



From 2008–2011 Great Recession to COVID-19 pandemic: an analysis of resilience metrics in European regions

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Abstract

We aim to clarify the usefulness of different measures of economic resilience in the context of global shocks. In relation to the Great Recession, Oil& European migrant crises, and COVID-19, we compute and validate from a statistical point of view, then characterize five metrics on 317 NUTS2 regions and 21 years. ROC curves and Cox regression compare them by the capacity to predict the post-shock state. Heterogenous behavior characterizes resistance, recovery, and loss. Furthermore, the non-linear resistance performs best in future state prediction, while the composite index has the lowest efficiency as a predictor of the regions' recovery.

Keywords Unemployment · Economic resilience · Composite index · COVID-19 · Cox regression · ROC curve

1 Introduction

Economic resilience has become a hot topic in the scientific world, especially after the financial crisis of 2008–2011. After the COVID-19 pandemic, the increase in the level of uncertainty has amplified concerns, as well as interest in the concept of resilience among both policymakers and researchers. Consequently, the European Union launched the Recovery and Resilience Plan in response to the pandemic crisis. The funds reach €672.5 billion and are split almost 50–50 percent between loans and

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grants European Commission (n.d.). This plan aims to help countries withstand and accelerate recovery after this pandemic. Following the restrictions endured during the pandemic period, the invasion of Ukraine in March 2022 enhanced further the global uncertainty. Although other countries relaxed or even eliminated the regulations related to COVID-19, China maintained its “Zero COVID” policy until the end of 2022. Blockages in the flow of goods closely related to the constraints imposed on Russia complete the grey picture of the economic situation. In this context, high unemployment level, large regional heterogeneity pointed out also by Lopes and Sargento (2023), and soaring inflation rates dominate the world.

Federal Reserve and European Central Bank react and increase interest rates roughly continuously reaching unexpectedly high, until the middle of 2023. Thus, policymakers, media, international institutions, and scientists warn about a recession with the risk of severe economic crisis—yet another possible brunt. Then, the European Committee of Regions understood the importance of economic resilience and demanded a scoreboard to measure regional vulnerabilities. This move arises as a defense instrument related to the slow and late response of the EU to the COVID-19 pandemic. They argue that the EU cannot be resilient without its components being resilient. However, based on the previous experience of contemporary shocks, we know that the territorial units have heterogeneous reactions or responses to such sudden events. Thus, the future behavior of the units after such circumstances is difficult to predict. The need to understand and measure economic resilience becomes even more stringent in the current rather gloomy context.

Despite the widespread usage of the notion of ‘resilience’, Rose (2004), Christopherson et al. (2010), Martin and Sunley (2015), Di Pietro et al. (2021), Elburz et al. (2021) or (Haile 2021) point out the difficulties and debates linked to conceptualization and definition. Furthermore, Elburz et al. (2021) underline confusion related to resilience and inappropriate usage of the term. Challenges appeared not only in defining and conceptualizing resilience but also in the ways to measure it appropriately. From national to regional level approaches, the authors propose different solutions for the concept and measures of economic resilience. Several scholars, among them Fingleton et al. (2012), Giannakis and Bruggeman (2017), and Cappelli et al. (2021), use a unidimensional measure. Others, like (Rose and Krausmann 2013), (Stanickova and Melecký, 2018), and (Pontarollo and Serpieri 2018) use a composite measure, arguing that a multidimensional approach of resilience could assess better the territorial behavior of a unit as a response to a particular anomaly. Additional problems appear when composite measures evaluate resilience. They enhance the debates linked to the concepts and measurement of the core notion. Also, in an economic resilience approach, each author adopts a concept and a model without having the absolute certainty that it was *the best* or at least a *good* choice. Weinans et al. (2021) present a global overview of resilience multivariate analysis as an amount of loss. The authors present pro and contra arguments but did not find the “best method”. They suggest just a guideline to approach the resilience measure.

The current situation, dominated by atypical events and uncertainty, is favorable to an economic resilience analysis. Among a wide range of areas of applicability, this course debates economic resilience on a particular branch the regional labor market. We measure the labor market resilience of regions after multiple crashes instead of

just after a single event. In line with Fingleton et al. (2012), our aim emerges from the assumption that more experimental results contribute to a better foundation. Therefore, our central target is to provide a quantitative analysis that guides academics and practitioners in choosing the appropriate metrics to evaluate resilience.

Previous studies applied mainly Gross Domestic Product (GDP) or Employment resilience. Our approach applies the unemployment rate based on many aspects. One is that famous international institutions like the International Labor Organization (ILO, n. d.) and the Reserve Bank of Australia (RBA, n.d.) underline that unemployment is (probably) the most used indicator on the labor market. Beyond this claim, the unemployment rate is also widely used as an explanatory variable in prominent economic laws such as the Okun Law and Phillips Curve. Further, the unemployment rate is also a mandatory source in other domains like psychology. Here, we find a notable background (Moorhouse and Caltabiano 2007; Sojo and Guarino 2011) that links the unemployment effects on individual health. The current inquiry does not land on a desert of science. Authors like Aksoy and Manasse (2018) and Monastiriotis and Martelli (2021), dissected labor market resilience from an unemployment perspective. Thus, the importance of the unemployment rate, the gaps in the literature, and the controversies aimed us to present this work.

Although many studies claim spatial analysis approach, there is no agreement yet about the best method. Then, despite an avalanche of resilience measures and techniques, we focus on the well-known and largely used ones with high specificity in the labor market. We start from the idea that a valuable resilience measure should also tell us what will happen with the units after the strike. Furthermore, we evaluate the resilience metrics by their capability to predict the final state at a given moment. We consider not only the status of the unit but also the time elapsed from the beginning of the kick to the moment of that status. Thus, the reader can find out whether a particular region is more likely to recover or not after the crisis by studying the values of genuine metrics like resistance or loss measured before the occurrence of the final event, here rebound.

The paper has four sections: The *first section* harmonizes various concepts of resilience, focusing on the economic and regional resilience notions. In a separate paragraph of the same section, we describe five recognized approaches for resilience measures previously applied in the economic arena. Section 2 deals with hypothesis data and methods. The *third section* presents the results, and the *fourth* contains discussion and conclusions.

2 Main concepts and related literature review

2.1 The main resilience concepts

Dealing with a concept as old as the Latin, it is difficult to synthesize its entire evolution in a few paragraphs. Despite that, we coalesce information related to this complex term. Forward, we focus on resilience in the economic branch.

2.1.1 A short historical perspective on resilience

The term seems to have origins in Latin from the verb “resilire” (Brinkmann et al. 2017). Gößling-Reisemann et al. (2018) claims also that terms like “resiler”, “resiliation” or “resiliment” were frequent in the fifteenth century in the French juridical language. Later after 1600, the term occurred in English, in physics. According to Flemming and Ledogar (2008), the sense of resilience was “jumping back”. In the nineteenth century, resilience came out in physical mechanics, meaning the capacity of a material to resist shocks. Gößling-Reisemann and colleagues attribute to William Rankine the paternity of the shock resistance concept. He defines the notion in a manual of technology. Further, resilience has the meaning of robustness (Alexander 2013). Among others, Martini and Platania (2019) or Elburz et al. (2021) suggest that the modern term was born in ecology in the eighth decade of the XX century. In this field, Holling (1973) receives the merit for the concept. Holling saw resilience as the capacity of a system to absorb changes. However, Luthar et al. (2000) and Kolar (2011) considered Norman Garmezy the pioneer of resilience research. They move thus the birth of the concept two years early, in the work of Garmezy (1971). Despite the controversy of its roots, after 1980, the notion spread its applicability and arrived in new domains. We underline the most well-known and used in the next paragraph.

2.1.2 The concept of resilience by typology

The paragraph dedicated to the historical perspective emphasizes that resilience fits with juridical and physical mechanics for more than 100 years. Also, there is already half of a century since the modern term was used in ecology or psychology. According to Brinkmann et al. (2017), the concept also appears in engineering, technology, geography, or geology. Here, from a seismic perspective, Bruneau et al. (2003) see resilience as the capacity of a system to avoid a quake, absorb it, and quickly rebound, if recover. The term is frequently used also in psychology and psychiatry. For example, Russo and colleagues (Russo et al. 2012) ascertain that resilience is the capacity of a person to avoid the negative consequences of extreme stress. An absence of this ability will compromise well-being. In education, resilience is often used to describe the capacity to adapt to certain circumstances (Casey et al 2012). In sociology, Adger (2000) seems to be the first to propose a definition of resilience in the year 2000. The ability of collectivities to cope with external stress caused by socio-political changes denotes social resilience. And because we are in an era defined by IT, cyber-resilience cannot be missed from the scientific vocabulary. Giving credit to Fredrik Bjork and colleagues, the idea of cyber-resilience has the bud at the Davos World Economic Forum in 2012. But a clear definition showed up in 2015. Thus, (Bjorck et al. 2015) gave birth to the notion of cyber resilience. They promote the term as “the ability to continuously deliver the intended outcome despite adverse cyber events”. Moving closer to the scope of this paper, we insist on the core definition applied in the economy.

2.1.3 The concept of economic resilience

According to many authors, among them Martin (2012) and Meng et al. (2022), Reggiani and colleagues gave the first definition of economic resilience (Reggiani et al. 2002). In economics, resilience refers to the ability of a system to absorb a loss (Rose 2004) or “the ability of a system to recover quickly from an adverse incident” (Briguglio et al. 2006). This capability can help a system bounce back from an adverse event. Ten years later, after the term delivery, Martin (2012) views resilience in a more complex manner as a mixture of four dimensions: resistance, recovery, re-orientation, and renewal. In 2014, (Hallegatte 2014) described resilience as the capability of a society or economy to minimize the loss of well-being. He also underlines the difference between instantaneous resilience and dynamic resilience. The first relates to the capacity for quick reaction-the resistance, while the last points to adaptability and recovery. In particular, in 2007, Kathryn Foster defined for the first time the notion of regional economic resilience as “the ability of a region to anticipate, to prepare for, to respond to, and recover from a disturbance” (Foster 2007). In the last 15 years, many authors, like Hudec et al. (2018) and Magro et. al (2022), adhered to and used successfully Foster’s definition.

Psychology, psychiatry, and physical mechanics look at resilience from the individual side. Education and sociology regard the term from individual and community perspectives. In ecology and economy, we may look at resilience from three perspectives: micro, meso, and macro (Rose and Krausmann 2013).

We highlight that resilience repeatedly links to different events that occurred unexpectedly. Starting from these basic ideas, we now look for the possibilities of measuring resilience.

2.1.4 Regional economic resilience (RER)

One already noticed that economic resilience is a relatively new concept. But regional economic resilience is even newer. The germs of RER appeared near the beginning of the XXI century. Although the problem of RER appeared even earlier (Reggiani et al. 2002) there is no explicit definition. Probably the first definition of economic resilience of regions appeared in Rose and Liao (2005). The authors assume that RER is “the inherent ability and adaptive response that enables firms and regions to avoid maximum potential losses”. Like any other new concept, regional economic resilience does not escape from reluctance. Controversies and debates arise soon on the field. Among the last debates, we recall Sutton et al. (2023) who made an extensive review, and concluded that RER is no longer an undeveloped and unclear concept. On the opposite side, Lemke et al. (2023) underline the unsolved issues and stress for a field interconnection for further developments of the concept. Despite the existent debates, two main branches live together in the plain of RER: the “bounce-back”-equilibrium branch versus the “bounce-forward”-adaptive and or evolutive side.

Authors like Reggiani et al. (2002) and Fingleton et al. (2012) are in favor of uni, or multi-equilibrium approach. The return to steady state is frequently used in engineering and ecology. The engineering perspective sees RER as the capacity

of regions to bounce back, to a pre-shock state of balance. The ecological view assumes RER as the ability of regions to absorb the shock and to maintain the existent state of equilibrium.

Martin (2012), Martin and Sunley (2015), Martin et al. (2016), Sutton and Arku (2022) and Lemke et al. (2023) choose the dynamic-adaptive form of RER. This wing complies with evolutionary and transformative resilience. The evolutionary concept sees the economies as capable to adapt and evolve, while the transformative focuses on the economies restructuring.

Following Martin and Sunley (2015) and Sutton and Arku (2022), four dimensions characterize the dynamic resilience of regions: the sensitivity to shock, resistance, robustness, and recoverability. Aligning with these ideas we propose a set of metrics that describe all RER forms.

2.2 Measures of resilience

There are many attempts to measure resilience. However, just like in the case of the concept, there is no consensus about how to measure it effectively (Rose and Krausmann 2013).

There is no doubt about the impact of shocks on the economy. Thus a vast literature presents the subject of economic resilience. In particular, Dube and Polese (2016), Giannakis and Bruggeman (2017), Aksoy and Manasse (2018), Goschin (2019), and Cappeli et al. (2021) or Lazzeretti et al. (2023) studied the resilience of the labor market. In consequence, without neglecting the importance of well-known studies related to economic resilience measures, like Reggiani et al. (2002), Foster (2007), Martin et al. (2016), Angulo et al. (2018) or Di Pietro et al. (2021), the current analysis focuses on the measurement of resilience which may be more feasible for the available unemployment data. We group the measures into unidimensional and multidimensional categories. The unidimensional resistance metrics are closer to the static approach of RER. Although they contain, by definition, static and dynamic hypothesis, the multidimensional metrics have a better connection with the dynamic approach.

2.2.1 Unidimensional approaches for resilience measures

Martin (2012) proposes linking the behavior of a sub-national territory to national performance. This tie appears via an elasticity measure called β_r . Here, the measure is the relative change ratio in the region and relative change at the country level. By comparing β_r with the unit, the author then tries to establish how sensitive a region is to a given reference or benchmark. Areas with sub-unitary β are resilient from the perspective of an indicator, like GDP per capita.

Sensier et al. (2016) extend the work of Sensier and Artis (2014) and consider economic dynamics as a succession of peaks and troughs. In their work, the employment resilience measure is a type of loss-related measure. It measures the relative change in the employment values between the peak and troughs. For the calculation, the authors link the region's pre-shock level and the rate of change in employment

$(\text{Employment}_{\text{Trough}} - \text{Employment}_{\text{Peak}})/\text{Employment}_{\text{Peak}}$. The authors also computed the duration, in years, for a region necessary to recover to its pre-shock level. Furthermore, they classify a region as resistant if its mean rate of change of employment is positive between two reference time points called peak and trough. These extreme points are established by reference to the national employment values.

Following the same principle, Goschin (2019) measures the resilience of GDP and employment based on a mechanical adjustment. The author computes that the resilience of the territorial unit i as the ratio between the percentage change of the indicator for territorial unit i and the percentual change at the national level. Lazzeretti et al. (2023) use the same approach and compute the resilience only based on the employment data. In line with this idea, Cappelli et al. (2021) apply a logarithmic transformation of the indicators in the labor market. One may conclude that Martin evaluates resilience by a linear change. Goschin, Cappelli, or Lazzeretti and their colleagues prefer a non-linear approach.

2.2.2 Multivariate measures of resilience

Bruneau et al. (2003) proposed a quantification of resilience by a loss measure. For example, a particular analyzed indicator reached X_0 value before a shock. The shock occurred at moment t_0 . We evaluate the system status at t_1 . Then, the resilience measure is $R = \int_{t_0}^{t_1} (X_0 - Y_t) dt$, where Y_t represents the indicator value at moment t , between the occurrence of shock (t_0) to the end of its assumed impact (t_1). Based on the same concept, (Hallegatte 2014) uses a Cobb–Douglas type function to evaluate the loss of output in the case of partially destroyed capital after a disaster. He computes resilience value like a difference between the expected and the empirical curves.

Following the works of (Briguglio et al. 2006) and Martin (2012), who see resilience as a multivariate result, Pontarollo and Serpieri (2018) aimed to create a composite index. The authors propose a form defined by four components. First is the mean value of the indicator before the shock. The second is the trend before the shock. The last two components are the resistance and the recovery. We capture the core information from each fundamental measure and method described above. Then, we adapt the arrangement to measure the NUTS2 regions unemployment resilience.

3 Data, hypothesis, instruments, and methods of analysis

3.1 Data sources

Following the importance of the subject described in the introduction, in the current analysis, the indicator explored is the 15–74 years unemployment rate (UR) for all genders. The dataset has 33 European countries, 317 NUTS 2 regions, and a time range from 2002 to 2022. In Appendix 1 we provide the list of them. Methodological

aspects related to UR calculation are available on the Eurostat web page (Eurostat 1). The core part of the data is available on the Eurostat Labor Force Survey database (Eurostat 2). Multiple factors like territorial changes, non-reporting, or the COVID-19 lockdown caused missing data in the source. We input missings using diverse sources and methods. Our goal was to minimize intervention on the data. Therefore, we input only 4% of all regions-time data matrix. Then, in the input process, we use predominantly the simple mean of nearby periods, the weighted mean of NUTS3 regions in componse, or the mean of the upper NUTS1 region. Appendix 2 offers imputation details and a list of other sources.

3.2 Instruments, hypothesis, and methods of analysis

3.2.1 Concepts related to resilience measure

3.2.1.1 Shocks Based on the existent studies, the three most significant disruptions within the 2002–2022 period are the Great Economic Recession (GER), in 2008–2011, the Oil and European Migrants Crises(O&EM) in 2014–2016, and COVID-19. The GER was unanimously recognized. Many authors, like Grigoli et al. 2017 or Cimpoeu et al. 2020 use the second. The WHO clearly delimited the COVID-19. They assumed the start of the COVID-19 Pandemic emergency in March 2020 and declared its end in May 2023. In addition, Sutton and Arku (2020) also exemplify shocks, mentioning, among others, GER, COVID-19 and post COVID economic crisis.

We explore the effects of this shock within 2020–2022, while at the moment of writing, no data was available for 2023. Further, our investigation connects various concepts and measures of resilience to these unusual events.

3.2.1.2 Pre-shocks periods In economics, the pre-shocks are frequently in use. Related to GER shock, economists consider the time interval before 2008. For example, Dimian et al. (2013) underline that 2000–2007 is a stable period for unemployment in most of European countries. Then, Carreira and Texeira (2016) used the 2004–07 interval as a baseline for future attempts. Following this approach, for the Oil crisis, the pre-shock period is 2012–2013, and for the COVID-19, the pre-period is 2017–2019.

3.2.1.3 The post-shock periods For the 2008–2011 event, the post-shock is the 2012–2013 interval, while for the Oil Crisis, it is 2017–2019. At the moment of writing, it is hard to define the post-disturbance period of COVID-19. The effects of this shock may prolong until 2023 or later.

3.2.2 Applied regional resilience measures

Based on most popular methods and measures, we derive for all three shocks, five resilience metrics. The first scenario considers resilience as the resistance to a particular shock. Following the example of Sensier et al. (2016), the shock

resistance for each region, i , is the slope from the linear regression model, $UR_{it} = \beta_{0i} + \beta_{1i}t + u_{it}$. It is applied for the interval defined by the last year before shock and T . The year T is the point within the shock interval where the UR registers the maximum value of the shock period. If we note “last year before shock” with 1, then “ T ” denotes the time horizon.

In the model, t covers the period, and u_{it} are unknown factors, assumed to be white noises (WN). For each region, i , we estimate the parameters via classic Ordinary Least Squares (OLS), and we characterize the behavior of the unemployment rate in the absence of shocks. Due to the short periods around the shocks (3–6 years), we neglect the property of stationarity and its contrecoups.

On the one hand, resilient regions have a negative or zero slope coefficient. On the other hand, the non-resilient ones will have a positive slope, β_{1i} . From this point forward, we call this proposal,

$$LR_i = \beta_{1i}, \quad \text{Linear Resistance, of the region } i \quad (1)$$

Following Goschin (2019), Cappelli et al. (2021), and Lazzaretto et al. (2023), mentioned in the 1.2.1 paragraph, we explore the resistance to a shock, by a non-linear resistance (NLR) which follows the relation:

$$NLR_i = \ln \left(\frac{UR_{\max, i, \text{with in the shock}}}{UR_{\text{last year before shock}}} \right) \quad (2)$$

Resilience is also the recovery after a particular shock. The recovery (REC) is the slope between two fixed points t_1, t_2 . Using the same model described in the case of linear resistance, we have $UR_{it} = \beta_{0i} + \beta_{2i}t + u_{it}$. The year t_1 gives the starting point, when region i reaches the maximum level of the unemployment rate ($UR_{\max}$), within the shock period, and the endpoint, t_2 , which is the first year post-shock.

$$REC_i = \beta_{2i} \quad (3)$$

But resilience might also be a measure of loss. Then, instead of the single metric, the current proposal joins resistance, peak, and recovery. In this case, the approach follows Bruneau et al. (2003) and Hallegatte’s (2014) method, captured here by BRH. For each region, the resilience is:

$$BRH_i = \int_{t=\text{first year of shock}}^{t=\text{last year of shock}} (f(\theta) - \hat{f}(\theta)) d\theta \quad (4)$$

$f(\theta)$ defines the behavior of unit i under the presence of shock, and $\hat{f}(\theta)$ estimates the dynamic change in the absence of shock.

The presence of discrete values leads us to approximate the integral by the Riemann sum. Many possibilities are available, among them, the left rule, right rule, mid-point rule, or the trapezoidal rule (Hughes-Hallett, et al. 2005). In our work, we choose the left rule, which implies, for three particular years, the following expression: $(EUR1-TUR1)*\Delta + (EUR2-TUR2)*\Delta + (EUR3-TUR3)*\Delta$, with $\Delta = 1$ (year). Then, we propose the general form:

$$BRH_i = \sum_{\text{first year of shock}}^{\text{last year of shock}} (EUR_{ti} - TUR_{ti}) * \Delta \quad (5)$$

In the BRH_i formula, the EUR_{ti} component is the known value of the unemployment rate in region i during the crisis. TUR_i is the theoretical or potential UR that occurs under economic shock omission in the same period. Hence, first, we estimate the parameters of the model $\ln(UR_{it}) = \alpha_{0i} + \alpha_{1i}t + w_{it}$, using the longest pre-shock available range in 2002–2007. The α_{0i} is the intercept, and α_{1i} is the slope of the above semi-log model. The index i accounts for time, and w captures the unknown factors (disturbance). Then, with the aid of the model, we forecast the values of TUR within the 2008–2011 interval. For the latter two anomalies, the pre-shock sample is too small. This thing causes high uncertainty on the parameters and future forecasted values. In consequence, we identify all local UR minimums. First, for the pre and post-shock periods [2011–2013] and [2017–2019]. Then, we find them within shocks [2008–2011], [2014–2016], and [2020–2021]. In the absence of the shocks, we assume that the UR will pass with a constant step from one minimum to another minimum. Neglecting the peaks, the constant step value Δ_i equals to $\frac{\min(UR_{2017-19}) - \min(UR_{2011-13})}{t_2 - t_1}$. Here, t_2 and t_1 are those years where the UR reaches the minimum. For the 2020–2022, the TUR equals to UR_{2019} values. For all shock periods, the EUR and TUR values fill the relation (5), and the BRH results after the summation of the differences.

The approach proposed by Bruneau and colleagues has only positive values. After mechanical shocks like earthquakes and floods, the state of the place cannot be better than the initial one. But in the labor market, due to multiple causes, the differences could also be less than zero. Some regions may register lower UR during the shocks compared to the pre-crisis periods. In such conditions, BRH_i is only the sum of positive values. The negative values are replaced by zero. This implies that more resilient regions have lower values of BRH_i , resistant region have $BRH_i = 0$, and less resilient regions will have larger BRH_i .

LR, REC slopes, and TUR values result from particular regression models. We validate all the regression models using the Fisher test when the time series has a length over two. Also, for each sub-sample longer than three units, Shapiro–Wilk (SW) and Breusch–Pagan–Godfrey (BPG) tests assess the normality and homoskedasticity hypothesis of the residuals.

Following Portarolo and Serpieri (2018), the last method applied in this study develops a composite index. The first component included in the index is the mean value of the indicator computed for the pre-shock period. Here, this component represents the simple mean of $UR_{2002}, \dots, UR_{2007}$ values. The number of terms included depends on the available period. The second component is the UR SLOPE. It is estimated based on the longest 2002–2007 available span. This component measures the “normal tendency” in the absence of shock. The third and fourth components are the linear resistance, LR, and the recovery component. We included here the values obtained using the (1) and (3) relations described above. In this approach, the Principal Component Analysis (PCA) technique uses the varimax criterion to extract

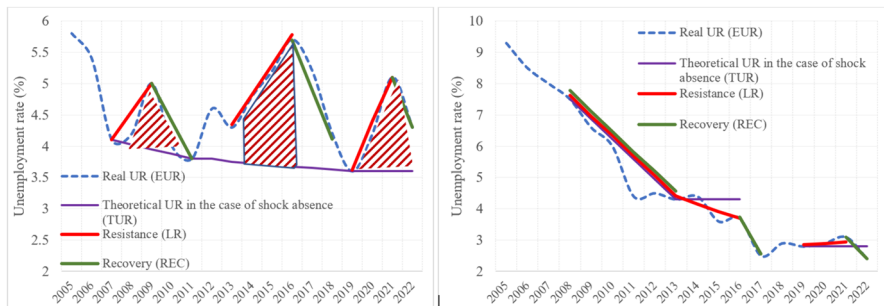
components. It searches for components with eigenvalues above 1. We explored several ways to construct the composite index. One includes means before shocks, slopes before, linear resistances, and linear recoveries. The second joins the means and slopes before shocks with NLRs and LR. Another variant explores the inclusion of means before shocks, slopes before, and BRHs. Our results, not presented here, suggest that the first choice is the best approach in terms of PCA yield and or specificity-sensitivity analysis performance. Therefore, we continue the discussion with a composite index based on the best choice. With the notion of resilience used above, a formalization of CIR is

$$CIR_i = a_1 \overline{UR}_{2002/3/4-07,i} + a_2 * SLOPE_i + a_3 * LR_i + a_4 * REC_i \quad (6)$$

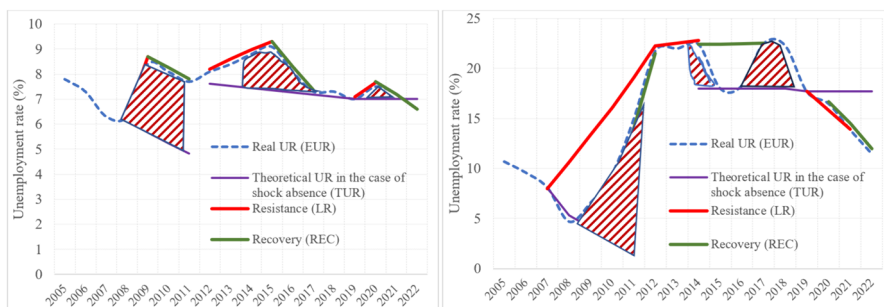
where $a_1 \dots a_4$ are weights achieved on the PCA.

Based on the above methodology for LR, REC, and BRH, Fig. 1 draws, in a stylized form, the resilience measures for four particular regions with different practices.

In line with the methodology described in this paragraph, we shine different behavior. Austrian region Burgenland (AT11) has a slow UR downward trend (EUR). It was not resistant to the analyzed shock. In all three cases, the LR is positive. Despite its non-resistance, the negative slope, REC, suggests that the region tends to recover to its pre-shock UR values. The Region FRK2, Rhone-Alpes have almost the same behavior as AT11, but its oscillations are around a moving up trend.



Resilience measure for Burgenland, Austria (AT11) in the left, and Kassel, Germany (DE73) in the right



Resilience measure for Rhone-Alpes, France (FRK2) in the left, and North Aegean, Greece (EL41) in the right

Fig. 1 Different resilience measures related to all three shocks

Predominantly, UR drops in the Kassel region from Germany (DE73). This German land is a typical example of a resistant region for the first two economic ruptures. Kassel is rather non-resistant to COVID-19. One may observe two negative LR values for 2008–2011 and 2014–2016. The shape continues with a tinny and positive slope for 2019–2021. The region will recover to its 2019 values in 2022. The fourth region, the Greek North Aegean (EL41), is more volatile. The LR is low, and the 2008–2011 hit strongly affected it. Next, O&EM shock tends to have a slighter impact. COVID-19, due to more relaxed policies in Greece, helps the region to reduce its UR to a minimum of the last ten years.

3.2.3 The sensitivity and specificity of resilience metrics related to prediction capacity of post-shock state

The Receiver Operating Characteristics (ROC) and specific area under the curve (AUC) techniques measure the specificity and sensitivity. Each resilience metric is evaluated related to the capacity of region status prediction. The AUC is tested against the 0.5 theoretical value that denotes no impact of analyzed metrics. The Youden Index values describe the cut-off points.

3.2.4 The capacity of resilience metrics to predict the status of the region after the shock

The capacity to predict the future state of the region is useful knowing that the resilient regions were able to resist and or adapt. They are able also to create a better response, and finally recover to the initial (pre-shock) state. The after-shock binary state of each region and time to recovery (TTR) are obtained assuming the next scenarios. If UR remains in all years within 2008–2013 below the 2003/2004–2007 values, then the region is resistant. If unemployment rises during the GER anomaly, by comparison to pre-shock, then drops to the initial values until 2013, then the region has recovered. This type of region receives a status equal to 1. In this case, TTR is the difference between the year when the region reaches an unemployment rate lower than or equal with UR_{2007} , and 2008. Otherwise, the region did not recover, and the last known state is 0. For the non-recovered regions, the maximum available follow-up time will be equal to five years.

For the Oil Crisis shock, a resistant region has all UR values within 2014–2016 below the 2012–13 pre-shock values. A region recovers after the Oil shock if its UR increased between 2014–2016, but returns to its pre-shock values no later than 2019. For instance, if a region recovers in 2017, then TTR is $2017 - 2014 = 3$ years. If the region has not recovered after the shock, TTR equals the difference between the last available year post-shock and the first year of the shock. Therefore, for the 2014–2016 anomaly, the available time to follow up is until 2019. For the COVID-19 stress period, a recovered region returns its UR value in [2021–2022] to the 2019 value. The maximum follow-up time here will be then only two years. After standardization, we introduce resilience metrics as individual continuous predictors along the state and time to recovery in a Cox Proportional Hazard Regression (CPH). We apply survival analysis (Cox 1972) to compare the prediction capacity of the

metrics. More specifically, we analyze the capacity of each measure to predict the instantaneous probability of recovery.

CPH was already used in the specific literature to find resilience drivers (Raj et al. 2014; Lewin et al. 2018). In the current study, CPH outperforms the classical Logit or Probit models applied, for example, by Di Pietro et al. (2021). Since the shock does not start to affect the regions and does not end at the same time (Cappelli et al. 2021) and the regions do not reach the recovery status at the same time (Fingleton (2012) the inclusion of time to event component in the CPH improves the analysis methods. Descriptives and econometric analysis were performed in R-Studio v. 4.3. The ROC analysis was made in Medcalc v22.009. PCA for CIR score was produced in SPSS v.19. The following sections present the results, discussions, and implications of the findings.

4 Results

4.1 General aspects of the unemployment rate. Variation and confirmation of hypothesized shocks

The pre-recession period 2004–07 has a very heterogeneous 15–74 unemployment rate. Regions with two-digit UR values, colored in red in Fig. 2, spread on the northern, south, and south-eastern continent parts. East Germany, Poland, and North and East Finland highlight the northern side. And Spain, Italy, Bulgaria, Greece, and Turkey dominate the southern part of the European picture. In contrast, regions from the U.K., Norway, Ireland, Iceland, and north of Italy have unemployment lower than the natural expected, 3–5%. Each of these two extreme clusters contains one-quarter of the total NUTS 2 regions.

In different parts of Europe, there are various trends in the unemployment rate during the first shock. For instance, Greece and Spain's upward jobless trend correlates with the economic downturn. Further, in Germany, economic growth causes a downward trend in unemployment. Also, the UR values are stationary in some parts of the continent, like in the North-East of Turkey, the West of Romania, and most Norwegian regions. In addition to heterogeneous behavior, a general tendency of UR growth is visible. The red color fills more and more regions from one year to another (Fig. 2). The number of units with UR above 10% was 49 in 2007. One year later it dropped to 45 and soared to 91 in 2009. In 2010, 108 NUTS 2 territories, or one-third of the total, had rates above 10 percent. The simple UR mean of the 317 regions had a minimum value in 2008 of 6.9%. Then, it progressively rose between 2009–2015, with a peak in 2013 and small oscillations from one year to another. The rate turned back to 8.5% in 2016. The second extreme period, defined by the O&EM crises, focuses on Central Europe, where unemployment dropped below 5%. The overall lighter color suggests a more facile burden. However, the red still dominates Spain, Poland, southern Italy, and Greece, where the values frequently surpass 18%. In 2014, 102 regions still had UR above 10%, and 62 of 317 dropped below 5%. After

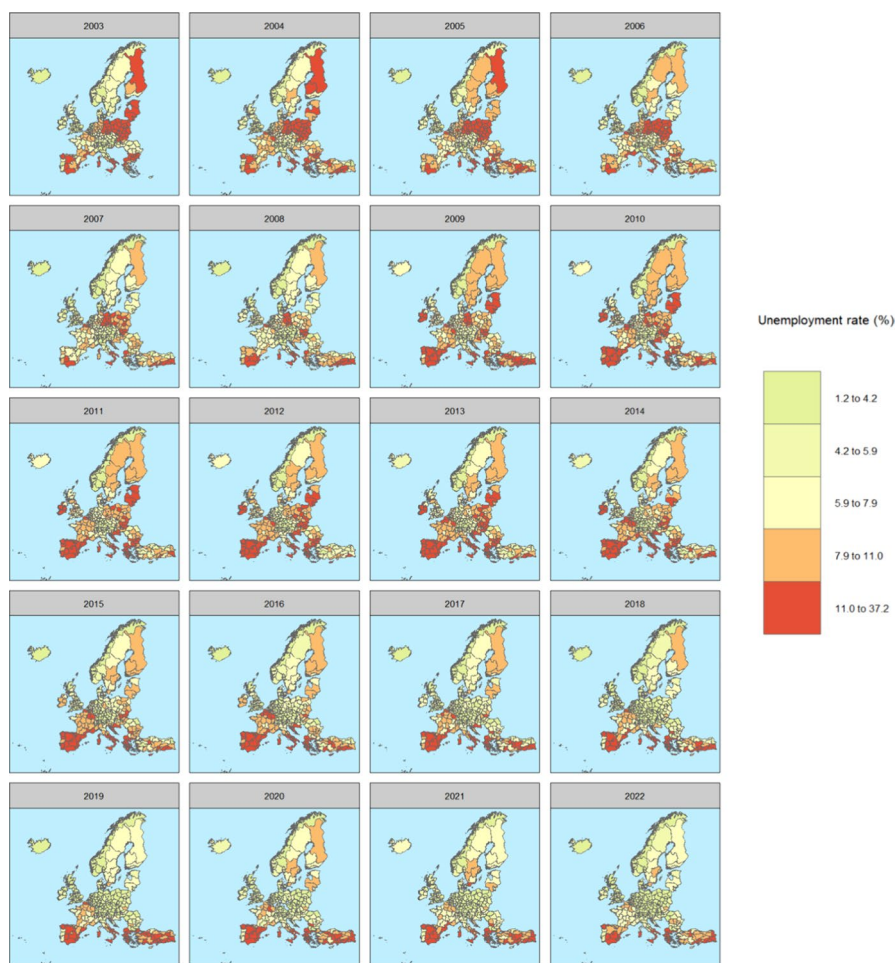


Fig. 2 Cross-sectional variation of UR during 2003–2022, quartile groups

2018, the simple mean rate rose again until 2021, above 7%. The number of regions with UR double than usually expected, 5%, falls in 2019 to 59, a minimum of the 2009–2021 interval.

During the pandemic, in 2020–21, only 59 NUTS 2 regions reached a UR value above 10%. In 2022, the situation was better. The number of administrative territories with two-digit values in the jobless rate counted 47. Such a small number of units with low unemployment appeared only in the pre-Great Recession. In the same year, the mean converges again to a more desirable value, 6.1%. Studying the content of Appendix 3, the reader discovers trends, spreads, and main descriptives for each country.

4.2 Resilience metrics analysis

4.2.1 Results regarding statistical validation of the derived resilience measures

In this phase, Econometric analysis involves 2124 regressions. Collecting data from the regression outputs, we check multiple assumptions. We test the statistical significance of LR's slopes, UR's models, and tendencies before shocks. The inquiry continues with the test of REC regression coefficients and the validation of the regression hypothesis. Allowing a 0.1 maximum risk, the results reveal that 40% of regression models are statistically significant. More than 95% of the regression models do not reject normality and homoscedasticity. Reading in detail the content of Appendix 4, 5, 6, one may examine the results by resilience component and shock. These results allow us to go further with derived parts and tests related to resilience measures.

One method, the composite resilience index (CIR), described in the methodology, implies the inclusion of a few components derived after principal component analysis. No principal component explains more than 60–70% of the initial variability. However, two principal components extract more than 80%. Finally, we compute the Composite Index of Resilience (CIR) by weighting the initial two components. Weights are equal to the proportion of variance extracted.

4.2.2 Variations of resilience across regions and shocks

Synthetic measures of resilience have common and different characteristics as well. On one side, as defined in the methodology, in each shock period BRH and NLR are left bounded by zero. On the other side, the composite index, the linear resistances, and the recovery slopes spin around zero.

Here, one may also notice the highest dispersion of BRH in each period. Except few cases, the values of CIR, LR, NLR, and REC are all bounded by -5 and 5 limits. The same plot emphasizes the highest homogeneity of NLR. Beyond these basics, the spread of points highlights the presence of outliers (Fig. 3). Taking into account these variations combined with the goal of territorial comparison, we provide a mapping of standardized measures. (Figs. 4, 5, 6).

A perspective on linear and non-linear resistance highlights a very similar territorial spread. In the Great Recession, Iceland, the UK, Germany, and Baltic countries record a low resistance (Fig. 4). In 2014–2016, in terms of LR or NLR, the crises affected with predominance the Nordic block, Finland, Sweden, and Norway, part of Germany. Then France, Italy, part of the Romanian regions, and almost all Turkey regions complete the list. The COVID-19 Pandemic resistance depends on multiple factors such as climate, the capacity of the medical system, economic structure, and severity of restrictions. At a glance, COVID-19 pressured more on the resistance of continent edges. On the north, the map highlights Iceland, Denmark, Estonia, Lithuania, and Latvia. In the south, we see Spain, Portugal or Greece.

The CIR and BRH complex metrics draw different patterns. In the first view, the composite measure, CIR, shows more homogenous regions. Dark green denotes greater unemployment resilience and covers Finland-Norway, France, and Germany in the 2008–2011 recession. Oil-Migrants crises highlight Baltic countries. The last

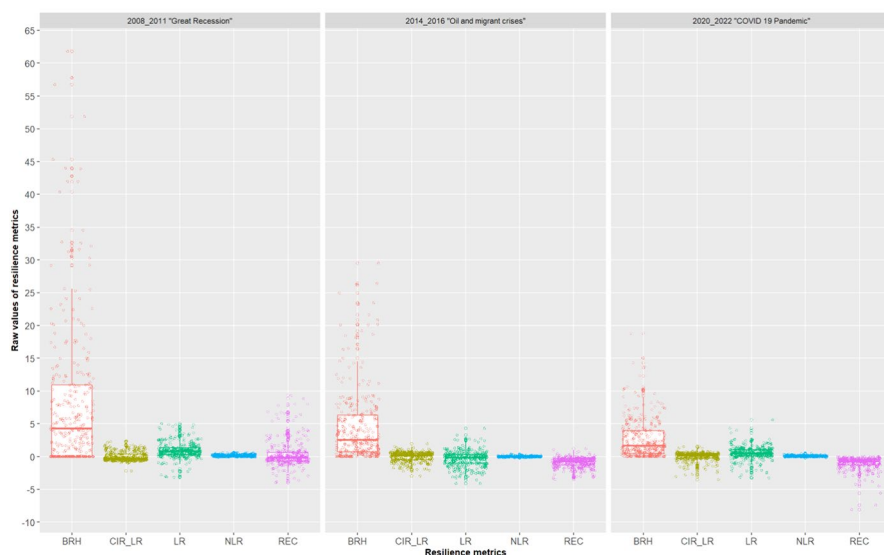


Fig. 3 Descriptive for resilience metrics by shock

shock event points to the Iberic Peninsula and the south of Europe. Due to its mean character, the composite measure reduces discrepancies between territorial units. The prominence of red versus the light green points that the BRH attracts the attention to the extremes. (Fig. 5).

The linear recovery rates determine a spread of the light red on the 2008–2011 map in Fig. 6. Some regions show positive signs of recovery, thus negative UR slopes, after this shock, especially on the extreme parts of the continent. But countries like France, Romania, Germany, and Poland are still covered in red. Such color flags that unemployment continued to grow after GER. Although the 2014–2016 Oil & Migrant Crises had lower intensity than the previous shock, the recovery rates are positive. The standardized values above 0.2 prevail in Germany and countries from the Scandinavian Peninsula. The current data does not allow us to compute all the recovery slopes for the COVID-19 shock. The shock did not show all its effects yet. Despite that, most of the regions show positive signs until 2022. The corresponding map from Fig. 6 shows a puzzling mix of positive and negative signs of recovery. The green dominates Romania, Turkey, Germany, Nordic and Baltic countries, while the red flags Portugal, Spain, Italy, and Greece.

4.3 Sensitivity and specificity analysis of resilience metrics

All resilience metrics reveal a good discrimination capacity between recovery-resistance state and non-recovery in GER. Statistical comparisons of each AUC vs. 0.5 target value achieve p-values below 0.05. Among all the compared measures, non-linear resistance seems to have the best capacity to discriminate between future

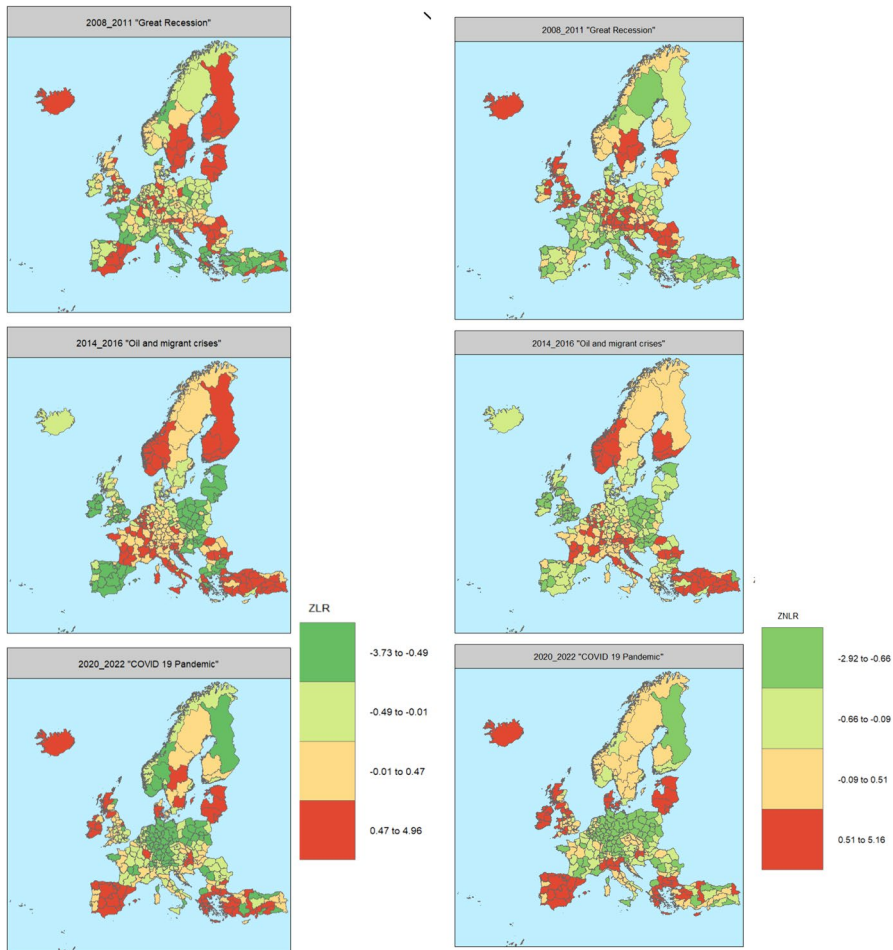


Fig. 4 Variation of standardized LR and NLR values across NUTS 2 regions by shock

states of regions. From a statistical point of view, the NLR derived after Goschin (2019), used by Cappelli et al. (2021) and Lazzeretti and colleagues (2023), performs better than all competitors except the linear recovery rate (REC). A negative value of NLR has 44% sensitivity and 96.6% specificity. Based on the Youden Index, the cut-off point remains positive at $NLR=0.09$ on the raw scale. At this point, sensitivity is 85% and specificity 80%. Thus, using the non-linear resistance predictor, one has the lowest chance of forecasting false recoveries and false non-recoveries after the first shock. (Fig. 7).

In the case of the Oil and Migrant Crises, the NLR measure performs again the best. However, AUC statistical comparisons do not flag significant differences in NLR against LR and CIR. Results emphasize that BRH performs the worst. In this case, the cut-off point of NLR is 0.038, where sensitivity is 88.4% and specificity is 78.8%. Therefore, non-linear resistance values below 0.038 will decrease sensitivity, but it will

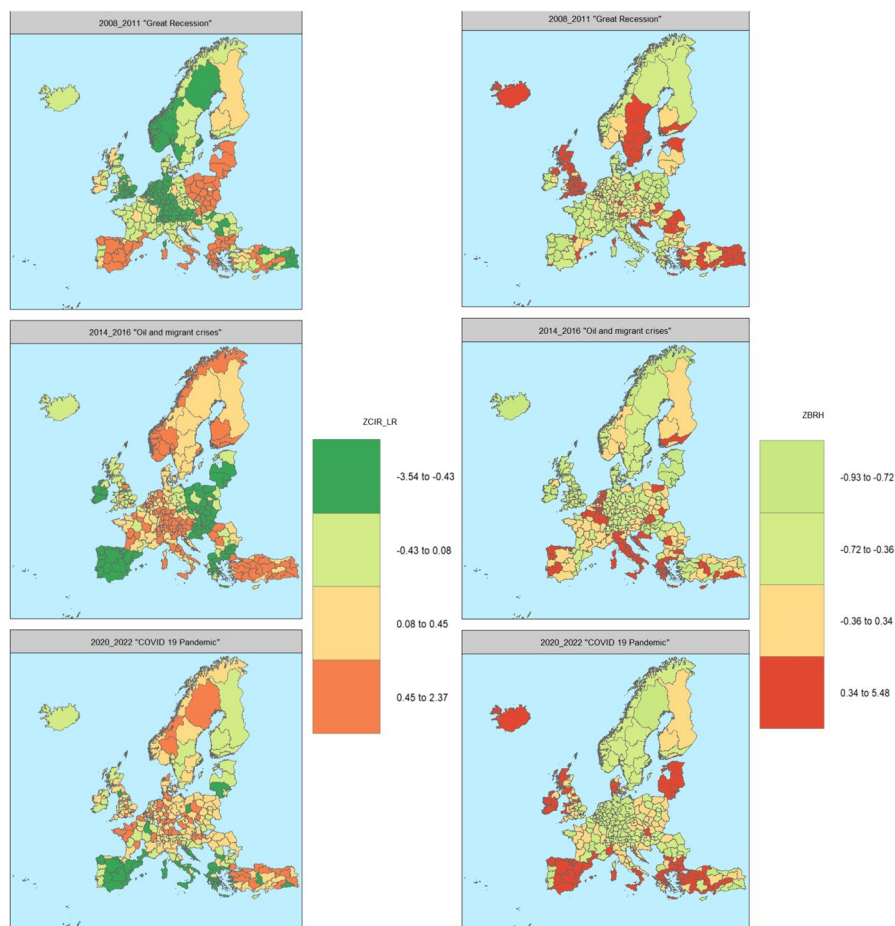


Fig. 5 Variation of standardized CIR and BRH values across NUTS 2 regions by shock

increase specificity. High specificity rates reduce the chance of estimating a false recovery state of regions.

On the COVID-19 shock, the non-linear resistance metric has the highest capacity to predict true-positive regions with a recovery state by 2022. BRH comes in second place, with an AUC of 0.749. Statistics pairwise comparisons sign significant differences ($p < 0.01$) between AUC curves, except for CIR against LR and REC. Surprisingly, the recovery rate REC and composite index, with AUC below 0.6, perform the worst among all measures for the Pandemic shock.

4.4 The capacity of resilience metrics to estimate the probability of recovery

The analysis informs that all five measures significantly impact the instantaneous probability of recovery in the first shock. At linear recovery rate and composite

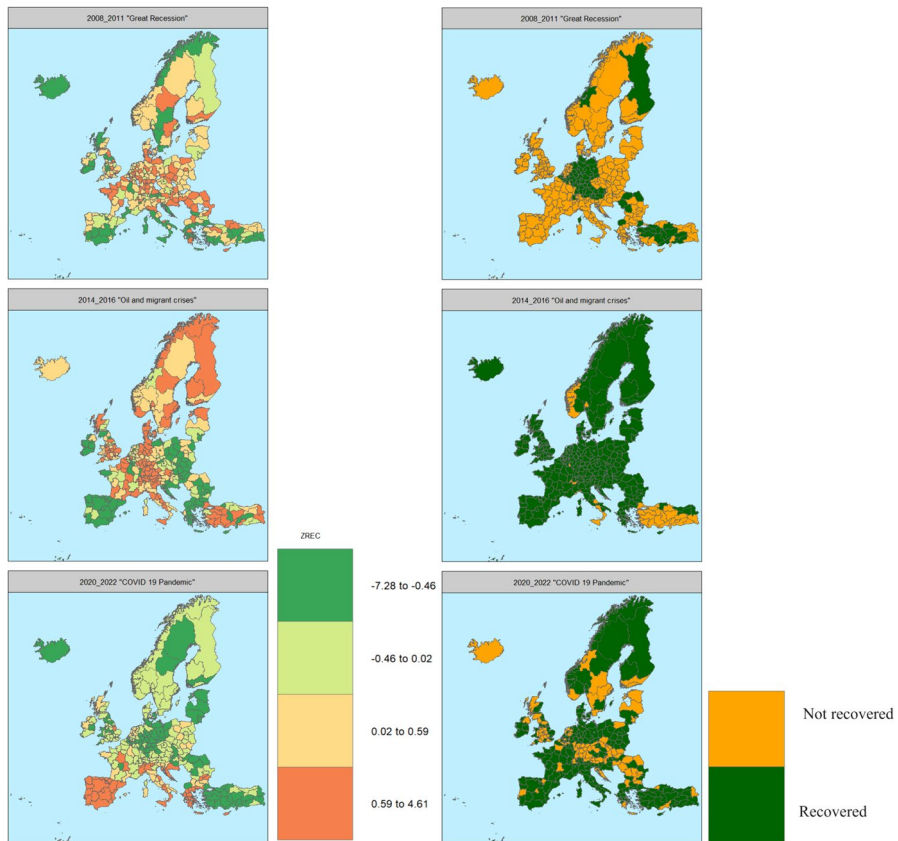


Fig. 6 Variation of recovery measure and regional status across NUTS 2 regions by shock

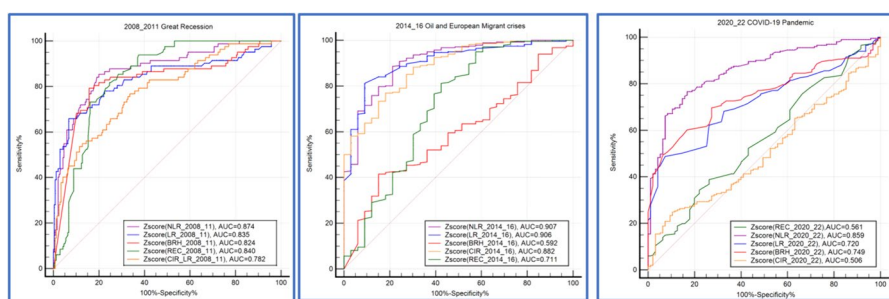


Fig. 7 Sensitivity-specificity analysis of all resilience measures by disturbance

index, p-values associated with HR exhibit the 0.05 threshold for COVID distress. Cox model results underline the importance of non-linear resistance to each shock in terms of recovery hazard. Holding the other factors constant, an increase of NLR by one standard unit, chances to recover will decrease by 86% in the first shock,

50% in the second, and 67% in the pandemic shock. An increase of LR and BRH standardized values diminishes the recovery chance with a wide spread of values. The chance varies by shock. For instance, during the Great Recession, an augmentation of LR by one standard unit implies a 65% less chance of recovery between 2008 and 2013. A similar increase in the last shock implies -54% chance to recover within 2020–2022. BRH standardized metrics have the largest heterogeneity between shock periods. In the first shock, a +1 standard unit of BRH causes a depreciation of chances to recover by 2013 with 74%. A similar change during the Oil and Migrant crises will affect the rebound chances by 2019 with only 15% (Table 1).

5 Discussions and conclusions

5.1 Discussions

From 2002 to 2022, the 317 NUTS 2 regions manifest considerable unemployment heterogeneity. Giant jobless rates prevail within shock intervals. In line with other studies (Fingleton 2012; Giannakis and Bruggeman 2017; Cappelli et al. 2021), the mapped values of the UR dynamic show different patterns across the analyzed European regions. The central tendency and variance indicators values are inversely associated with shock periods. Although the mean and range of UR values seem to decrease during crisis periods, the heterogeneity increases. In line with Sutton and Arku (2022), these results suggest that a global perspective on descriptive indicators is not enough. When the aim of the study deals with the shock analyses, additional inquiries must accompany it.

Consequently, the approaches that derive measures of resilience as a reference to a country or continent's mean are questionable. The result will be biased, regardless of the usage of the ratio between the region and national mean or the ratio of slopes. Sharing the view of Weinans (2021), values below and above the mean will always exist, regardless of the analyzed indicator. The problem appears in particular cases when all the regions are resilient or non-resilient due to some core causes. Taking Austria as an example, according to Eurostat, this country registered a maximum

Table 1 Cox regression results and the impact of different resilience measures on HR to recovery

Feature	HR (95% C.I.) to recover within		
	2008–2013	2014–2019	2020–2022
LR	0.350(0.283–0.434)***	0.578(0.511–0.655)***	0.462(0.391–0.546)***
NLR	0.139(0.093–0.208)***	0.502(0.434–0.581)***	0.329(0.275–0.394)***
BRH	0.155(0.077–0.310)***	0.846(0.737–0.970)**	0.707(0.585–0.854)***
REC	0.331(0.242–0.451)***	0.833(0.749–0.926)***	0.910(0.809–1.023)
CIR	0.282 (0.191–0.418)***	0.563(0.484–0.656)***	0.976(0.797–1.195)

*** $p < 0.01$

** $p < 0.05$

UR of 5.3% in 2009 and a minimum of 4.1% in 2008. Exploring the eight Austrian NUTS-2 regions, by comparing the regional values to the national mean, we achieve four resilient regions (sub-unitary measures by reference to the mean), and four non-resilient. A detailed review unveils that seven of eight regions experienced a high increase in unemployment rates in 2009 by comparison with the previous 2007–08 minimum. The current calculations hint fast-growing rates, like +22% for AT11, +27% for AT12, +28% for AT21, +32% AT22, +56% for AT31, +29% AT32, +37% AT34, and a 5% reduction for AT31. Seven regions are non-resilient from UR's viewpoint in the GER. However, the method that compares the values with the national mean, will split them into two classes. Four will be in a resilient class, and four in a non-resilient one. This split choice based on the mean avoids the observation of the real behavior in the shock. Therefore, a potential use of the individual LR and NLR measures bypasses this inconvenience.

But, using only the resistance measures, like LR or NLR, we only find out how prepared a region was to deal with the shock. Nothing more about how strong was the hit. Nor how long it would take for it to regain its initial state. The recovery measures help us identify how the region will behave after the shock but tell us nothing about the past.

A suitable solution for resilience evaluation may be aggregated compounds like CIR or BRH. Not least because they depend on the resistance and recovery rates and initial state. They may reveal more information about the trajectory of the territorial unit during and in the neighboring period of shock.

BRH performs at the top in the GER event. Apart from numerical interpretation, they are closer to the accepted definition of resilience. In this sense, we recall Hallegat's (2014) statement, that resilient regions are those who are able “to resist”, “to cope”, “to react”, “to adapt” and “to recover”.

Multicollinearity and multidimensional analyses intend to find one synthetic score for all inputs. Jolliffe and Cadima (2016) recommend an absolute inter-correlation above 0.8. Such a thing is problematic in many examples, including the present one. Knowing this barrier, we may accept the lowest performance of the composite index in our case. In a problem of future status estimation, the CIR represents the last choice.

Aggregated measures such as CIR and BRH display the story as a whole, but none tells us something about the constituent parts. Some papers (Martin et al. 2016; Goschin 2019) associate different factors with resilience. One proposes a multidimensional solution to provide a deeper understanding of the link between shocks and resilience. Choosing one measure instead of others may cause different results. This drives the user to potentially false conclusions. Even if BRH is the closest to the theoretical concept, it has a top performance only for the Great Recession. The existence of a decent pre-brunt sample can influence this intriguing outcome. Assessing the uncertainty of the discussed resilience metrics, one may find no association with performance in the prediction of the future state of regions. However, their performance in the labor market may be very sensitive to the time series dimension. On a high-dimensional dataset, the behavior may be different. Further capabilities worth to be investigated in other contexts. The current comparative proposal with the most recent three shocks may be pioneering work in the manner of approach. This paper

also opens the gate for future works that may study the estimation of theoretical values, TUR, by different methods.

On more expanded time series, one may probe the capabilities of ARIMA models to derive BRH measures and their implicit performances. A new framework analysis with and without a spatial autocorrelation component could be also an interesting issue.

The capability of a particular component to predict the future status does not correlate to statistical significance. In this sense, we emphasize that recovery slope (REC) has the best rate of significance among others (Appendix 3, 4, 5). Nevertheless, it has one of the lowest capabilities of prediction in the sense of AUC and Cox regression.

5.2 Conclusions

One of the most important indicators of the labor market, the unemployment rate, has a high heterogeneity at NUTS 2 level. Beyond the high variations of the source indicator, dynamic changes are also variable. These inconveniences and many unknown factors create difficulties in defining a spatial homogenous measure of regional UR resilience. Analyzing various types of shocks, we find that resilience measures have different characteristics when the goal is to predict recovery after a hit.

Using five metrics, we gathered more details about the explored anomaly. Beyond that, we may see possible post-shock tendencies. More available information offers more possibilities for regions to react and adapt.

Over all three shocks, our analysis suggests that a non-linear measure of resistance (NLR) performs best in terms of future state prediction.

In our view, policymakers and academics alike should join individual and composite measures simultaneously to evaluate regional resilience. In this view, CIR is less performant. Despite that, a distance that is not huge to others in terms of AUC, argues that CIR is a promising candidate with possible further adjustments.

Part of the scientist may see the results that highlight especially the overall performance of NLR as controversial. This arise in the context of a preference for the adaptive RER. Despite these concerns, many papers (Çağlayan Akay et al. 2020, Khraief 2020, Caporale 2022) present a mix of stationarity and hysteresis properties of unemployment. Thus, our results open the idea that the choice of dynamic vs. static approach for RER may depend on the core characteristics of the target indicator. Therefore, a bounce-back tactic could be the best choice for stationary indicators like UR in particular cases. At the same time a bounce-forward tactic could be more feasible for dynamic indicators like GDP. In agreement with Lemke et al. (2023), it seems that RER still has things to unveil.

Appendix 1

See Table 2.

Table 2 List of countries and regions

No.	Country	NUTS 2 code and name
1	Austria(n = 9)	AT11_Burgenland (AT); AT12_Niederösterreich; AT13_Wien; AT21_Kärnten; AT22_Steiermark; AT31_Oberösterreich; AT32_Salzburg; AT33_Tirol; AT34_Vorarlberg
2	Belgium(n = 11)	BE10_Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest; BE21_Prov. Antwerpen; BE22_Prov. Limburg (BE); BE23_Prov. Oost-Vlaanderen; BE24_Prov. Vlaams-Brabant; BE25_Prov. West-Vlaanderen; BE31_Prov. Brabant wallon; BE32_Prov. Hainaut; BE33_Prov. Liège; BE34_Prov. Luxembourg (BE); BE35_Prov. Namur
3	Bulgaria(n = 6)	BG31_Severozapaden; BG32_Severen tsentralen; BG33_Severoiztochen; BG34_Yugoiztochen; BG41_Yugozapaden; BG42_Yuzhen tsentralen
4	Cyprus (n = 1)	CY00_Kypros
5	Czech Republic (n = 8)	CZ01_Praha; CZ02_Střední; CZ03_Jihovýchod; CZ04_Severovýchod; CZ05_Severovýchod; CZ06_Jihovýchod; CZ07_Střední Morava; CZ08_Moravskoslezsko
6	Switzerland(n = 7)	CH01_Région lémanique; CH02_Espace Mittelland; CH03_Nordwestschweiz
		CH04_Zürich; CH05_Ostschweiz; CH06_Zentralschweiz; CH07_Ticino
7	Germany(n = 38)	DE11_Stuttgart; DE12_Karlsruhe; DE13_Freiburg; DE14_Tübingen; DE21_Oberbayern; DE22_Niederbayern; DE23_Oberpfalz; DE24_Oberfranken; DE25_Mittelfranken; DE26_Unterfranken; DE27_Schwaben; DE30_Berlin; DE40_Brandenburg; DE50_Bremen; DE60_Hamburg; DE71_Darmstadt; DE72_Gießen; DE73_Kassel; DE80_Mecklenburg-Vorpommern; DE91_Braunschweig; DE92_Hannover; DE93_Lüneburg; DE94_Weser-Ems; DEA1_Düsseldorf; DEA2_Köln; DEA3_Münster; EA4_Detmold; DEA5_Arnsberg; DEB1_Koblenz; DEB2_Trier; DEB3_Rheinhesen-Pfalz; DEC0_Saarland; DED2_Dresden; DED4_Chemnitz; DED5_Leipzig; DEE0_Sachsen-Anhalt; DEF0_Schleswig-Holstein; DEG0_Thüringen
8	Denmark(n = 5)	DK01_Hovedstaden; DK02_Sjælland; DK03_Syddanmark; DK04_Midtjylland; DK05_Nordjylland
9	Estonia(n = 1)	EE00_Eesti
10	Greece(n = 13)	EL30_Attiki; EL41_Voreio Aigaio; EL42_Notio Aigaio; EL43_Kriti; EL51_Anatoliki Makedonia, Thraki; EL52_Kentriki Makedonia; EL53_Dytiki Makedonia; EL54_Ipeiros; EL61_Thessalia; EL62_Ionia Nisia; EL63_Dytiki Ellada; EL64_Stereia Ellada; EL65_Peloponnisos

Table 2 (continued)

No.	Country	NUTS 2 code and name
11	Spain(n = 19)	ES11_Galicia;ES12_Principado de Asturias;ES13_Cantabria;ES21_País Vasco; ES22_Comunidad Foral de Navarra;ES23_La Rioja;ES24_Aragón;ES30_Comunidad de Madrid; ES41_Castilla y León; ES42_Castilla-la Mancha;ES43_Extremadura;ES51_Cataluña; ES52_Comunitat Valenciana;ES53_Illes Balears;ES61_Andalucía;ES62_Región de Murcia; ES63_Ciudad de Ceuta;ES64_Ciudad de Melilla;ES70_Canarias
12	Finland (n = 4)	FI19_Länsi-Suomi;FI1B_Helsinki-Uusimaa;FI1C_Etelä-Suomi;FI1D_Pohjois- ja Itä-Suomi
13	France(n = 22)	FR10_Île de France;FRB0_Centre—Val de Loire;FRC1_Bourgogne;FRC2_Franche-Comté FRD1_Basse-Normandie;FRD2_Haute-Normandie;FRE1_Nord-Pas-deCalais;FRE2_Picardie;FRF1_ Alsace; FRF2_Champagne-Ardenne;FRF3_Lorraine;FRG0_Pays-de-laLoire;FRH0_Bretagne;FRJ1_Aquitaine; FRJ2_Limousin;FRJ3_Poitou-Charentes;FRJ1_Languedoc-Roussillon;FRJ2_Midi-Pyrénées;FRK1_ Auvergne;FRK2_Rhône-Alpes;FRL0_Provence-Alpes-Côte d’Azur;FRM0_Corse
14	Croatia (n = 2)	HR03_Jadranska Hrvatska;HR04_Kontinentalna Hrvatska (NUTS 2016)
15	Hungary (n = 8)	HU11_Budapest;HU12_Pest;HU21_Közép-Dunántúl;HU22_Nyugat-Dunántúl;HU23_Dél-Dunántúl; HU31_Észak-Magyarország;HU32_Észak-Alföld;HU33_Dél-Alföld
16	Ireland (n = 3)	IE04_Northern and Western;IE05_Southern;IE06_Eastern and Midland
17	Iceland (n = 1)	IS00_Island
18	Italy(n = 21)	ITC1_Piemonte;ITC2_Valle d’Aosta/Vallée d’Aoste;ITC3_Liguria;ITC4_Lombardia;ITF1_Abruzzo; ITF2_Molise;ITF3_Campania;ITF4_Puglia;ITF5_Basilicata;ITF6_Calabria;ITG1_Sicilia;ITG2_Sardegna; ITH1_Provincia Autonoma di Bolzano/Bozen;ITH2_Provincia Autonoma di Trento;ITH3_Veneto; ITH4_Friuli-Venezia Giulia;ITH5_Emilía-Romagna;ITL1_Toscana;ITL2_Umbria;ITL3_Marche;ITL4_ Lazio
19	Lithuania (n = 2)	LT01_Sostines regionas;LT02_Vidurio ir vakaru Lietuvos regionas
20	Luxembourg(n = 1)	LU00_Luxembourg
21	Latvia(n = 1)	LV00_Latvija
22	North Macedonia(n = 1)	MK00_Severna Makedonija
23	Malta (n = 1)	MT00_Malta

Table 2 (continued)

No.	Country	NUTS 2 code and name
24	The Netherlands(n = 12)	NL11_Groningen;NL12_Friesland(NL);NL13_Drenthe;NL21_Overijssel;NL22_Gelderland; NL23_Flevoland;NL31_Utrecht;NL32_Noord-Holland;NL33_Zuid-Holland;NL34_Zeeland; NL41_Noord-Brabant;NL42_Limburg (NL)
25	Norway(n = 7)	NO01_Oslo og Akershus (statistical region 2016); NO02_Innlandet;NO03_Sør-Østlandet (statistical region 2016);NO04_Agder og Rogaland (statistical region 2016); NO05_Vestlandet (statistical region 2016);NO06_Trøndelag;NO07_Nord-Norge
26	Poland(n = 17)	PL21_Malopolskie; PL22_Slaskie;PL41_Wielkopolskie;PL42_Zachodniopomorskie;PL43_Lubuskie; PL51_Dolnoslaskie;PL52_Opolskie;PL61_Kujawsko-Pomorskie;PL62_Warminsko-Mazurskie;PL63_Pomorskie;PL71_Lodzkie;PL72_Swietokrzyskie;PL81_Lubelskie;PL82_Podkarpackie;PL84_Podlaskie;PL91_Warszawski stoleczny; PL92_Mazowiecki regionalny
27	Portugal(n = 7)	PT11_Norte; PT15_Algarve; PT16_Centro (PT);PT17_Área Metropolitana de Lisboa PT18_Alentejo;PT20_Região Autónoma dos Açores (PT);PT30_Região Autónoma da Madeira (PT)
28	Romania(n = 8)	RO11_Nord-Vest;RO12_Centru;RO21_Nord-Est;RO22_Sud-Est;RO31_Sud – Muntenia RO32_Bucuresti – Ilfov;RO41_Sud-Vest Oltenia;RO42_Vest
29	Sweden(n = 8)	SE11_Stockholm; SE12_Östra Mellansverige; SE21_Småland med öarna;SE22_Sydsverige; SE23_Västsverige;SE31_Norra Mellansverige;SE32_Mellersta Norrland;SE33_Övre Norrland
30	Slovenia(n = 2)	SI03_Vzhodna Slovenija;SI04_Zahodna Slovenija;
31	Slovakia (n = 4)	SK01_Bratislavský kraj;SK02_Západné Slovensko;SK03_Stredné Slovensko; SK04_Východné Slovensko

Table 2 (continued)

No.	Country	NUTS 2 code and name
32	Turkey(n = 26)	TR10_Istanbul; TR21_Tekirdag, Edirne, Kırklareli; TR22_Balıkesir, Canakkale TR31_Izmir; TR32_Aydin, Denizli, Mugla; TR33_Manisa, Afyonkarahisar, Kütahya, Usak; TR41_Bursa, Eskişehir, Bilecik; TR42_Kocaeli, Sakarya, Düzce, Bolu, Yalova; TR51_Ankara; TR52_Konya, Karaman; TR61_Antalya, Isparta, Burdur; TR62_Adana, Mersin; TR63_Hatay, Kahramanmaraş, Osmaniye; TR71_Kirikkale, Aksaray, Nigde, Nevşehir, Kırşehir; TR72_Kayseri, Sivas, Yozgat; TR81_Zonguldak, Karabük, Bartın; TR82_Kastamonu, Çankiri, Sinop; TR83_Samsun, Tokat, Çorum, Amasya; TR90_Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane; TRA1_Erzurum, Erzincan, Bayburt; TRA2_Agri, Kars, Iğdir, Ardahan; TRB1_Malatya, Elazığ, Bingöl, Tunceli; TRB2_Van, Mus, Bitlis, Hakkari; TRC1_Gaziantep, Adıyaman, Kilis; TRC2_Sanlıurfa, Diyarbakır; TRC3_Mardin, Batman, Siirt
33	United Kingdom(n = 41)	UKC1_Tees Valley and Durham; UKC2_Northumberland and Tyne and Wear; UKD1_Cumbria; UKD3_Greater Manchester; UKD4_Lancashire; UKD6_Cheshire; UKD7_Merseyside; UKE1_East Yorkshire and Northern Lincolnshire; UKE2_North Yorkshire; UKE3_South Yorkshire; UKE4_West Yorkshire; UKF1_Derbyshire and Nottinghamshire; UKF2_Leicestershire, Rutland and Northampton-shire UKF3_Lincolnshire; UKG1_Herefordshire, Worcestershire and Warwickshire; UKG2_Shropshire and Staffordshire; UKG3_West Midlands; UKH1_East Anglia; UKH2_Bedfordshire and Hertfordshire UKH3_Essex; UKI3_Inner London – West; UKI4_Inner London – East; UKI5_Outer London—East and North East; UKI6_Outer London – South; UKI7_Outer London—West and North West UKJ1_Berkshire, Buckinghamshire and Oxfordshire; UKJ2_Surrey, East and West Sussex; UKJ3_Hamp-shire and Isle of Wight; UKJ4_Kent; UKK1_Gloucestershire, Wiltshire and Bristol/Bath area; UKK2_Dorset and Somerset; UKK3_Cornwall and Isles of Scilly; UKK4_Devon; UKL1_West Wales and The Valleys UKL2_East Wales; UKM5_North Eastern Scotland; UKM6_Highlands and Islands; UKM7_Eastern Scot-land; UKM8_West Central Scotland; UKM9_Southern Scotland; UKN0_Northern Ireland (UK)

Appendix 2

See Table 3.

Table 3 Imputation sources and methods for unavailable unemployment rates

Country	Regions	Period	Additional data source	Imputation method(s)
Denmark	DK01-DK05	2002–05	N/A ^a	Missing values were replaced by the national mean N.C
	F19, F1C, F11D	2002–04	https://ec.europa.eu/eurostat/documents/2995521/5240078/1-16112006-BP-EN.PDF/pdf/9ec8169d-d82e-4dae-9417-90ff5ab9839d?t=14146 87073000	
France	F11B	2004	N/A	The value for 2004 was replaced with the value available in 2005
	FRI2	2004	https://ec.europa.eu/eurostat/documents/2995521/5240078/1-16112006-BP-EN.PDF/pdf/9ec8169d-d82e-4dae-9417-90ff5ab9839d?t=14146 87073000	
	FRY, respectively, Guadeloupe, Martinique, Guyane, La Réunion, Mayotte	2002–20	N/A	
Hrvatska	HR03-HR04	2004–05	N/A	These regions were excluded from the current analysis
	HU11; HU12	2002–08	N/A	
Italy	ITH5, ITH3, ITC2	2002–04	https://ec.europa.eu/eurostat/documents/2995521/5240078/1-16112006-BP-EN.PDF/pdf/9ec8169d-d82e-4dae-9417-90ff5ab9839d?t=14146 87073000	Values for this period were replaced by the national mean Values for Buda and Pesta NUTS2 regions received the Kozep Magyarorszag (HU10) value for the 2002–2008 period N.C

Table 3 (continued)

Country	Regions	Period	Additional data source	Imputation method(s)
Ireland	IE04, IE05, IE06	2002–12	https://www.google.com/publdata/explore?ds=j8jdrju88aksr_&ctype=l&met_y=unemployment&rdim=country&hl=en#!ctype=l&strail=false&bcs=d&nselm=h&met_y=unemployment_rate&scale_y=lin&ind_y=false&rdim=country&idim=subregion:IE011&ifdim=country&hl=en_US&dl=en_US&ind=false	Weighted averages of corresponding NUTS3 regions
Lithuania	LT01, LT02	2002–12	N/A	LT01 and LT02 values are equalized to national mean between 2002–2012
North Macedonia	MK00	2003–22	https://makstat.stat.gov.mk/PXWeb/pxweb/en/MakStat/MakStat_PazarNaTrud_StapkiDrugIndikatori/088_PazTrud_Mk_StapNev_ml.px/table/tableViewLayout2/	N.C
Norway	NO1, NO3, NO4, NO5	2016–22	https://www.ssb.no/en/statbank/table/13498/tableViewLayout1/	N.C
Poland	PL43	2020–22	Poland National Institute of Statistics https://zielo.nagora.stat.gov.pl/en/publications/labour-salaries/labour-market-in-lubuskie-voivodship-in-2021,1,14.html rocznik.statystyczny.wojewodztwa_lubuskiego_2022_en.pdf	N.C
Portugal	PT20 PT30	2004–05 2004	N/A N/A	For PT20, we set 2004 and 2005 values to 2006 For PT30, we set the 2004 value to the neighboring year, 2005

Table 3 (continued)

Country	Regions	Period	Additional data source	Imputation method(s)
Turkey	All regions	2021–22	Most of the additional values were found on the Turkish National Institute of Statistics's web page	N.C
	All regions	2005	https://betam.bahcesehir.edu.tr/wp-content/uploads/2015/06/ResearchBrief130.pdf http://www.mdgfund.org/sites/default/files/YEM_STUDY_Turkey_Antalya%20Labour%20Market%20Analysis.pdf	N.C
UK	All regions	2004	G. Gozgor (2013) Unemployment Persistence and Inflation Convergence: Evidence from Regions of Turkey, Regional and Sectoral Economic Studies, 13(1), Appendix II, pp. 63–64, available at https://core.ac.uk/download/pdf/47257693.pdf	N.C
	All regions	2020–21	https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/unemployment/datasets/regionalunemploymentbyage02/current	We input the unemployment rate by NUTS1 mean, computed using the source from ONS:

^aN/A=other source not available; N.C. = no data changes/no additional method us

Appendix 3

See Fig. 8.



Fig. 8 Box-plots and UR trends for each country

Appendix 4

See Table 4.

Table 4 Statistical results related to resilience measures or its components for 2008–11 shock

Sub-period	Num of regions	Assumption tested	% of models that accomplish the assumption			
			Slope_before	TUR	LR	REC
2002–07	n=281	Overall model significance	33.1%	34.4%	NC	NC
		Residual normality	95.9%	94.3%		
		Residual homoskedasticity	92.8%	94.3%		
2003–07	n=1	Overall model significance	0%	0%		
		Residual normality	100%	100%		
		Residual homoskedasticity	100%	100%		
2004–07	n=35	Overall model significance	37.1%	31.4%		
		Residual normality	97.1%	97.1%		
		Residual homoskedasticity	100%	97.1%		
2007–08	n=22	Overall model significance	NC	NC	NT	
		Residual normality				
		Residual homoskedasticity				
2007–09	n=86	Overall model significance			5.8%	
		Residual normality			NT	
		Residual homoskedasticity				
2007–10	n=95	Overall model significance			46.3%	
		Residual normality			97.9%	
		Residual homoskedasticity			100%	
2007–11	n=114	Overall model significance			76.3%	
		Residual normality			100%	
		Residual homoskedasticity			94.7%	
2008–12	n=22	Overall model significance				81.8%
		Residual normality				95.5%
		Residual homoskedasticity				100%
2009–12	n=86	Overall model significance				57.0%
		Residual normality				96.5%
		Residual homoskedasticity				100%
2010–12	n=95	Overall model significance				16.8%
		Residual normality				NT
		Residual homoskedasticity				
2011–12	n=114	Overall model significance				NT
		Residual normality				
		Residual homoskedasticity				
Overall	sum of n	Overall model significance	33.4%	34.1%	46.1%	40.9%
		Residual normality	96.1%	94.6%	99.0%	96.2%
		Residual homoskedasticity	93.6%	94.6%	97.1%	100%

NT= not tested due to small sample size; NER= not estimated by regression model; NC=not the case/metric definition does not include the period

Appendix 5

See Table 5.

Table 5 Statistical results related to resilience measures or its components for 2014–16 shock

Sub-period	Num of regions	Assumption tested	% of total regions which accomplish the assumption			
			Slope_before	TUR	LR	REC
2012–13	n = 317	Overall model significance	NT	NER	NC	NC
		Residual normality				
		Residual homoskedasticity				
2013–14	n = 231	Overall model significance	NC	NER	NT	
		Residual normality				
		Residual homoskedasticity				
2013–15	n = 51	Overall model significance			17.6%	
		Residual normality			NT	
		Residual homoskedasticity				
2013–16	n = 35	Overall model significance			45.7%	
		Residual normality			94.3%	
		Residual homoskedasticity			100%	
2014–17	n = 231	Overall model significance			NC	76.2%
		Residual normality				95.7%
		Residual homoskedasticity				100%
2015–17	n = 51	Overall model significance				39.2%
		Residual normality				NT
		Residual homoskedasticity				
2016–17	n = 35	Overall model significance				NT
		Residual normality				
		Residual homoskedasticity				
Overall	sum of n	Overall model significance	NT	NER	29.1%	69.5%
		Residual normality			94.3%	95.7%
		Residual homoskedasticity			100%	100%

NT=not tested due to small sample size; NER=not estimated by regression model; NC=not the case/metric definition does not include the period

Appendix 6

See Table 6.

Table 6 Statistical results related to resilience measures or its components for 2020–22 shock

Sub-period	Num of regions	Assumption tested	% of total regions that accomplish the assumption			
			Slope_before	TUR	LR	REC
2017–19	n = 317	Overall model significance	28.1%	NER	NC	NC
		Residual normality	NT			
		Residual homoskedasticity				
2019–20	n = 164	Overall model significance	NC		NT	
		Residual normality				
		Residual homoskedasticity				
2019–21	n = 130	Overall model significance			30.0%	
		Residual normality				
		Residual homoskedasticity				
2019–22	n = 12	Overall model significance			16.7%	
		Residual normality			100%	
		Residual homoskedasticity			100%	
2020–22	n = 165	Overall model significance			NC	24.8%
		Residual normality				NT
		Residual homoskedasticity				
2021–22	n = 136	Overall model significance				NT
		Residual normality				
		Residual homoskedasticity				
Overall	sum of n	Overall model significance	28.1%	NER	28.7%	24.8%
		Residual normality	NT		100%	
		Residual homoskedasticity			100%	

NT= not tested due to small sample size; NER= not estimated by regression model; NC=not the case/metric definition does not include the period

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Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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