy and society 8 (2), 331–342.

Li, J., Zhang, Y., Niu, X., 2021. *The COVID-19 pandemic reduces trust behavior.* Economics Letters 199, 109700.

Li, Y., Liu, X., Li, X., Xue, C., Zhang, B., Wang, Y., 2023. *Interruption time series analysis using autoregressive integrated moving average model: evaluating the impact of COVID-19 on the epidemic trend of gonorrhea in China.* BMC Public Health 23 (1), 2073.

Linden, A., 2018. *Combining synthetic controls and interrupted time series analysis to improve causal inference in program evaluation.* Journal of evaluation in clinical practice 24 (2), 447–453.

Linden, A., Adams, J. L., 2011. *Applying a propensity score-based weighting model to interrupted time series data: improving causal inference in programme evaluation.* Journal of evaluation in clinical practice 17 (6), 1231–1238.

Martin, R., 2012. *Regional economic resilience, hysteresis and recessionary shocks.* Journal of economic geography 12 (1), 1–32.

Menchetti, F., Cipollini, F., Mealli, F., 09 2023. *Combining counterfactual outcomes and ARIMA models for policy evaluation.* The Econometrics Journal 26.

Modi, C., Böhm, V., Ferraro, S., Stein, G., Seljak, U., 2021. *Estimating COVID-19 mortality in Italy early in the COVID-19 pandemic.* Nature communications 12 (1), 2729.

Nifo, A., Vecchione, G., 2014. *Do Institutions Play a Role in Skilled Migration? The Case of Italy*. Regional Studies 48 (10), 1628–1649.

Nunn, N., 2020. *The Historical Roots of Economic Development*. Science 367 (6485), eaaz9986.

OECD, 2021. *The territorial impact of COVID-19: Managing the crisis and recovery across levels of government*. Tech. rep., OECD Publishing, Paris.

Papanicolas, I., Ledesma, J., 2025. *Measuring health system resilience: Understanding the relationship between excess mortality and health system performance*. Health Policy, 105430.

Penfold, R. B., Zhang, F., 2013. *Use of interrupted time series analysis in evaluating health care quality improvements*. Academic pediatrics 13 (6), S38–S44.

Previtali, P., Salvati, E., 2023. *Governance robustness put to the test by Covid-19. The case of Local Area Plans in the Lombardy Region*. European Planning Studies 31 (12), 2637–2658.

Rizzi, P., Graziano, P., Dallara, A., 2018. *A capacity approach to territorial resilience: The case of European regions*. The Annals of Regional Science 60, 285–328.

Rodríguez-Pose, A., Burlina, C., 2021. *Institutions and the uneven geography of the first wave of the COVID-19 pandemic*. Journal of Regional Science 61 (4), 728–752.

Rodrik, D., Subramanian, A., Trebbi, F., 2004. *Institutions rule: the primacy of institutions over geography and integration in economic development*. Journal of Economic Growth 9 (2), 131–165.

Santi, L., Golinelli, D., Tampieri, A., Farina, G., Greco, M., Rosa, S., Beleffi, M., Biavati, B., Campinoti, F., Guerrini, S., et al., 2021. *Non-COVID-19 patients in times of pandemic: Emergency department visits, hospitalizations and cause-specific mortality in Northern Italy*. Plos one 16 (3), e0248995.

Schaffer, A. L., Dobbins, T. A., Pearson, S.-A., Mar 2021. *Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: a guide for evaluating large-scale health interventions*. BMC Medical Research Methodology 21 (1), 58.

Sensier, M., Bristow, G., Healy, A., 2016. *Measuring regional economic resilience across Europe: Operationalizing a complex concept*. Spatial Economic Analysis 11 (2), 128–151.

Suzuki, W. Y., Laurini, M. P., Nakabashi, L., 2022. *Spatial Heterogeneities, Institutions, and Income: Evidence for Brazil*. Papers in Regional Science 101 (3), 537–571.

Tabellini, G., 2010. *Culture and Institutions: Economic Development in the Regions of Europe*. Journal of the European Economic Association 8 (4), 677–716.

Wagner, A. K., Soumerai, S. B., Zhang, F., Ross-Degnan, D., 2002. *Segmented regression analysis of interrupted time series studies in medication use research.* Journal of clinical pharmacy and therapeutics 27 (4), 299–309.

Wang, H., Paulson, K. R., Pease, S. A., Watson, S., Comfort, H., Zheng, P., Murray, C. J. L., 2022. *Estimating excess mortality due to the COVID-19 pandemic: a systematic analysis of COVID-19-related mortality, 2020–21.* The Lancet 399 (10334), 1513–1536.

Appendix A. Sample goodness of fit

Period	Model	RMSE	MAE	MAPE
In-sample	XGBoost	0.102	0.052	0.60%
(Jan 2003 - Sep 2018)	ARIMA	2.297	1.609	19.73%
Out-of-sample	XGBoost	2.971	2.005	20.97%
(Oct 2018 - Jan 2020)	ARIMA	2.492	1.765	18.30%

Table A.1: Sample goodness of fit: in-sample and out-of-sample accuracy

Please note that in Table A.1 n-sample metrics are computed over the training period used to calibrate each model. Out-of-sample metrics are computed over the PRE period, which is genuinely out-of-sample for both models: XGBoost was trained exclusively on data up to September 2018, while the ARIMA counterfactual was estimated on the same window and projected forward.

Appendix B. Municipal Administration Quality Index (MAQI)

Pillar	Elementary Indicator	Polarity	Data Source
I. Bureaucracy Quality	Average years of education (public employees)	+	State General Accounting Dept. (Conto Annuale - MEF)
	Turnover rate	−	
	Personnel per 1,000 inhabitants	+	
	Average annual absences	−	
II. Local Politicians Quality	Average years of education (politicians)	+	Ministry of the Interior (Anagrafe degli Amministratori)
	Gender balance index (gap)	−	
	Share of white-collar workers	+	
III. Financial Sustainability	Spending rigidity	−	Ministry of the Interior (Certificati Consuntivi)
	Spending capacity	+	
	Collection capacity	+	
	Share of budget allocated to investments	+	

Table B.2: Structure of the Municipal Administration Quality Index (MAQI): Pillars, Indicators, and Data Sources

NOTES: The table lists the elementary indicators used to construct the MAQI. The *Polarity* column indicates the direction of the relationship with administrative quality (+ positive, − negative).
SOURCES: Sources are derived from the official description in the MAQI methodology.

Appendix C. Description and statistics of variables used in the empirical analysis

Variable	Description	Source	Role in Analysis
Outcome Variables (Resilience Indices)			
Cex_A	Resilience index for the 'Acute Phase'. Measured as the cumulative difference between observed and counterfactual mortality.	Authors' calc. on ISTAT data	Dependent Var.
Cex_B	Resilience index for the 'Recovery Phase'. Measured as the cumulative difference between observed and counterfactual mortality.	Authors' calc. on ISTAT data	Dependent Var.
First-Stage Controls (Counterfactual Construction)			
Mobility	Mobility index capturing the movement of individuals within the LMA, used to adjust exposure risk.	ISTAT commuting matrix	First-Stage Input
PM2.5	Average concentration of Particulate Matter ($< 2.5\mu m$). Aggregated to LMA level via spatial Kriging.	CAMS / Copernicus	First-Stage Input
Institutional Quality (MAQI Components)			
Pillar I	*Bureaucracy Quality*: Composite index based on public employees' education, turnover rate, and absenteeism.	MEF (Conto Annuale)	Explanatory Var.
Pillar II	*Political Quality*: Composite index based on local politicians' education level, gender balance, and professional background.	Min. Interior (Anagrafe)	Main Interest Var.
Pillar III	*Financial Sustainability*: Composite index based on spending rigidity, collection capacity, and investment share.	Min. Interior (Bilanci)	Explanatory Var.
Second-Stage Controls (Socio-economic & Environmental)			
Income	Per capita taxable income (log-transformed). Proxy for economic well-being.	MEF (Tax Returns)	Control
Dist. GPs	Average distance (km) to the nearest General Practitioner. Proxy for primary healthcare accessibility.	Min. Health / ISTAT	Control
% Elderly	Share of resident population aged over 65. Proxy for demographic vulnerability.	ISTAT	Control

Table C.3: Description of variables used in the empirical analysis

NOTES: MEF = Ministry of Economy and Finance; ISTAT = Italian National Institute of Statistics; CAMS = Copernicus Atmosphere Monitoring Service. All municipal-level variables are aggregated to the LMA level using population-weighted averages (except for PM2.5, which uses area kriging). To ensure exogeneity, all explanatory variables (MAQI, Income, Distance to GPs) are measured as of 2019, prior to the onset of the pandemic.

Statistic	N	Mean	St. Dev.	Min	Max
Resilience Index (Cex_B)	583	0.794	0.857	−2.342	7.007
Acute Phase Index (Cex_A)	583	1.313	1.085	−2.132	8.535
MAQI Pillar I	583	99.285	2.275	86.385	105.122
MAQI Pillar II	583	111.562	5.380	92.417	126.797
MAQI Pillar III	583	102.880	2.793	92.159	114.296
Income (log)	583	1.399	4.622	0.034	77.951
Mobility Index	583	0.475	0.060	0.330	0.600
PM 2.5 air quality	583	13.309	3.874	4.572	33.386
% Elderly	583	0.241	0.032	0.143	0.343
Dist. GPs	583	21.614	27.254	0.000	211.055

Table C.4: Descriptive statistics of the consolidated LMA dataset

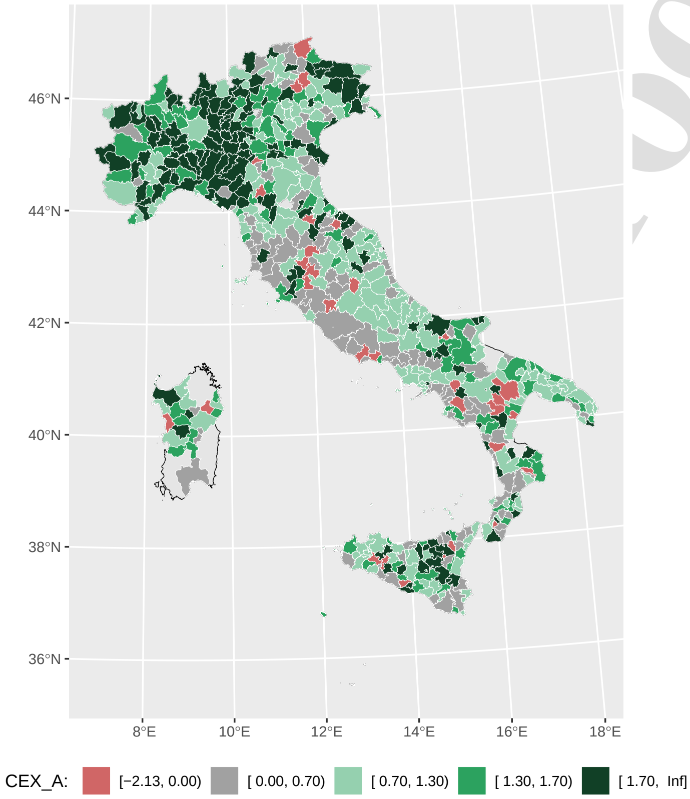

Figure C.1: Resilience index map for the 'Acute Phase', CEX_A

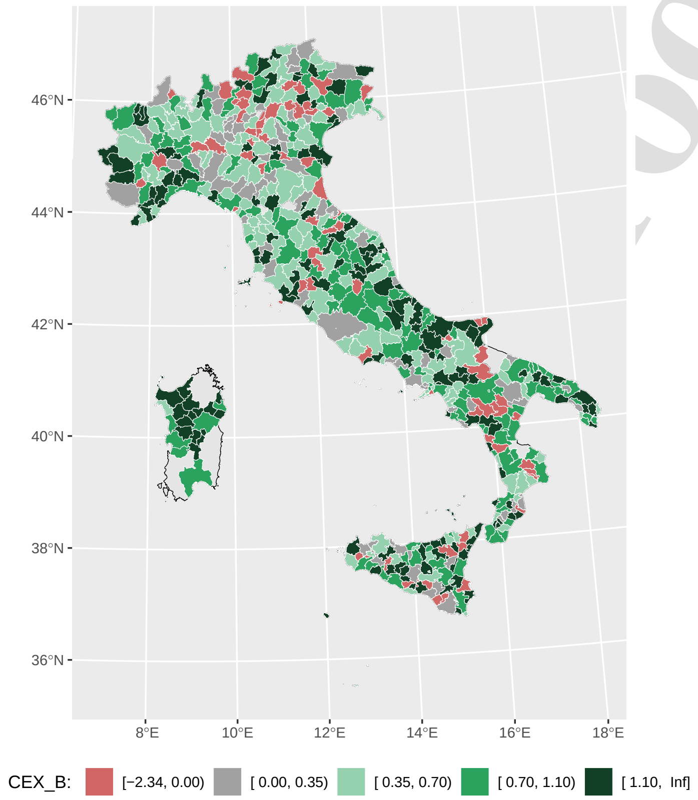

Figure C.2: Resilience index map for the 'Recovery Phase', CEX_B

Better Politicians, Fewer Deaths? Local Resilience in Overcoming the Pandemic Crisis in Italy

Stefania Fontana[b], Calogero Guccio[b], Giacomo Pignataro[b,c], Francesco Vidoli[a]

[a]*University of Urbino Carlo Bo, Department of Economics, Society and Politics, Via Aurelio Saffi, 42, Urbino, 61029, PU, Italy*
[b]*University of Catania, Department of Economics and Business, Corso Italia, 55, Catania, 95129, CT, Italy*
[c]*Politecnico di Milano, Department of Management, Economics and Industrial Engineering, Via Raffaele Lambruschini, 4/B, Milano, 20156, MI, Italy*

*Corresponding author
URL: stefania.fontana@unict.it (Stefania Fontana)

Highlights

- Monthly mortality data (2004–2023) used to assess local resilience to COVID-19
- Machine learning ITS reveals uneven local resilience to COVID-19
- Local institutional quality strongly predicts resilience to pandemic shocks
- Quality of local politicians is the key driver of local performance

Ethics Approval Statement

Ethics approval was not required for this study, as it uses only aggregated administrative data and does not involve human participants.

Credit author statement

SF: Conceptualization, Methodology, Data Curation, Writing Original Draft, Writing Review and Edit;

CG: Conceptualization, Methodology, Writing Original Draft, Writing Review and Edit;

GP: Conceptualization, Methodology, Writing Original Draft, Writing Review and Edit;

FV: Conceptualization, Methodology, Data curation, Formal Analysis, Writing Original Draft, Writing Review and Edit