HEDG

HEALTH, ECONOMETRICS AND DATA GROUP

THE UNIVERSITY of York

WP 25/06

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July 2025

http://www.york.ac.uk/economics/postgrad/herc/hedg/wps/

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

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**Abstract**

The quality of institutions is widely recognized as a fundamental determinant of public sector performance across various levels of governance. In this paper, we investigate the role of institutional quality in shaping the resilience of Italian municipalities during the COVID-19 pandemic. To this end, we introduce a novel non-parametric approach to construct a resilience index based on historical mortality data, which serves as a counterfactual benchmark, estimated at the local level, for assessing pandemic-related outcomes. This methodology enables a more nuanced and context-specific measurement of resilience. We apply the index to municipal-level mortality data in Italy from 2004 to 2023 to evaluate the heterogeneous ability of municipalities to withstand and recover from the pandemic crisis. By linking this resilience index with detailed municipal-level indicators of institutional quality, we find that higher institutional quality is strongly associated with greater resilience in managing the crisis. Moreover, when disentangling the specific components of institutional quality, we identify the quality of local politicians as the most significant factor driving differential performance. Our results are robust to a variety of sensitivity checks.

*Keywords:* Institutional quality, Health sector resilience, Resilience indices,

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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. While much focus has been placed on national policies and healthcare infrastructure, the pandemic also underscored the critical role of local governance and institutional quality in mitigating adverse outcomes. In particular, the ability of local communities to adapt to, absorb, and recover from the crisis - what we refer to as resilience - has emerged as a key determinant of how communities fared during this period.

Resilience, however, remains a challenging concept to measure empirically, especially in decentralized settings where historical, political, and social conditions vary widely. This paper seeks to address that challenge by proposing a novel, data-driven approach to measure the resilience of Italian municipalities during the COVID-19 pandemic. We develop a new resilience index based on a geographically adapted Interrupted Time Series (ITS) methodology, using historical mortality data from 2004 to 2023. This allows us to construct municipality-specific counterfactuals to assess how each locality performed relative to its expected mortality trajectory, providing a nuanced and context-sensitive indicator of resilience.

Beyond measuring the direct impact of the COVID-19 pandemic, this paper investigates its institutional and political determinants at the local level. Specifically, we ask whether municipalities with higher institutional quality exhibited greater resilience in coping with the crisis. This question situates our study within a broader literature in economics and political science that examines how historical and contemporary shocks, be they economic, political, military, or health-related, shape institutional performance and societal outcomes over time.

Prominent scholars such as Alesina and Giuliano (2015) and Nunn (2020) argue that major shocks can have lasting effects, influencing not only institutional structures but also cultural norms—particularly trust. Trust, in turn, plays a foundational role in supporting economic development by facilitating innovation, trade, financial intermediation, and labour market efficiency (Algan and Cahuc, 2013). However, trust is not uniformly distributed; it varies widely both across and within countries (Tabellini, 2010). During crises, trust in political institutions defined as confidence in governments, parliaments, and political leaders, becomes especially vital. A growing body of evidence shows that negative shocks, such as recessions or pandemics, can erode this trust, particularly when governments are seen as ineffective or unaccountable (Algan et al., 2017; Kroknes et al., 2015; Aksoy et al., 2020). This erosion often weakens the legitimacy and effectiveness of public policies (Funke et al., 2020; Acemoglu et al., 2013), and contributes to declining institutional trust during health shocks (Bottasso et al., 2022; Li et al., 2021; Cannonier and Burke, 2025).

This paper contributes to this literature in two relevant ways. First, it proposes a novel, data-driven methodology for measuring municipal resilience, using long-run mortality data and a non-parametric geographically adapted Interrupted Time Series (ITS) approach to generate counterfactuals and identify local deviations during the pandemic. Second, it provides empirical evidence that institutional quality, particularly the competence of local political leadership, is a key determinant of how municipalities responded to the COVID-19 crisis. These contributions offer both theoretical insights and practical relevance for policymakers seeking to bolster institutional capacity and restore public trust in anticipation of future shocks.

Italy offers an especially fertile ground for such an inquiry. On one hand, it was among the first countries severely hit by the pandemic, with high mortality rates exacerbated by limited preparedness and significant territorial disparities in the impact. On the other hand, Italy has long been recognized for its institutional heterogeneity. Historical legacies, including the contrast between medieval republican communes and autocratic regimes, continue to influence the effectiveness of public administration today (Diliberto and Sideri, 2015; Guiso et al., 2016). As a result, the country presents a unique setting to examine how deep-rooted institutional differences shape local capacities to manage systemic crises.

In this study, we employ the Municipal Administration Quality Index (MAQI) to examine whether higher institutional quality translates into greater municipal resilience during the pandemic. Our results show that municipalities with higher MAQI scores consistently performed better in navigating the crisis. Among the various components of institutional quality, the quality of political leadership emerges as the most significant determinant. These findings underscore the critical role that competent, transparent, and accountable institutions play in enabling local communities to withstand and recover from systemic shocks.

The rest of the paper is as follows. Section 2 reviews the relevant literature on health systems' resilience and the ITS approach. Section 3 details the methodology used to develop the health resilience indicator, including data sources, model specifications, and analytical techniques. In Section 4, we present the empirical results of applying the ITS approach to Italian mortality data, highlighting key insights and observed spatial patterns. Section 5 discusses the implications of our findings for policy and practice, offering recommendations to improve the resilience of the health system. Finally, Section 6 concludes the paper, summarising the main contributions and proposing directions for further studies.

## 2. Literature

### *2.1. Resilience: issues and measurements*

The concept of resilience in many areas of human knowledge describes agents' responses to changes, often not as atoms in an empty space, but as molecules in a space that conditions motion and growth.

In physics, resilience refers to the ability of a material or object to absorb energy when it is deformed elastically and then release that energy as it returns to its original shape. However, the concept of resilience is closely tied to the conditions under which a material or object is deformed and subsequently allowed to recover. External constraints, such as forces, boundary conditions, and environmental factors, play a significant role in determining how a material behaves under stress and how it recovers afterward.

In philosophy, for example, Nussbaum (2003) explored how emotions can play a constructive role in resilience, arguing that they are integral to our moral reasoning and our ability to cope with adversity. Resilience here involves developing robust emotional intelligence that allows individuals to navigate complex emotional landscapes and maintain psychological well-being. She argues that resilience is not just about stoically enduring hardship but involves an intelligent emotional engagement with our circumstances, allowing us to respond with empathy, creativity, and growth acknowledging the importance of community and social support systems in fostering resilience. The presence of a supportive network - whether it is family, friends, or a broader community - can provide emotional, practical, and moral support during times of crisis.

Resilience in economics refers to the ability of an economy to withstand, adapt to, and recover from shocks, disturbances, or crises. It encompasses both the robustness of economic systems to absorb impacts without significant changes and their ability to bounce back - in a given period of time - to a stable or improved state after a disruption. Although resilience is often seen as an internal quality of an economy - its ability to withstand shocks, adapt, and recover - external conditions are crucial because they influence both the nature of the shocks facing an economy and its capacity to respond to them. External conditions shape the environment in which an economy operates and influence both the types and magnitudes of shocks that an economy may face and its capacity to respond effectively.

Taking into account all these considerations, we think that in our subsequent approach to the economic evaluation of resilience it is crucial to evaluate the Italian national health system, which is complex and finely distributed over the territory, as a "territorial and administrative constraint" given the type of demand and the local resources it can draw on; in other words, it is necessary to first evaluate the system locally, "piece by piece", taking into account the conditional latent variables of each part of the territory, and then assess the supra-regional regularities that shaped the response of individual local agents.

### *2.2. Setting the analytical framework*

Obtaining a quantitative measure of resilience is not a simple task. The concept of resilience involves the ability of a system to withstand an external shock and the dynamic process of recovery from it. It also entails how quickly the system regains its pre-crisis state, or whether it is able to adapt itself to the changing environment and find a new equilibrium post-crisis.

Some of the first attempts to measure resilience can be traced back to the literature on regional economics, where it was used to analyse regional differences in response to macroeconomic shocks. Some authors originally adopted a capacity approach (Briguglio et al., 2009; Rizzi et al., 2018), which involves creating composite indicators that consider a combination of resilience drivers: structural characteristics, behavioural factors, and available resources that can help a system withstand shocks. Rather than capturing the dynamic reaction of a system to the shock, these indicators try to evaluate the potential capacity of a system to withstand disturbances, which we previously referred to as conditional latent variables. Therefore, the choice of variables to be included in the index requires *a priori* theoretical considerations regarding what determines resilience. Although providing interesting insights on the readiness of economic systems for disturbances, the major drawback of such indicators is the risk of conflating resilience *drivers* and resilience *outcomes* (Sensier et al., 2016).

An alternative approach widely used in the literature on regional economics is that of *revealed resilience* (Alessi et al., 2020). This approach relies on resilience outcome variables that at least in part reveal the resilience of economic systems, such as GDP and the employment rate (Martin, 2012; Cellini and Torrisi, 2014; Lagravinese, 2015). Observing the response over time of such variables to external shocks can provide answers to questions such as how much and how quickly GDP decreased or how long it took to recover, thus capturing both the *resistance* and the *recovery* dimensions of resilience.

Among the most commonly used revealed resilience indicators are the sensitivity and recovery measures *à la Martin* (introduced in Martin, 2012). These indicators provide a relative measure of resilience by comparing the performance (for example, the decline in GDP during the shock and/or its recovery in the post-shock period) of a specific region against a benchmark, often represented by the overall performance of the country or a subset of similar regions defined by predetermined characteristics or shock intensity Fingleton et al. (2012); Lagravinese (2015); Di Caro and Fratesi (2018); Faggian et al. (2018).

For an appropriate application of these indicators, it is essential to ex-ante identify significant variables whose trends over time reflect different resilience performances. Moreover, it is crucial to correctly determine the onset of the shock, a task that is usually achieved through data-driven methods or time series techniques (Di Caro et al., 2020).

Indicators *à la Martin* are widely used in the literature on regional economic resilience, as they enable the mapping of resilience performance in a simple and understandable way. Moreover, since they reflect resilience outcomes rather than resilience capacity, they allow for further research into the determinants of resilience, thus explaining what makes a system more or less capable of absorbing and recovering after a shock (Fingleton et al., 2012; Sensier et al., 2016; Alessi et al., 2020).

However, a significant drawback of such indicators is that they are relative measures that assess resilience performance compared to a benchmark. The choice of the benchmark is not neutral and can lead to different outcomes depending on the selected benchmark. This issue becomes particularly relevant in comparative studies across different regions, especially when the shock impacts each region differently in terms of timing and intensity, as was the case with the pandemic waves in Italy, which affected various regions at different times and with varying levels of severity.

Some attempts have been made to address this limitation by adopting absolute metrics that compare each unit with itself by simply using historical values (Sensier et al., 2016; Alessi et al., 2020), or by estimating a counterfactual path and comparing it with the observed one (Fratesi and Perucca, 2018). However, a common limitation of both relative and absolute indicators is that they treat the different phases of resilience separately (for instance, shock impact and post-shock recovery), calculating various metrics that individually account for each phase. As a result, they do not provide a single and comprehensive measure of resilience.

In subsequent sections, we explore the use of the ITS method to measure a single resilience indicator in a localised approach. This approach retains the advantages of revealed resilience indicators, allowing the mapping of resilience performance and also enabling further investigations of resilience determinants. Moreover, it eliminates the need for the arbitrary selection of a benchmark by comparing observed performance of each unit after a shock with its own estimated counterfactual path (which would have happened in the absence of the shock). Finally, ITS indicators effectively capture the performance of individual units in the different phases of the shock (impact and recovery), taking into account the different local settings that can affect the performance of individual territories.

### *2.3. Interrupted time series analysis in health domain*

Interrupted time series analysis is regarded as one of the most robust quasi-experimental designs for evaluating the impact of health interventions when randomized trials are not feasible (Bernal et al., 2018b). Unlike traditional methods that rely on comparisons between treated and untreated (control) populations, ITS assesses changes in outcomes over time within a single population, using data collected at regular intervals before and after the intervention. A core assumption of this design is that pre-intervention trends can be extrapolated to estimate counterfactual outcomes, thus allowing for causal inference even without randomization and when control groups are not available (Jandoc et al., 2015; Bernal et al., 2017).[1] By accounting for underlying secular trends, ITS also helps reduce the bias inherent in simple pre-post comparisons (Penfold and Zhang, 2013).

Over the past two decades, ITS has been increasingly applied to evaluate the effectiveness of a broad range of health programs and policies. Applications span areas such as vaccination campaigns (Bernal et al., 2019), smoking regulations (Barone-Adesi et al., 2011), road safety interventions (Grundy et al., 2009; Dennis et al., 2013), health system quality interventions (Hategeka et al., 2020), drug utilization research (Jandoc et al., 2015). Moreover, ITS has proven useful in assessing the health impact of unplanned shocks such as the global financial crisis (Bernal et al., 2013) and the COVID-19 pandemic (Li et al., 2023).

ITS studies employ various statistical approaches to quantify the impact of the interventions being studied, the most commonly employed being the segmented regressions (Hudson et al., 2019). In its simplest form, this approach splits the data into pre- and post-intervention periods, modelling both immediate changes in level and longer-term shifts in trend following the intervention (Wagner et al., 2002; Bernal et al., 2017; Kontopantelis et al., 2015). To better capture the complexity of temporal patterns in time series data, autoregressive integrated moving average (ARIMA, Box and Jenkins, 1970) models have also gained popularity for their flexibility in explicitly modelling autocorrelation, nonstationarity, and seasonality (Schaffer et al., 2021).

As detailed in sections 3 and 4, our paper advances the ITS methodology by complementing the traditional ARIMA approach[2] with a machine learning algorithm, Extreme Gradient Boosting (XGBoost, Hastie et al., 2009; Chen and Guestrin, 2016), to provide a more robust estimation of the counterfactual scenario. Moreover, unlike standard ITS analysis, we adopt a localized approach, estimating effects at the Labour Market Area (LMA) level instead of pooling results into a single global average. This more granular analysis captures conditional latent variables and spatial heterogeneity that would be overlooked in aggregate analyses, allowing for the identification of region-

[1] While ITS is typically applied within a single population, it can also be extended to multiple-group designs, where the inclusion of a comparable control group further strengthens the method's internal validity (Linden and Adams, 2011; Linden, 2018; Bernal et al., 2018a).

[2] As a robustness check, ARIMA approach was employed. The corresponding results are available from the authors upon request.

specific resilience patterns.

## 3. Methods

The reconstruction of the counterfactual post-intervention period is based on information from the baseline period. Mathematically, this relationship can be expressed as:

$$Y_{post} = f(Y_{baseline}, \epsilon_{baseline}, CLV) \tag{1}$$

where $CLV$ denotes conditional latent variables that influence both the response and the recovery dynamics across different territories. Accurately controlling for these latent variables poses a significant challenge, as it necessitates capturing complex, high-dimensional, and often non-linear dependencies across spatial points. These difficulties are further compounded by noise, scalability concerns, and computational constraints. Furthermore, detailed granular information (*e.g.*, on a monthly basis) may not always be available, thereby limiting the ability to rigorously verify the boundary conditions of the estimated counterfactual.

A localized modelling approach is generally more effective for controlling conditional latent variables, as it accounts for spatial heterogeneity and interdependencies while providing more granular estimates that reveal hidden spatial patterns. The counterfactual at each spatial unit $i$ can thus be modelled as:

$$Y^i_{post} = f(Y^i_{baseline}, \epsilon^i_{baseline}), \forall i \tag{2}$$

To implement this counterfactual estimation, two complementary time series methods will be used, XGBoost and ARIMA; the integration of these methodologies allows for a robust estimation of the counterfactual scenario, balancing predictive accuracy and interpretability while addressing the inherent challenges of spatial and temporal dependency structures.

XGBoost is a machine learning algorithm based on decision trees and gradient boosting framework, widely used for regression, classification and ranking problems. In recent years, it has gained popularity for its performance and precision in unsupervised learning tasks, building decision trees sequentially - where each new tree corrects the errors of the previous ones - and producing a strong set of trees.

XGBoost can model complex, non-linear relationships and capture interactions between features, which is valuable for time-series data with structural changes optimising the model by minimising a loss function, typically the mean squared error (MSE) by gradient descent methods. Through regularisation techniques such as $L1$ (Lasso) and $L2$ (Ridge), XGBoost can prevent overfitting, making it suitable for data sets with high variance or noise.

The application of XGBoost to ITS involves using the machine learning algorithm to model the relationship between the time-series data and the intervention. XGBoost can effectively capture non-linear relationships and interactions between variables, which makes it suitable for modelling complex time-series data with structural breaks due to interventions.
To apply XGBoost to an interrupted time series, the data have to be structured such that the time series is divided into pre- and post-intervention periods. The XGBoost model is then trained to predict the outcome variable based on previous lagged values for the pre-intervention period, capturing both the underlying trend and any changes due to the intervention. The post-intervention data are then used to assess the impact of the intervention.

ARIMA models are a widely used statistical approach to analyse and forecast time series data and they are particularly effective when the data exhibit non-stationarity, which is often the case in real-world scenarios. An ARIMA model is characterised by three parameters: $p$, $d$, and $q$, which denote the order of the autoregressive part, the degree of differencing required to make the series stationary, and the order of the moving average part, respectively. ARIMA models in the ITS framework (Schaffer et al., 2021) are well suited for this purpose, as they can account for autocorrelation within the data, seasonality, and other structural patterns, thus providing a robust framework for detecting and quantifying intervention effects.
Unlike the XGBoost method, the application of such a method to several different series, however, must be supervised, *i.e.* it requires the timely estimation of these parameters separately for each series; the use of an automatic parameter selection procedure[3] attempts to circumvent this feasibility problem, but still remains - in our opinion - a second-best compared to the non-parametric method. For this reason, the ARIMA method, in our application, has been used to check the robustness of the estimates obtained with the XGBoost method.

[3]The `auto.arima` function of the `R forecast` package.

## 4. Municipal Resilience in the Face of the COVID-19 Crisis in Italy

### *4.1. 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 provides a robust proxy for assessing health system resilience. 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.

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). 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. Through this process, the initial dataset covering approximately 8,000 municipalities was consolidated into a more manageable framework consisting of 600 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.

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 nonlinear 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.

For the second-stage analysis, as referenced in Section 5, 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 municipal 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, 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 address this gap, Cerqua et al. (2025) have introduced MAQI, the first comprehensive index to systematically measure institutional quality at the municipal level in Italy. Covering nearly all municipalities over the 2001–2021 period, MAQI evaluates bureaucratic efficiency, fiscal performance, and the valence attributes of political leadership. 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.

*4.2. 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.
The district of Bergamo, a region profoundly impacted during the initial phase of the pandemic, is presented (Figure 1) as a representative case study.

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.

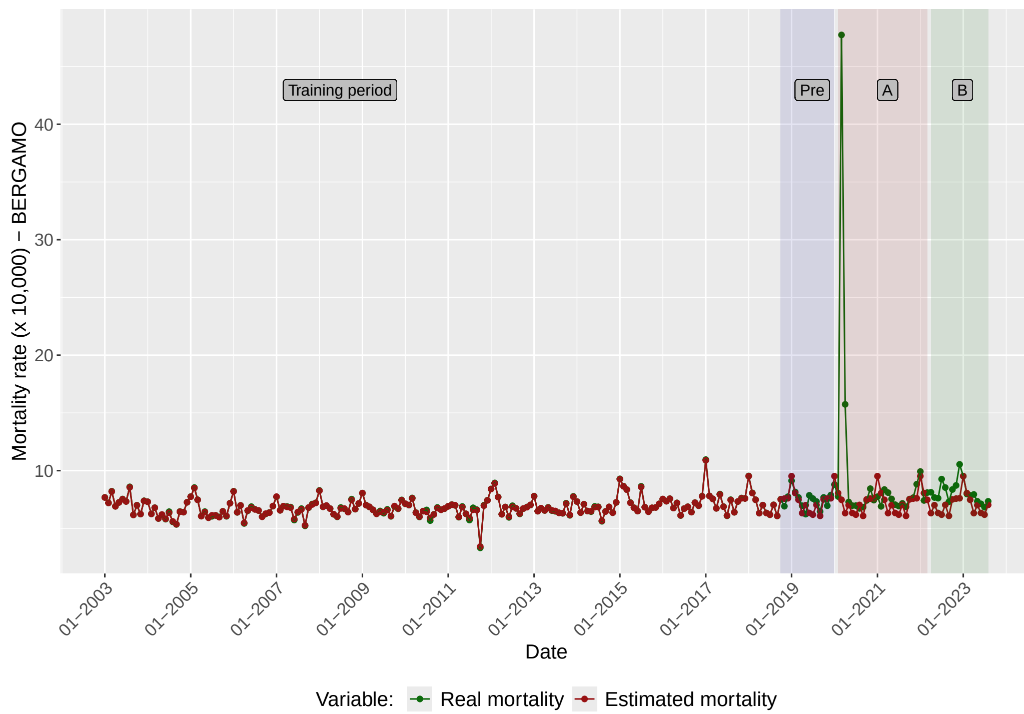


Figure 1: Real and estimated mortality for the different periods, Bergamo LMA, years 2003-2023

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.

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

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

Please note it was decided to measure only the excess mortality (marked with a +) without compensating for periods of lower mortality in order to highlight the pandemic impact even better; consequently, the index was normalised for periods ($t$) in which this excess was positive.
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.

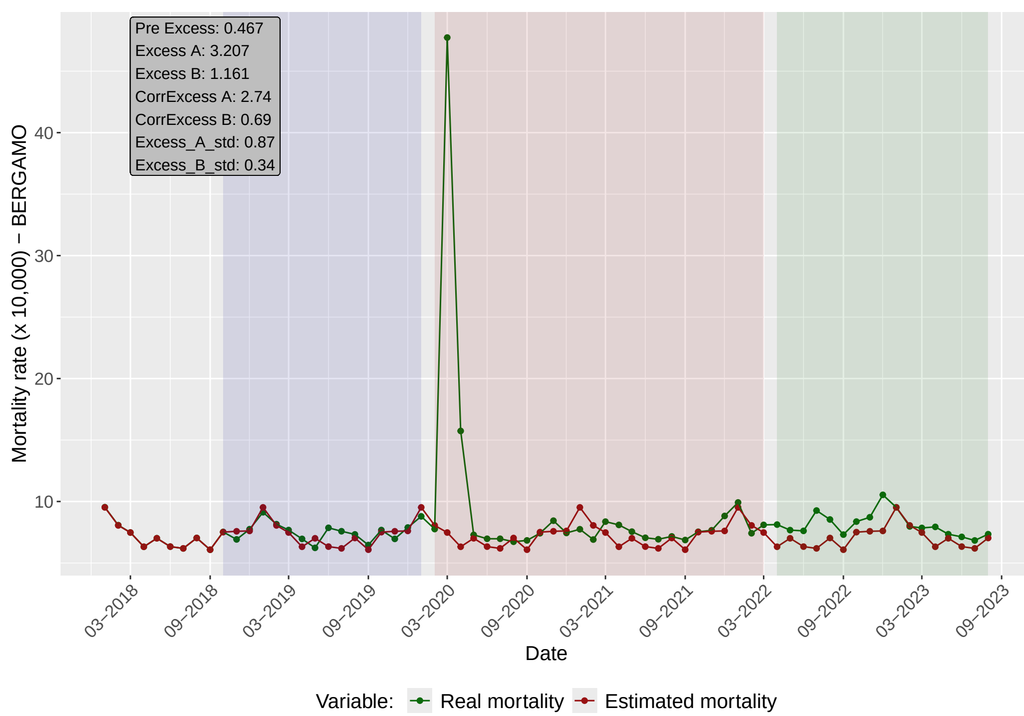


Figure 2: Real and estimated mortality for the different periods with $EX_A$, $CEX_A$, $EX_B$ and $CEX_B$ measures, Bergamo LMA, years 2018-2023

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

## 5. 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 1).

| $CEX_A$ | 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 1: 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?

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

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 2 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 overidentification, 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 (overidentification test of all instruments): | | | | | | 0.785 |
| Chi-sq(1) P-val = | | | | | | 0.3757 |

Table 2: 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.

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

Table 3 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 ($\rho$) 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 ($\phi$ not significant).

| | GMM<br>(1) | Sp.GMM1<br>(2) | Sp.GMM2<br>(3) | Sp.GMM3<br>(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] |
| $\rho$ | | 0.3529*** | 0.3349** | 0.3711** |
| | | [0.071] | [0.134] | [0.152] |
| $\phi$ | | | | -0.0164 |
| | | | | [0.191] |
| Observations | 583 | 583 | 583 | 583 |

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

Table 3: Two-step GMM models with and without spatial lag, robust SEs in parentheses

## 6. Final remarks

This paper proposes a novel, data-driven methodology to assess the resilience of municipalities during the COVID-19 pandemic, introducing the first counterfactual-based resilience index at the municipal level in Italy. 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 municipal 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 municipalities 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.

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.

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