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The Measurement of Economic Resilience: A Proposal

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Abstract
Global crises (2008 and 2020) have determined insecure conditions in economic and financial systems. The recovery has been particularly slow in Europe compared to the USA, though a certain heterogeneity in the recovery speed was observed among European countries. Results from household surveys have highlighted that households are worried about their ability to recover from economic losses. The aim of this work is to propose a definition of economic resilience and a new measure, which can be calculated at individual or household level. The measurement suggested is based on the comparison of the levels of an economic resource observed over a period after a loss. The measure is proven to satisfy some desirable properties. An application of the proposed measures to the SOEP longitudinal dataset highlights the household characteristics that mostly affect economic resilience in Germany.

Keywords Economic resilience · Dynamic indices · Panel surveys

JEL D63 · I31 · I32

1 Introduction

Global crises (2008 and 2020) have intensely impacted economic and financial systems, thus highlighting the importance of the ability to cope with shocks and changes (Joossens et al., 2022). The National Recovery and Resilience Plan (NRRP) has in fact positioned resilience at the forefront of EU initiatives, aiming to strengthen the capacity of Member States to respond to economic, social and environmental shocks and structural changes in a fair, sustainable and inclusive manner.

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In addition to the economic crises, some socio-demographic and occupational changes have profoundly changed the structure and nature of our societies in recent decades. In particular, the spread of income instability, the growth of temporary jobs, the difficulties of reconciling care and work, and the increase in the number of non-self-sufficient people, have increased economic vulnerability and reduced resilience capacity (Ranci, 2010). The reduction in the average family size and the fragility of family unions have also significantly reduced the possibility of relying on parental networks in the event of economic losses, diminishing the role of social shock absorber historically played by the household (Ferrera, 2019).

Nevertheless, despite the current popularity of the concept of resilience and the interest in its measurement, there are not many contributions in the literature on its empirical measurement. Most of the authors have focused on the measurement of economic resilience at the aggregate level, that is, for regions or countries. At this level, economic resilience is generally defined as the ability of a region/country to cope with an economic shock and to quickly recover after entering a recession (ESPON, 2014), and it is measured in terms of GDP (Martin, 2012) or through composite measures aimed at considering different outcomes (Alessi et al., 2020; Benczur et al., 2020; Marulanda Fraume et al., 2020; Sánchez & Jiménez-Fernández, 2023).

Few authors have set out to empirically measure economic resilience at the individual level till now (Asheim et al., 2020; Cissé & Barrett, 2018). At the individual level, resilience has been similarly defined as an individual's ability to react in adverse situations and circumstances (Williams & Druy, 2009). An important contribution comes from Asheim et al. (2020), who examine the concept of recovery from disturbances and introduce an axiomatic approach to measuring individual resilience.

However, the measure by Asheim et al. (2020) has certain limitations. It offers an assessment of resilience within a specific, arbitrarily chosen observation period, rather than capturing its dynamic nature. Additionally, it does not account for the duration of the disturbance and the time required for recovery. Finally, it does not allow for a sufficient degree of differentiation across individuals.

Within this context, our work contributes by proposing a novel measure of economic resilience, which aims to overcome some of the limitations of the measures proposed previously. It can be calculated at individual level and is based on a definition of economic resilience. Our approach defines resilience as the ability to recover from a disturbance, which, in economic terms, means recovering from the loss of an economic resource. Therefore, our measure represents an attempt to quantify recovery resilience. In our approach, economic resilience is recognized as a dynamic concept (McKnight & Rucci, 2020). This means that an individual's resilience may vary over time and adapt to the specific circumstances of a loss, reflecting the evolutionary nature of individuals' ability to recover in different situations.

Our approach to measuring individual economic resilience differs from the previous studies in the following ways. Firstly, we propose an absolute (in the sense of translation-invariant) measure that can be calculated over time, automatically accounting for only the most recent down spell. In other words, our approach assesses resilience based on the individual's most recent economic loss, without the constraint of the same beginning of a crisis for all individuals. Secondly, our measure allows for continuous calculation throughout the period in which a loss is experienced, providing a real-time perspective on recovery. Third, another key advantage of our measure is its consideration of recovery time, where slower recoveries are penalized in comparison to quicker ones,

emphasizing the importance of timely economic resilience. Finally, our measure offers the advantage of satisfying some desirable properties.

In practice, the starting point of our analysis is a stream of values of an economic resource (income, for example) belonging to an individual or a household and observed over a period of time. Our measure is based on the comparison between resource levels observed at consecutive points in time, following the cue by Gallo et al. (2024), who find that measures of economic insecurity based on such comparison are able to capture the resilience of individuals. The value of the resource before the loss, as well as the minimum level reached at the end of the loss, are considered reference values for assessing resilience.

The measurement of economic resilience at micro-level requires longitudinal data that follow households' economic conditions for a sufficiently long period of time. Therefore, we apply the proposed measure to the German Socio-Economic Panel data to study the determinants of households' resilience in Germany from 2006 to 2019. Results allow us to measure how much it is more difficult to be resilient for households with children, and if the breadwinner is divorced or separated. On the other hand, results also highlight the effect on resilience of the breadwinners' educational level and their condition in the labour market.

The remainder of this paper is structured as follows. Section 2 provides a background divided into two parts: a brief review of the conceptualization of resilience (Subsect. 2.1) and a brief review of the literature on the measure of economic resilience (Subsect. 2.2). Section 3 presents the measure suggested, starting from some premises (Subsect. 3.1), followed by the explanation of the measure (Subsect. 3.2) and its properties (Subsect. 3.3). Section 4 is devoted to the empirical analysis: in Subsect. 4.1 the data used are described, while in Subsects. 4.2 and 4.3 the measure is used to compare economic resilience in subpopulations and to study the determinants of resilience respectively. Section 5 provides the concluding remarks.

2 Background

2.1 The Concept of Resilience

What does "economic resilience" mean? In literature, some definitions of economic resilience come from other fields, where the concept of resilience has been widely discussed, like materials science, ecology, evolutionary theory, psychology, etc. The first definition of resilience comes from materials science (Holling, 1973; Pimm, 1984; Walker et al., 2006), where it is defined as the ability of a system to return to its initial equilibrium state following a shock or disturbance. The key element of this definition is the concept of equilibrium to which the system tends to return. It is not adequate for an economic system, as it does not consider the possibility that a shock may modify the initial equilibrium state or that a system can return to the initial equilibrium situation even through a restructuring of itself.

Another definition comes from ecology, where resilience is the ability of a system to sustain a certain level of disturbance without changing its state and structure. In other words, resilience is measured by the amplitude of the shock that the system is able to absorb before changing equilibria (Holling, 1973, 1996, 2001; McGlade et al., 2006; Walker et al., 2006). In this context, the concept of multiple equilibria is introduced, and

the possibility that the system can evolve into different states than those before the disturbance is considered.

A third definition of resilience finds its origins in evolutionary theory. After a shock, the system has the capacity to adapt and spontaneously reorganize its structure in economic, institutional and social terms, and to find new growth paths (Martin & Sunley, 2007). In this case, we can talk about "adaptive resilience", a dynamic process defined in terms of the possibility of bouncing forward, rather than in terms of returning to a previous situation (Martin & Sunley, 2015).

Adger (2000) explores potential links between social resilience and ecological resilience, and defines social resilience as the ability of communities to cope with external stresses and disturbances as a result of social, political and environmental change. It was the conceptualization provided in ecology that affected the studies in social sciences (Folke, 2006).

In psychology resilience can be considered as the ability to face an adverse event. It has been conceptualized in many ways and many scales have been proposed to study psychological resilience. The different conceptualizations define resilience as an individual fixed characteristic (Nicholson, 2014), a process (Luthar et al., 2000), or both (Richardson, 2002).

In psychological and organizational resilience literature, resilience is typically linked to adversity, suggesting that experiencing adversity is a prerequisite for resilience (Luthar et al., 2000; Weick & Sutcliffe, 2007). Individuals are subjected to a variety of ever-changing challenges and must constantly relate to non-homogeneous contexts. This requires their ability to adapt to changes and react to adversity (Bhamra et al., 2011).

Unforeseen events test the individual's ability to recover. What makes the difference is how individuals manage adversity (Weick & Sutcliffe, 2007). As argued by Weick and Sutcliffe (2007), unexpected events often test individuals and organizations' resilience, measuring how much they are able to cope with adverse events and, therefore, also their ability to recover.

2.2 The Measurement of Economic Resilience

After the two global crises (2008 and 2020), the discussion on economic resilience has intensified. Benczúr et al. (2020) concentrate on the 2008 economic crisis and provide a definition of resilience as "the societal ability to preserve and generate well-being in the presence of shocks and persistent structural changes in a sustainable manner, without hindering the well-being of future generations". After the COVID-19 crisis, the European Commission outlines resilience as a priority. It becomes a new compass for EU policies, by reducing vulnerabilities and strengthening capacities (European Commission, 2020). Giovannini et al. (2020) study the effect of the COVID-19 pandemic and guess that this shock should represent an opportunity to progress and "bounce forward" through adaptation and transformation with the help of appropriate policies and interventions. Moreover, they stress the link between individuals and societies, by stating that a society is resilient if individuals are resilient, and individuals' resilience should be supported by the institutions.

As already mentioned, the contributions on the measurement of resilience in the literature focus above all on the macro level. However, even at this level, there is no commonly accepted methodology for measuring resilience empirically (Alessi et al., 2020). A couple of aspects common to the most recent proposals are: i) considering resilience as

a multidimensional concept that needs to be measured by considering several, not only economic, phenomena; ii) adopting a multiple-step approach to summarize different indicators.

Alessi et al. (2020), for example, adopt a three-step approach to measure the resilience of EU Member States. Assuming a common pre-crisis year for all countries, they apply resilience metrics corresponding to different time dimensions to a large number of key indicators of economic performance and societal well-being. Then they aggregate the metrics obtained for each indicator to produce composite measures of resilience.

A similar multi-step approach is followed by Benczúr et al. (2020) to measure the EU regional response to the 2008 economic crisis. They also assume the crisis hit all regions in the same way. However, they look at the response of a society as a dynamic phenomenon that needs continuous monitoring and thus develop a measure also accounting for the "time of recovery".

Sánchez and Jiménez-Fernández (2023) focus on both EU countries and EU regions and provide a composite index of socio-economic vulnerability that encompasses some indicators of resilience. Their composite index for a region is obtained by aggregating distances between the regional value of an indicator and the best value observed among the regions. The heterogeneity between regions within the countries is then studied through a multilevel model.

To identify which country characteristics help or make resilience more difficult, Marulanda Fraume et al. (2020) propose an index of total risk given by a function of the physical vulnerability of countries' assets and social, economic and financial issues. The physical and socio-economic components are calculated as composite measures of several indicators. The authors examine weaknesses and strengths of more than 200 countries, highlighting the possibilities to improve those countries' socio-economic conditions that may foster the capacity for resilience.

On the other hand, studies carried out at the individual level generally propose measures that are free from reference to a specific shock. Barrett and Constas (2014), for example, conceptualize development resilience as the capacity over time of a person to avoid poverty in the face of various stressors and in the wake of myriad shocks. Following this definition, Cissé and Barrett (2018) propose an econometric strategy for estimating individual-level development resilience from panel data, by modelling the mean of a wellbeing variable in period t as a function of lagged wellbeing and a vector of household characteristics, including shocks directly experienced by the household or risks to which it is exposed. Notably, their approach considers value streams without predefined characteristics, allowing them to start in different economic phases (gain or loss) and encompass multiple down spells.

In other works carried out at the individual level, resilience has been simply defined as an individual's ability to react in adverse situations and circumstances (Williams & Druy, 2009). Within the scope of this definition, we have already mentioned Asheim et al. (2020), who propose and axiomatize a measure according to an exponential resilience model. Their framework tracks an individual outcome variable over time and measures resilience based on a stream of that outcome's values. Their index is applied by Riera Mallol (2023) to examine the consequences of experiencing warfare at birth, childhood or young adulthood on individual psychological resilience in late adulthood.

Finally, other contributions come from the literature on individual psychological resilience to economic shocks. These proposals rely on self-reported information, especially answers to subjective survey questions (Joossens et al., 2022; Martin et al., 2015; Sánchez et al., 2024; Stevenson et al., 2020). Joossens et al. (2022), for example, propose a measure of individual resilience based on the combination of questions about self-perceived

abilities to bounce back from hardship in life, personal attitudes and the ability to cope with potential economic distress. Stevenson et al. (2020) study the confidence of individuals in their family's ability to deal with financial problems, and the relationship between this confidence and other psychological aspects, such as family identification. Both these works then link the subjective perceptions considered using a model.

3 Measurement of Economic Resilience: a New Proposal

3.1 The Premises

We propose a measure of resilience starting from some premises. First of all, we want to assign a value to an individual for each point in time, distinguishing between different phases of the trend of the resource over time.

We denote the current point in time with t_c. With respect to the previous point in time, $t_c - 1$, the resource at time t_c may increase, decrease or show a constant level.

An individual is defined as "resilient" at time t_c if both the following conditions are observed: i) an increment in her resource level is observed between $t_c - 1$ and t_c and, ii) going back in time, a previous loss is found. A loss is a "drop" in the resource level between two consecutive points in time. To visualize this concept better, graphs a) and b) in Fig. 1 show examples of resilient cases at time t_c. Only individuals who have experienced a loss may be resilient. In this case, the measure will have a positive value.

On the other hand, an individual is defined as "fragile" at time t_c if both the following conditions are observed: i) her resource level decreases between time $t_c - 1$ and t_c and, ii) going back in time, the point in time at which the drop starts is found. Examples of fragile cases at time t_c are given in graphs c) and d) in Fig. 1. We want our measure to also include this case, which we will call "fragility" phase. In this phase, the measure will take a negative value.

Finally, if the individual is keeping a constant value between time $t_c - 1$ and time t_c, we consider the same value of the measure obtained for the previous points in time ($t_c - 2$ and $t_c - 1$), thus assuming that the level of resilience/fragility does not vary. In this case, the resilience or fragility phase is over, but the individual is keeping the reached level. In other words, the individual is consolidating her recovery/loss.

Following Asheim et al. (2020), to exclude trivial cases, we do not consider individuals whose resource always increases, decreases or is constant over the period considered.

During the recovery phase, the resource level may overcome the initial resource level, that is the resource level before the drop. This case may be called "extra recovery". Moreover, the amount of the drop and the amount of the possible recovery after the drop matter, as well as the reaction time after the drop, that is how much time passes before the recovery. Summarising, we want to propose a measure that: i) compares the drop and the possible recovery; ii) penalises a delay in the recovery; and iii) rewards any extra recovery. This implies identifying: the point in time before the previous drop (t_{top}) and the value of the resource at this point in time ($x_{t_{top}}$); the point in time corresponding to the end of drop (t_{bottom}) and the value of the resource at this point in time ($x_{t_{bottom}}$), as well as the time distance between t_c, t_{top} and t_{bottom}. Figure 2 shows some examples of recovery from t_{bottom} and t_c: a recovery lower than t_{top} (case a)); a recovery up to t_{top} immediately after t_{bottom} and then

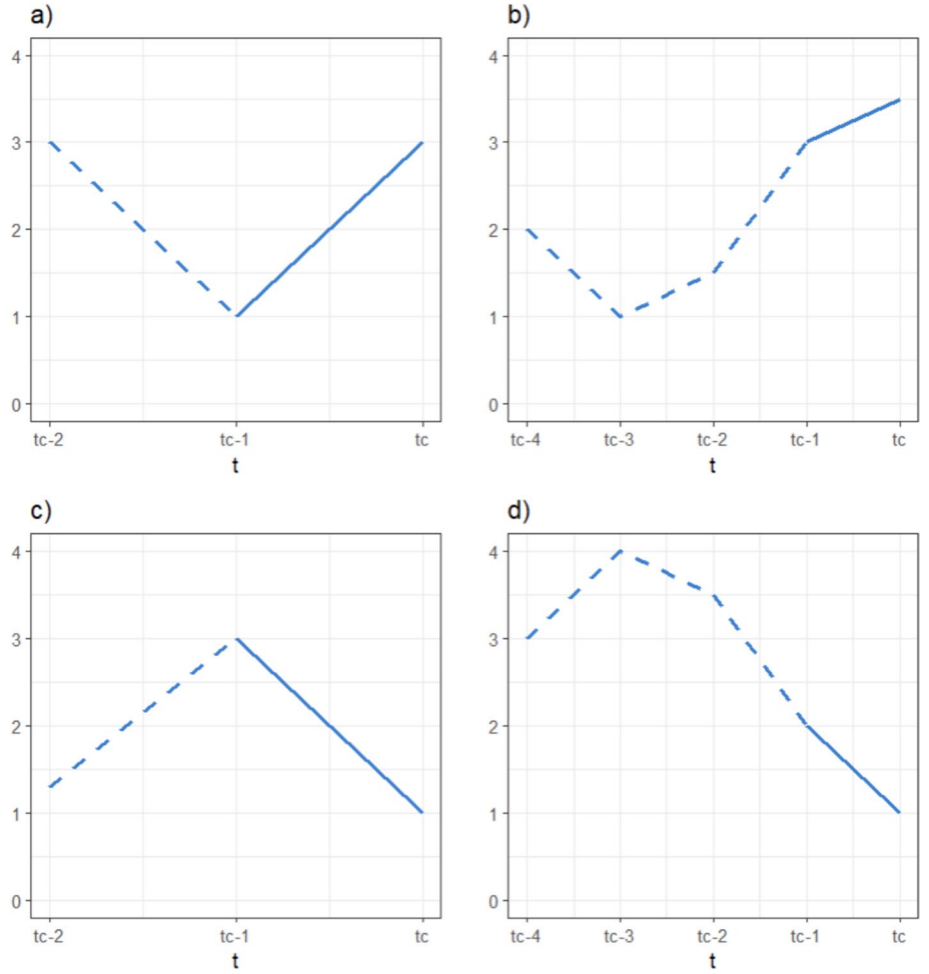

Fig. 1 Examples of: **a**) and **b**) recovery phase at time t_c; **c**) and **d**) fragility phase at time t_c

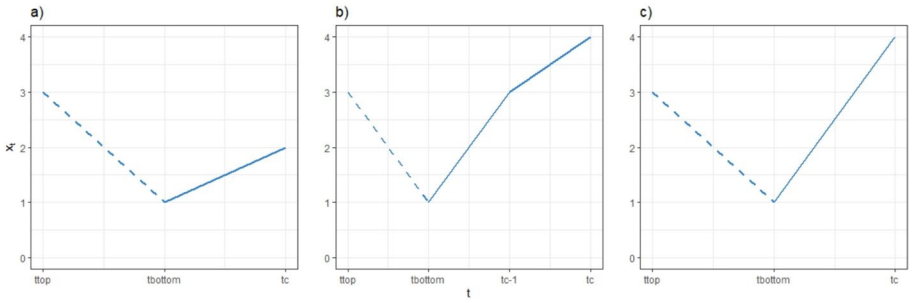

Fig. 2 Examples of: **a**) recovery below $x_{t_{top}}$; **b**) extra recovery between $t_c - 1$ and t_c; **c**) partially extra recovery

a completely extra recovery between $t_c - 1$ and t_c (case b)); and a partially extra recovery (case c)).

In the case of fragility, how much time the individual has spent in the fragility phase counts, and we want to penalise time spent in an uninterrupted down phase. Figure 3 shows some examples of the fragility phase and constant phases.

3.2 The Measure

Here we introduce some notations. The resource of interest is denoted by X. To evaluate the resilience of a set of individuals, we consider the stream of their resource values observed for a number of consecutive points in time, including the current time t_c and a variable number of previous points in time. Hence, the length of a stream may vary.

Denoting by T the length of the stream and by $\boldsymbol{x}_{t_c}$ the stream considered at current time t_c, $T \in \mathbf{T}$ and $\mathbf{T} = \mathbb{N}\backslash\{1\}$ is the set of positive integers excluding 1. In fact, the minimum value for T is 2, as at least two points in time, $t_c - 1$ and t_c, must be available. Therefore $\boldsymbol{x}_{t_c}$ may be chosen from $\mathrm{U}_{T\in\mathbf{T}}\mathbb{R}^T$.

The measure is based on the sum of absolute differences between consecutive values $x_t - x_{t-1}$ calculated over a stream of the resource values. We distinguish between the calculus of the measure in case of recovery between the two last points in time, $x_{t_c} > x_{t_c-1}$, in case of a fragility phase, $x_{t_c} < x_{t_c-1}$, and in case of constant values, $x_{t_c} = x_{t_c-1}$.

Starting with the case of recovery between the last two consecutive points in time, $t_c - 1$ and t_c, the stream of values used includes $\left(x_{t_{bottom}}, x_{t_{bottom}+1}, \ldots, x_{t_c}\right)$. This is a monotonically increasing stream of values. Moreover, the comparison with the resource level before the drop must be included. Therefore, the complete stream of values involved may be written as $\boldsymbol{x}_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}+1}, \ldots, x_{t_c}; x_{t_{top}}\right)$.

Considering the premises described in the previous section, the measure is based on the sum of absolute differences between consecutive values $\left(x_t - x_{t-1}\right)$ of the resource observed after the end of the drop. These differences, which are positive in the case of a recovery phase, are associated with different weights, whether the resource levels x_t and x_{t-1} overcome or not the initial value, $x_{t_{top}}$. In particular, we may have the following cases: 1) $x_t \le x_{t_{top}}$; 2) $x_{t-1} \ge x_{t_{top}}$; 3) $x_t > x_{t_{top}}$ and $x_{t-1} < x_{t_{top}}$. In the second case (extra recovery) the difference $\left(x_t - x_{t-1}\right)$ is rewarded with a coefficient greater than 1. In the third case, the

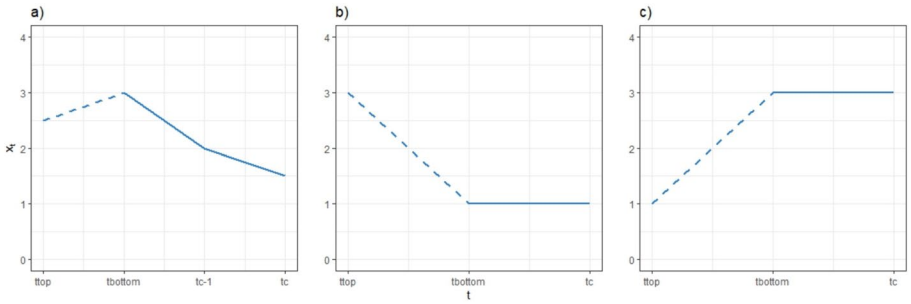

Fig. 3 Examples of: **a**) fragility phase; **b**) constant phase after a fragility phase; **c**) constant phase after a recovery phase

difference $\left(x_t - x_{t-1}\right)$ is divided into two parts: the recovery lower than the initial value and the extra-recovery. The latter is multiplied be the reward coefficient greater than 1.

Moreover, resilience closer to the initial drop must have a greater impact on the measure. To this purpose, each difference is weighted with a coefficient whose value decreases moving away from the initial drop.

Moving to the case of a fragility phase between the last two consecutive points in time, as already said, we go back in time looking for the point in time after which the drop starts t_{top}. The stream of values used to calculate the measure can be written as $\boldsymbol{x}_{t_c} = \left(x_{t_{top}}, x_{t_{top}+1}, \ldots, x_{t_c}\right)$. This is a monotonically decreasing stream of values.

The more time passes in a declining phase, without the individual being able to interrupt it, the more fragility increases. That is, we want to penalize the fact of remaining in this phase for longer periods by multiplying the resource changes by a coefficient that increases as the time spent in the down phase increases.

Finally, in a constant phase between the last two consecutive points in time, the value obtained for the previous point in time is considered.

A measure respecting all these premises is a function $R : \mathbb{R}^T \to \mathbb{R}$:

$$R\left(\boldsymbol{x}_{t_c}\right) = \begin{cases} \sum_{\substack{t = t_{bottom}+1 \\ x_t \le x_{t_{top}}}}^{t_c} \delta^{t-(t_{bottom}+1)}\left(x_t - x_{t-1}\right) + \alpha \sum_{\substack{t = t_{bottom}+1 \\ x_{t-1} \ge x_{t_{top}}}}^{t_c} \delta^{t-(t_{bottom}+1)}\left(x_t - x_{t-1}\right) + \\ \quad + \sum_{\substack{t = t_{bottom}+1 \\ x_t > x_{t_{top}} \\ x_{t-1} < x_{t_{top}}}}^{t_c} \delta^{t-(t_{bottom}+1)}\left[\alpha\left(x_t - x_{t_{top}}\right) + \left(x_{t_{top}} - x_{t-1}\right)\right] & \text{if} \quad x_{t_c} > x_{t_c-1} \\ \sum_{t = t_{top}+1}^{t_c} \gamma^{t-\left(t_{top}+1\right)}\left(x_t - x_{t-1}\right) & \text{if} \quad x_{t_c} < x_{t_c-1} \\ R\left(\boldsymbol{x}_{t_c-1}\right) & \text{if} \quad x_{t_c} = x_{t_c-1} \end{cases} \tag{1}$$

where δ is an inter-temporal weight that must take a value in the range (0,1) in order to give an increasingly low relevance to the positive variations going forward in time. Therefore $\delta \in (0,1)$.

In the resilient phase, the first sum includes variations in which the last value x_t does not overcome the initial value $x_{t_{top}}$. The second sum includes variations in which the first value x_{t-1} overcomes the initial value $x_{t_{top}}$. In this case, all the variations are given the same coefficient $\alpha > 1$ aimed to reward the extra recovery. The third sum includes variations with $x_t > x_{t_{top}}$ and $x_{t-1} < x_{t_{top}}$ (partial extra recovery). In this case, the variation is divided into two parts: the extra recovery, which is given a higher weight α, and the recovery up to the initial value, which is given a weight equal to 1.

In the fragility phase, differences are given an inter-temporal weight γ as well, aimed to penalise the fact of not being able to exit such a phase. Therefore, in this case, γ must be greater than 1.

Note that the measure takes a positive or negative value at time t_c depending on the comparison between x_{t_c} and x_{t_c-1} or, in other words, on the type of phase the individual experiences at time t_c (resilience or fragility). The same individual can experience different phases and, hence, have positive and negative values of the measure, at different points in time in the considered period. For example, an individual can have negative values of the

measure (fragility phase) in the first years and then positive values (resilience phase) in the subsequent years of the period considered.

The measure provides a score for point in time t_c. The measure is dynamic, in the sense that it can be calculated for different points in time for each individual. The level of resilience of an individual varies over time, depending on the point in time at which it is measured.

To give some calculation examples, let us consider resilience cases a), b) and c) reported in Fig. 2. The streams are $\boldsymbol{x}^a_{t_c} = (1,2;3)$, $\boldsymbol{x}^b_{t_c} = (1,3,4;3)$, $\boldsymbol{x}^c_{t_c} = (1,4;3)$. In all three cases, we have a loss of 2 (3–1) between t_{top} and t_{bottom}, followed by a recovery. Note that, in case b), the loss occurs at one point in time before the other two cases. This is one characteristic of our measure: it refers to a precise point in time but can be based on streams of different lengths, depending on how long ago the recovery began. If we set $\delta = 0.9$ and $\alpha = 1.1$, we obtain $R\left(\boldsymbol{x}^a_{t_c}\right) = 1$, $R\left(\boldsymbol{x}^b_{t_c}\right) = 2.99$ and $R\left(\boldsymbol{x}^c_{t_c}\right) = 3.1$. Case b) and case c) are more resilient than case a) which, at time t_c, has not returned to its pre-loss level. Moreover, in cases b) and c) the extra recovery is rewarded through α. Nevertheless, case c) obtains a higher score than case b) due to its immediate recovery.

Note that for case b) the measure can also be calculated for the point in time immediately preceding, considering the stream $(1,3;3)$. In this case $R\left(\boldsymbol{x}^b_{t_c}\right) = 2$. For the following point in time we have seen that its score is 2.99: the measure is updated, by considering that the individual is continuing its path of resilience.

To give an example for the fragility phase, we consider the first case reported in Fig. 3, where $\boldsymbol{x}_{t_c} = (3,2,1.5)$. If we set $\gamma = 1.1$, we obtain a score equal to -1.55. In this case, γ penalises the fact of remaining in the fragility phase for more than one period of time.

3.3 The Properties of the Measure

The measures proposed are proven to satisfy some desirable properties, such as recovery monotonicity, proximity monotonicity, linear homogeneity, translation invariance and quasilinearity. Mathematical proofs are reported in the Appendix.

Recovery Monotonicity It is important that the resilience measure be monotonic with respect to the resource values experienced in the recovery phase. In particular, if all values in the recovery phase increase (while all other values remain unchanged), resilience increases. This property is crucial to preserve the ordering between streams, and therefore the preferability of one recovery path over another.

The measure suggested is based on the sum of differences between values observed at consecutive points in time. For this reason, if all values of the recovery phase increase, while the other values involved ($x_{t_{top}}$ and $x_{t_{bottom}}$) are kept constant, resilience increases.

If $x_{t_c} > x_{t_c-1}$ (resilience phase), and given two streams having the same length T ($\forall T \in \mathbf{T}$), $\boldsymbol{x}_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}+1}, \ldots, x_{t_c}; x_{t_{top}}\right)$ and $\boldsymbol{x}'_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}+1}\prime, \ldots, x_{t_c}\prime; x_{t_{top}}\right)$, if $x_t\prime > x_t$ for every $t = t_{bottom}+1, \ldots, t_c$, then $R\left(\boldsymbol{x}'_{t_c}\right) > R\left(\boldsymbol{x}_{t_c}\right)$.

The same is true in the fragility phase. If all values of the fragility phase increase, while the other value involved ($x_{t_{top}}$) is kept constant, the measure increases. In other words, if $x_{t_c} < x_{t_c-1}$ (fragility phase), and given two streams having the same length,

$\boldsymbol{x}_{t_c} = \left(x_{t_{top}}, x_{t_{top}+1}, \ldots, x_{t_c}\right)$ and $\boldsymbol{x}'_{t_c} = \left(x_{t_{top}}, x_{t_{top}+1}\prime, \ldots, x_{t_c}\prime\right)$, if $x_t\prime > x_t$ for $t = t_{top}+1, \ldots, t_c$, then $R\left(\boldsymbol{x}'_{t_c}\right) > R\left(\boldsymbol{x}_{t_c}\right)$.

For example, if $\boldsymbol{x}_{t_c} = (10, 50, 70, 100; 200)$ and $\boldsymbol{x}'_{t_c} = (10, 100, 130, 200; 200)$, whatever the values of $\delta \in (0,1)$ and $\alpha > 1$, $R\left(\boldsymbol{x}'_{t_c}\right) > R\left(\boldsymbol{x}_{t_c}\right)$. For example, if $\delta = 0.9$, then $R\left(\boldsymbol{x}_{t_c}\right) = 82.3$ and $R\left(\boldsymbol{x}'_{t_c}\right) = 173.7$.

Proximity Monotonicity This property is defined for the resilience phase with respect to the end of the drop (t_{bottom}), as resilience closer to the end of the drop has a greater impact on the measure. This is assured by parameter $\delta \in (0,1)$. In other words, recovery that occurs closer to t_{bottom} has a greater impact on the measure than recovery that occurs later.

This property is important because it rewards a reaction to the loss that occurs shortly after the loss rather than a recovery that occurs later in time. It is a way of including reaction time in the measurement, penalizing a delay.

To illustrate this property, we write the stream in terms of increases $a_t = x_t - x_{t-1}, a_t \in \mathbb{R}_+, t = 1, \ldots, T-1$: $\boldsymbol{x}_{t_c} = (x_{t_{bottom}}, x_{t_{bottom}} + a_1, \ldots, x_{t_{bottom}} + a_1 + \cdots + a_{t-1} a_t, +a_t, \ldots, x_{t_{bottom}} + a_1 + \cdots + a_{t-1} + a_t + \cdots + a_{T-1} = x_{t_c}; x_{t_{top}})$.

Assuming that the increase at time t is greater than the increase at time $t-1$, $a_t > a_{t-1}$, if we swap this two increases in the stream, we obtain $\boldsymbol{x}^*_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}} + a_1, \ldots, x_{t_{bottom}} + a_1 + \cdots + a_t + a_{t-1}, \ldots, x_{t_{bottom}} + a_1 + \cdots + a_t + a_{t-1} + \cdots + a_{T-1} = x_{tc}; x_{t_{top}}\right)$, then $R\left(\boldsymbol{x}^*_{t_c}\right) > R\left(\boldsymbol{x}_{t_c}\right)$.

The property is also satisfied for the fragility phase but, in this case, fragility closer to the beginning of the drop has a lower impact on the measure. This is assured by the parameter $\gamma > 1$.

We can write the stream in terms of decreases $a_t = x_t - x_{t-1}, a_t \in \mathbb{R}_-, t = 1, \ldots, T-1$: $\boldsymbol{x}_{t_c} = \left(x_{t_{top}}, x_{t_{top}} + a_1, \ldots, x_{t_{top}} + a_1 + \cdots + a_{t-1} + a_t, \ldots, x_{t_{top}} + a_1 + \cdots + a_{t-1} + a_t + \cdots + a_{T-1} = x_{t_c}\right)$. Assuming $|a_t| > |a_{t-1}|$, if we swap these two decreases in the stream: $\boldsymbol{x}^*_{t_c} = \left(x_{t_{top}}, x_{t_{top}} + a_1, \ldots, x_{t_{top}} + a_1 + \cdots + a_t + a_{t-1}, \ldots, x_{t_{top}} + a_1 + \cdots + a_t + a_{t-1} + \cdots + a_{T-1} = x_{t_c}\right)$, then $R\left(\boldsymbol{x}^*_{t_c}\right) > R\left(\boldsymbol{x}_{t_c}\right)$, as decreases further away from the beginning of the drop are considered more serious.

For example, considering $T - 1 = 2$, $x_{t_{bottom}} = 10$, $x_{t_{top}} = 100$, $a_1 = 20$ and $a_2 = 50$, then $\boldsymbol{x}_{t_c} = (10, 30, 80; 100)$. If we swap the two increases, $a_1 = 50$ and $a_2 = 20$, we obtain $\boldsymbol{x}^*_{t_c} = (10, 60, 80; 100)$, then whatever the values of $\delta \in (0,1)$ and $\alpha > 1$, $R\left(\boldsymbol{x}^*_{t_c}\right) > R\left(\boldsymbol{x}_{t_c}\right)$. For example, if $\delta = 0.9$, then $R\left(\boldsymbol{x}_{t_c}\right) = 65$ and $R\left(\boldsymbol{x}^*_{t_c}\right) = 68$.

Linear Homogeneity Another property considered very useful in the theory of economic index numbers is linear homogeneity. It implies that, if all the arguments of a function are increased by a certain proportion, the result of the function will increase by the same proportion. This is a foundational property for understanding how the measure is affected by changes in scale.

According to this property, if a resource stream is multiplied by a positive constant, the value of the measure multiplied by the same constant is obtained. In other words, for all $b \in \mathbb{R}_{++}$:

$$R\left(b\boldsymbol{x}_{t_c}\right) = bR\left(\boldsymbol{x}_{t_c}\right).$$

Translation Invariance This is another property often considered in the economic indices' literature. It requires that the value of the measure remains unchanged when the same amount is added to all the resource levels included in the stream. It derives from the choice of evaluating resilience in terms of differences between resource values. How much the resource has increased/decreased matters, regardless of resource levels. In other words, this property ensures that the measure is not affected by a uniform increase or decrease in all resource values.

Given $d \in \mathbb{R}$, and denoting with $\boldsymbol{x}''_{t_c} = \left(x_{t_{bottom}} + d, x_{t_{bottom}+1} + d, \ldots, x_{t_c} + d; x_{t_{top}} + d\right)$, it is straightforward to prove that $R\left(\boldsymbol{x}''_{t_c}\right) = R\left(\boldsymbol{x}_{t_c}\right)$. The property is also satisfied for the fragility phase.

Quasilinearity This property is derived from the axiom phrased in the context of economic insecurity (Bossert et al., 2023; Gallo et al., 2024). It is very important as it concerns the possibility of decomposing and updating the measure in light of the new current resource level.

It states that the level of resilience/fragility associated with the stream $\boldsymbol{x}_{t_c}$ can be expressed as a quasilinear function of the level of insecurity associated with the stream $\boldsymbol{x}_{t_c-1}$ and a function of the two quantities x_{t_c} and x_{t_c-1}:

$$R\left(\boldsymbol{x}_{t_c}\right) = R\left(\boldsymbol{x}_{t_c-1}\right) + F\left(x_{t_c}, x_{t_c-1}\right).$$

The previous expression highlights the usefulness of this property in measuring resilience: the function $F\left(x_{t_c}, x_{t_c-1}\right)$ represents the "update" made to the measure when a new observation becomes available.

4 Empirical Analysis

In this section the measure proposed is applied to real data, to demonstrate its practical application and empirical contribution. The section is structured as follows. Subsect. 4.1 describes the dataset used. In Subsect. 4.2, resilience is compared across some subpopulations in order to verify the presence of groups in which resilience is more or less pronounced. Finally, Subsect. 4.3 aims at studying the determinants of individual economic resilience.

4.1 Data

We use data from the German Socio-Economic Panel (SOEP), a well-known representative panel study that covers from 1984 to 2020 with approximately 11,000 private households. Respondents range from 16 to 91 years old and they are asked around 150 different questions about many topics, including: earnings, household composition, health, education and many more (Goebel et al., 2018). The dataset we use is an unbalanced panel of 27,497 households interviewed annually from 2005 to 2020. The measure is calculated for each household using the household equivalent disposable income obtained based on the usual modified OECD scale (Grabka, 2022). In each wave of the survey the income refers to the previous year. This income is also deflated, to have it at 2019 real values, using the deflator provided by the Federal Statistical Office.

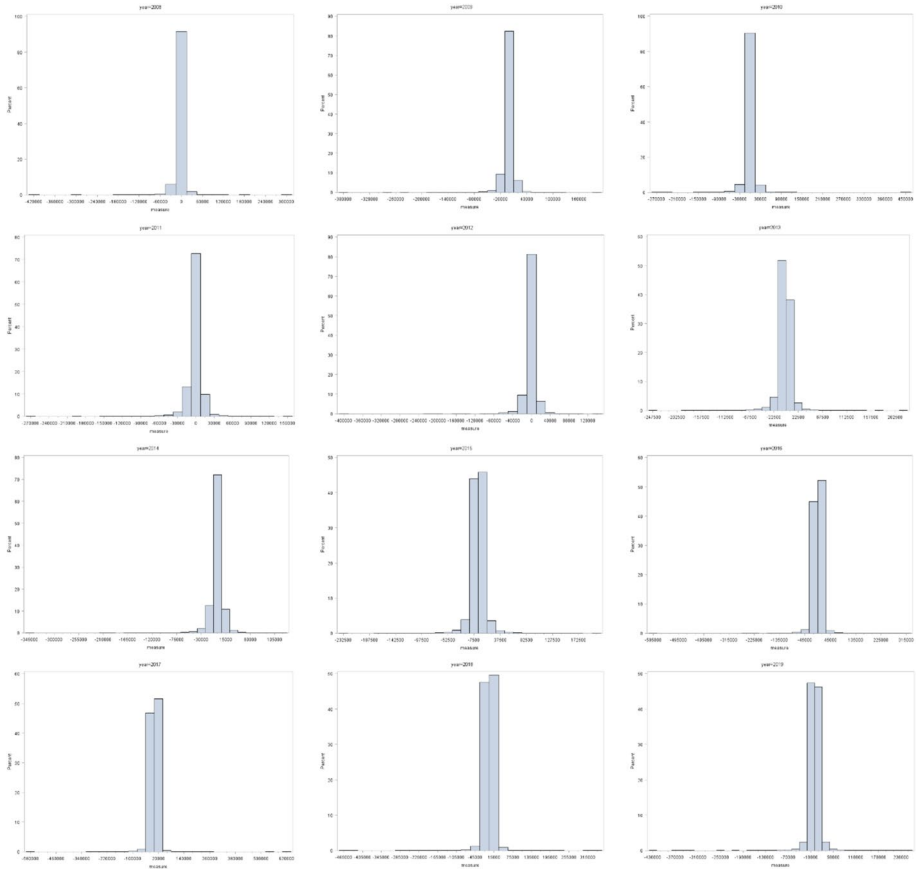

Fig. 4 Histograms of $R(\boldsymbol{x})$ scores by survey year. Source: our elaboration on SOEP data

The measure is obtained for all those households/years for which the information necessary to calculate measure (1) is available, which are 19,661 households over the period 2007–2020 (14 years).

Considering that small changes in the household yearly income may easily happen due to different reasons (for example, a different number of hours/days worked or small changes in the personal incomes) and do not represent changes that significantly modify the economic conditions of the household, we consider as "constant" two consecutive levels of household income whose difference is lower than a relative threshold. We set this threshold at $\pm 5\%$.

The measure is calculated setting $\delta = 0.9$ and $\gamma = 1.1$. These values are chosen arbitrarily, based on the following considerations: a lower value for δ would not give enough relevance to increases far from t_{bottom}. Similarly, higher values for γ would penalize too much those decreases far from t_{top}. The value for δ is in line with the value used in empirical applications for the intertemporal parameter included in some measures of "economic insecurity" (see, for example, Bossert et al., 2023 and Gallo et al., 2024).

Focusing on the last available year (income reference year 2019), some descriptive statistics for the resilience measure are calculated using the survey sample weights. The mean

is equal to −20.89, the median is −511.76 and the coefficient of variation is −3,814,258. The minimum is −431,124 and the maximum is 257,329. These values highlight that the scores provided by the measure are, on average, close to 0, but the distribution is highly variable and a bit skewed. In particular, the distribution is characterized by the presence of negative and positive outliers, as expected, given the structure of the measure and the resource considered. This is observed for all the survey years (Fig. 4).

4.2 Resilience in Subpopulations

In this section, we compare resilience across subpopulations in order to verify the presence of groups in which resilience is more pronounced according to the suggested index. We focus on the last year of the period considered. To define the subpopulations, we consider some characteristics of the household and some characteristics of the head of the household defined as the breadwinner. The household characteristics are: being resident in East or West Germany, the household size, the number of children and household disposable equivalized income in classes. Income classes are defined based on the quartiles of this variable's distribution rounded to the nearest thousand. The head of the household characteristics are: the gender, age class, marital status, educational level and employment status.

Table 1 reports the means calculated for subgroups using the survey weights. Results highlight that households living in East Germany are more resilient in 2019, on average, than households living in West Germany. Even though the average equivalized household income is much higher for households in West Germany than in East Germany (respectively 26,268 and 21,719 euros), the measure of resilience shows that households in East Germany have experienced a greater recovery from losses. This result is explained by the trend over time of the average household income calculated using SOEP data for West and East Germany (Fig. 5). East Germany experienced a higher increase in the mean income than West Germany from 2017 to 2019. This result is also in line with recent evidence for Eastern German (IFO, 2024): the East German economy is growing more strongly than Germany as a whole and its output is expected to increase significantly more than in Germany as a whole in 2024 (respectively by 1.1 and 0.4%).

Moreover, resilience shows a non-linear relationship with household size, as it increases moving from one-member households to households with two components and then reduces again, with households having 5 or more members experiencing the lowest level of economic resilience on average. This pattern can be due to the greater presence of non-working individuals or young workers in large households. This evidence is confirmed by the averages obtained for the number of children, which decrease as the number of children increases. In particular, for these two characteristics, the only modalities with a positive mean of the measure are "household with two components" and "no children".

Moreover, resilience increases as the income class increases. The income in classes is the characteristic for which the highest differences between the resilience means are observed. It is, as expected, the characteristic most related to economic resilience.

Moving to the characteristics of the head of the household, if female the household is more resilient on average than if it is male. We think that this result is strictly related to the definition of "head of the household" that we use, that is the breadwinner. Moreover, resilience shows a fluctuating relationship with the head of the household age, as it increases moving from the first age class (18–30 years old) to the intermediate age class (41–50 years old), then decreases moving to 61–70 years old class, and increases again for the last age class (over 70).

Table 1 $R(\boldsymbol{x})$ sub-groups means by demographic and economic characteristics of the household (2019)

Household characteristic	Classes	Mean of $R(\boldsymbol{x})$
Territory	East Germany	328.11
	West Germany	−98.70
Household size	1	−21.25
	2	286.39
	3	−173.45
	4	−332.16
	5 or more	−1761.75
Number of children	0	190.02
	1	−231.70
	2	−1207.83
	3 or more	−3178.42
Income classes	Less than 15.000	−3801.03
	[15.000; 22.000)	−1050.30
	[22.000; 31.000)	392.83
	More than or equal to 31.000	3864.95
Head of the household characteristic		
Gender	F	278.21
	M	−241.17
Age class	18–30	−981.43
	31–40	282.39
	41–50	1221.87
	51–60	913.06
	61–70	−1579.99
	Over 70	−213.79
Marital status	Married/living with a partner	−387.84
	Single	1049.96
	Widowed	342.36
	Divorced or separated	−323.80
Educational level	Less than High School	−434.25
	High School	94.21
	More than High School	97.89
Employment status	Pensioner	−739.87
	Others not employed	−1115.80
	Apprentice	−1708.97
	Self-employed	−906.15
	Blue collar	360.55
	White collar and civil servant	1454.38

Source: Our elaborations on SOEP data

If the heads of the household are married (including "living with a partner"), divorced or separated, resilience appears more difficult on average than if they are single. Then, resilience increases on average with the educational level of the head of the household, even though a higher difference would be expected between "High School" and "More than

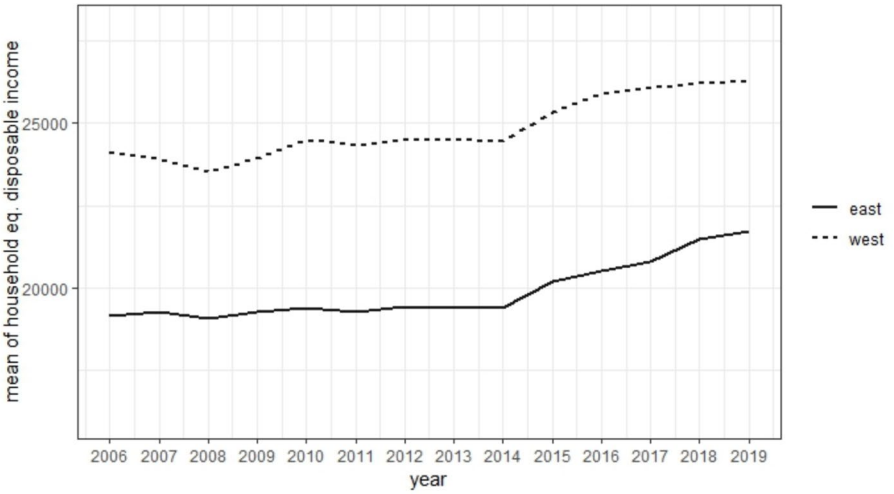

Fig. 5 Trend of the mean of the household equivalent disposable income in East and West Germany. Source: Our elaborations on SOEP data

High School". With regard to labour market conditions, the highest average is obtained for "white collar and civil servant", followed by "blue collar". The lowest average corresponds to "apprentice", which shows lower resilience than not-employed conditions (pensioner or other not employed).

4.3 The Determinants of Resilience

Results discussed in the previous section, are obtained by considering one characteristic at a time, therefore cross-effects of two or more characteristics may be hidden. In this section, we want to show the potential of a measure of resilience calculated at the household level and to study the possible determinants of household resilience. To these purposes, we use the measure suggested as the dependent variable in a two-way fixed effects regression for panel data, which allows us to deal with unobserved time-invariant individual and time effects. The alternative would be to assume random specific effects, under the assumption of independence among the unobserved effects and all the covariates of the model. We check this possibility using the Hausman test, which compares the fixed effects model and the random effects model. The null hypothesis is rejected at the 1% level, thus suggesting the use of the fixed effects approach.

Denoting for simplicity the point in time only with t and the generic household with i, the regression model can be written as follows:

$$R(\boldsymbol{x}_{i,t}) = \beta_0 + \boldsymbol{\beta}_1 \boldsymbol{Z}_{i,t} + \alpha_i + \omega_t + \varepsilon_{i,t} \tag{2}$$

The dependent variable is the resilience measure calculated for household i at time t, β_0 is the constant term, vector $\boldsymbol{Z}_{i,t}$ contains some exogenous[1] characteristics of the household, vector $\boldsymbol{\beta}_1$ contains the regression coefficients, α_i represents the individual unobserved effects, ω_t the annual effects, and $\varepsilon_{i,t}$ the error terms.

Concerning explanatory variables, we followed the body of literature mentioned in Sect. 2. We include those characteristics of the household as well as of the head of the household, defined as the breadwinner, that may be related to the ability to be resilient.

In particular, the characteristics of the household included in $\boldsymbol{Z}$ are the household size and the number of children, which are always included as determinants in models for economic well-being. Moreover, we include a dummy variable equal to 1 whether the household lives in West Germany, to verify whether the higher resilience on average, observed in the previous subsection, is also confirmed by the regression analysis. Then, following Martin et al. (2015) and Joossens et al. (2022), the following characteristics of the breadwinner of the household are included: the gender (dummy equal to 1 if male), the age, the number of years of education, the marital status with three dummies equal to 1 respectively if the breadwinner is "married or living with a partner", "single" or "widowed" (the excluded modality is "divorced or separated"), and the employment status with five dummies for "apprentice", "self-employed", "blue collar", "white collar" and "other non-employed" (the excluded modality is "pensioner"). The squared household size and the squared age of the breadwinner are also added to allow for non-linear relationships.

The unobservable individual effects α_i represent the unobserved human attitude of the household's members to be resilient. They may capture personal and psychological aspects of the income-earners in the household, such as their personality traits, their emotional capacity to react to shocks and resourcefulness in career and job search.

As economic resilience is calculated using information on household equivalent income, the standard errors are clustered at the household level. Estimated model parameters are presented in Table 2.

Family size does not in itself affect economic resilience, rather the number of children matters. One more dependent child decreases the measure by about 1,719, ceteris paribus. The West dummy takes a positive value, but it is not significant. Therefore, living in West Germany does not significantly affect the resilience ceteris paribus.

The age of the head of the household shows a significant non-linear relationship with resilience: the resilience increases with the breadwinner's age till 48, then it decreases. Therefore, we observe a relationship between age and resilience that is in line with the well-established "inverse-U" relationship between age and wage discussed in the literature: wages increase with the worker's experience and then begin to fall in the late stage of the working life, reflecting falling productivity as individuals grow older (Myck, 2010; Scarfe et al., 2023).

Another relevant determinant is, as expected, the breadwinner's years of education: if the years of education increase by 1, then the measure increases by 488. Similarly, Joossens et al. (2022) find that the longer individuals are educated, the higher their resilience. This result can also be explained by the fact that higher-educated individuals are likely to earn higher income, have similar partners and live in richer contexts. Therefore, they are likely to belong to households less exposed to financial difficulties (Becchetti et al., 2024).

[1] Exogeneity of covariates is tested using Durbin and Wu-Hausman tests. Both tests lead to accept the hypothesis of exogeneity.

Table 2 Determinants of economic resilience: parameter estimates in two-way fixed effects panel data model

Covariate	Estimate	SE
Household size	−87.00	370.55
Household size squared	−20.20	48.68
Number of children	−1719.14***	157.78
West Germany	1043.84	986.47
Male	1225.34***	291.97
Age	191.85***	52.93
Age squared	−2.08***	0.52
Years of education	488.00***	111.03
Marital status (excluded modality: "divorced or separated")		
Married	1985.48***	411.21
Single	1775.13***	641.22
Widowed	2800.54***	508.37
Employment status (excluded modality: "pensioner")		
Apprentice	2776.92***	659.63
Blue collar	3664.53***	370.90
White collar	3864.42***	402.54
Self-employed	6738.66***	817.70
Other non-employed	363.56	562.23
Number of observations 97,346		
Number of households 18,338		
R^2 0.0073		

Notes: ***1% significance, **5% significance and *10% significance

Source: Own elaborations on SOEP data

In contrast to the descriptives calculated solely for the year 2019, the resilience is much higher if the breadwinner is male (+1,225). Regarding this last result, there are conflicting opinions in the literature. A strand of the literature affirms the higher sensitivity of men to adverse socio-economic conditions than women, who appear more resilient thanks to their superior built-in mechanism for adaptation to adverse conditions (Cullen et al., 2016). Other authors consider women often more vulnerable to economic shocks than men, since women tend to engage in part-time work more often than men, making them vulnerable to reductions in working time in periods of economic duress (André et al., 2023; OECD, 2020).

Moreover, resilience is much higher whether the breadwinners are married, single, and above all widowed, than if they are divorced or separated. As observed also by Becchetti et al. (2024), separated and divorced individuals are more likely to be exposed to household economic difficulties, as they lost a household risk diversification mechanism that may help to face financial shocks. Our results are partially in line with the profiling of individual resilience across the EU provided by Joossens et al. (2022), who find divorced and widowed individuals significantly less resilient than the other categories.

Regarding the employment status, some unexpected results are obtained. Resilience is found to be significantly higher if the breadwinners are apprentices, blue collars, white collars and self-employed, than if they are pensioners. The other breadwinners who are

not employed are comparable to pensioners. Unemployed and pensioners are found to be the least resilient in Joossens et al. (2022) too. This finding may be interpreted as a greater difficulty in recovery when an individual is not working. Besides, self-employed workers show the highest coefficient, highlighting an unexpected ability to recover on average over the period considered. Germany experienced a unique rise in the level of self-employment in the first two decades following unification, favoured by the manifold policy initiatives to promote entrepreneurship in Germany (Fritsch et al., 2015). The German self-employed's resilience is highlighted by Bertschek et al. (2023), who find a strong ability to overcome crises especially for self-employed who run highly digitalized businesses. By examining financial resilience in various EU countries, McKnight and Rucci (2020) also find that households with a self-employed head performed better than those with an employed head.

5 Conclusions

The recent global economic crises have brought the concept of resilience to the forefront of both political agendas and scientific research. The ability to be resilient has emerged as a crucial virtue for individuals and households, as well as for the entire economic system.

This article originally contributes to the research in this field by proposing a measure of individual resilience, based on a definition of economic resilience. Our measure incorporates the dynamic nature of the individual capacity to recover after a loss, through the possibility of being updated based on how the recovery from the loss evolves over time. Moreover, our measure satisfies some desirable properties.

The measure is applied to a panel dataset of German households. Our empirical results show the key role of some household characteristics in promoting resilience.

Nevertheless, our measure is not without limitations. As for the other measures suggested in the literature, there is a dose of subjectiveness in our approach. Specifically, it considers the time required for recovery and the comparison with the resource value prior to the drop, but it does not consider the duration of the drop itself. Additionally, the measure depends on certain parameters that can be set arbitrarily.

A future direction in this regard involves conducting additional robustness checks to determine how the measure responds to different parameter values or tuning proposals, as well as exploring extensions that take into account the duration of the drop. Another interesting avenue is to compare this measure with traditional poverty and inequality indicators.

Finally, our measure is one of the few measures suggested in the literature to empirically measure economic resilience at the individual level. We argue that our proposal may contribute to studying the determinants and the consequences of individual resilience on some individual conditions or behaviours. An implication of this work is also the necessity to strengthen policies addressing the issue of economic resilience, especially among less advantaged households, considering the recent succession of global economic crises. This could be done, for example, by protecting household livelihoods and providing adequate social safety nets. The measure proposed can be usefully applied to evaluate the effects of those interventions designed by governments to foster economic resilience.

Appendix: mathematical proofs

Recovery monotonicity According to this property, if all values in the recovery phase increase (while all other values remain unchanged), resilience increases.

For the sake of simplicity, we consider a recovery phase without extra recovery.

We consider two streams having the same length T ($\forall T \in \mathbf{T}$) $\boldsymbol{x}_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}+1}, \ldots, x_{t_c}; x_{t_{top}}\right)$ and $\boldsymbol{x}'_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}+1}\prime, \ldots, x_{t_c}\prime; x_{t_{top}}\right)$, where $x_t\prime > x_t$ for every $t = t_{bottom} + 1, \ldots, t_c$.

We write the values in $\boldsymbol{x}'_{t_c}$ in terms of differences with respect to the values in $\boldsymbol{x}_{t_c}$: $\boldsymbol{x}'_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}+1} + d_1, x_{t_{bottom}+2} + d_2, \ldots, x_{t_c} + d_{T-1}; x_{t_{top}}\right)$
where $d_t \in \mathbb{R}_{++} (t = 1, \ldots, T-1)$.

Therefore.

$$R(\boldsymbol{x}_{t_c}) = \delta^0\left(x_{t_{bottom}+1} - x_{t_{bottom}}\right) + \delta\left(x_{t_{bottom}+2} - x_{t_{bottom}+1}\right) + \cdots + \delta^{T-2}\left(x_{t_c-1} - x_{t_c-2}\right) + \delta^{T-1}\left(x_{t_c} - x_{t_c-1}\right)$$

and

$$\begin{aligned} R\left(\boldsymbol{x}'_{t_c}\right) &= \delta^0\left(x_{t_{bottom}+1} + d_1 - x_{t_{bottom}}\right) + \delta\left(x_{t_{bottom}+2} + d_2 - x_{t_{bottom}+1} - d_1\right) \\ &+ \cdots + \delta^{T-2}\left(x_{t_c-1} + d_{T-2} - x_{t_c-2} - d_{T-3}\right) + \delta^{T-1}\left(x_{t_c} + d_{T-1} - x_{t_c-1} - d_{T-2}\right). \end{aligned}$$

The difference between $R\left(\boldsymbol{x}'_{t_c}\right)$ and $R\left(\boldsymbol{x}_{t_c}\right)$ is given by:

$$\begin{aligned} R\left(\boldsymbol{x}'_{t_c}\right) - R\left(\boldsymbol{x}_{t_c}\right) &= \delta^0 d_1 + \delta d_2 - \delta d_1 + \cdots + \delta^{T-2} d_{T-2} - \delta^{T-2} d_{T-3} + \delta^{T-1} d_{T-1} - \delta^{T-1} d_{T-2} = \\ &= d_1\left(\delta^0 - \delta\right) + d_2\left(\delta - \delta^2\right) + \cdots + d_{T-2}\left(\delta^{T-2} - \delta^{T-1}\right) + d_{T-1}\delta^{T-1}. \end{aligned}$$

Given that $\delta \in (0,1)$, the difference is always positive.

The same is obtained in the case of extra recovery and in the case of a fragility phase.

Proximity monotonicity According to this property, resilience closer to the end of the drop has a greater impact on the measure.

Consider a stream of length T ($\forall T \in \mathbf{T}$) observed in a recovery phase. The stream written in terms of increases $a_t = x_t - x_{t-1}, a_t \in \mathbb{R}_+, t = 1, \ldots, T-1$, is given by.

$$\boldsymbol{x}_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}} + a_1, \ldots, x_{t_{bottom}} + a_1 + \cdots + a_{t-1} + a_t, \ldots, x_{t_{bottom}} + a_1 + \cdots + a_{t-1} + a_t + \cdots + a_{T-1} = x_{t_c}; x_{t_{top}}\right).$$

Let assuming that $a_t > a_{t-1}$. If we swap these two increases in the previous stream, we obtain the stream $\boldsymbol{x}^*_{t_c} = \left(x_{t_{bottom}}, x_{t_{bottom}} + a_1, \ldots, x_{t_{bottom}} + a_1 + \cdots + a_t + a_{t-1}, \ldots, x_{t_{bottom}} + a_1 + \cdots + a_t + a_{t-1} + \cdots + a_{T-1} = x_{t_c}; x_{t_{top}}\right)$.

Assuming for the sake of simplicity that all the stream values are lower than $x_{t_{top}}$, we have:

$$R(\boldsymbol{x}_{t_c}) = \delta^0 a_1 + \cdots + \delta^{t-2} a_{t-1} + \delta^{t-1} a_t + \cdots + \delta^{T-2} a_{T-1}$$

and

$$R\left(\boldsymbol{x}^*_{t_c}\right) = \delta^0 a_1 + \cdots + \delta^{t-2} a_t + \delta^{t-1} a_{t-1} + \cdots + \delta^{T-2} a_{T-1}$$

Taking the difference

$$R\left(\boldsymbol{x}_{t_c}^*\right) - R\left(\boldsymbol{x}_{t_c}\right) = \delta^{t-2}a_t + \delta^{t-1}a_{t-1} - \delta^{t-2}a_{t-1} - \delta^{t-1}a_t = \\ = \delta^{t-2}\left(a_t - a_{t-1}\right) + \delta^{t-1}\left(a_{t-1} - a_t\right)$$

$\left(a_t - a_{t-1}\right)$ is positive and $\left(a_{t-1} - a_t\right)$ is its negative counterpart. Being δ^{t-2} greater then δ^{t-1} it follows then $R\left(\boldsymbol{x}_{t_c}^*\right) > R\left(\boldsymbol{x}_{t_c}\right)$.

In case of extra recovery it is easy to demonstrate that the result does not change, as well as in the fragility case.

Linear homogeneity For all $b \in \mathbb{R}_{++}$:

$$R\left(b\boldsymbol{x}_{t_c}\right) = bR\left(\boldsymbol{x}_{t_c}\right).$$

This result depends on the fact that the measure is additive.

Proof.

$$R(b\boldsymbol{x}_{t_c}) = \begin{cases} \sum_{t=t_{bottom}+1}^{t_c} \delta^{t-(t_{bottom}+1)}\left(bx_t - bx_{t-1}\right) + \alpha \sum_{t=t_{bottom}+1}^{t_c} \delta^{t-(t_{bottom}+1)}\left(bx_t - bx_{t-1}\right) + \\ bx_t \le bx_{t_{top}} \qquad bx_{t-1} \ge bx_{t_{top}} \\ \quad + \sum_{t=t_{bottom}+1}^{t_c} \delta^{t-(t_{bottom}+1)}\left[\alpha\left(bx_t - bx_{t_{top}}\right) + \left(bx_{t_{top}} - bx_{t-1}\right)\right] & if \quad bx_{t_c} > bx_{t_c-1} \\ \quad bx_t > bx_{t_{top}} \\ \quad bx_{t-1} < bx_{t_{top}} \\ \sum_{t=t_{top}+1}^{t_c} \gamma^{t-(t_{top}+1)}\left(bx_t - bx_{t-1}\right) & if \quad bx_{t_c} < bx_{t_c-1} \\ R(b\boldsymbol{x}_{t_c-1}) & if \quad bx_{t_c} = bx_{t_c-1} \end{cases}$$

$$= \begin{cases} b\sum_{t=t_{bottom}+1}^{t_c} \delta^{t-(t_{bottom}+1)}\left(x_t - x_{t-1}\right) + \alpha b \sum_{t=t_{bottom}+1}^{t_c} \delta^{t-(t_{bottom}+1)}\left(x_t - x_{t-1}\right) + \\ x_t \le x_{t_{top}} \qquad x_{t-1} \ge x_{t_{top}} \\ \quad + b\sum_{t=t_{bottom}+1}^{t_c} \delta^{t-(t_{bottom}+1)}\left[\alpha\left(x_t - x_{t_{top}}\right) + \left(x_{t_{top}} - x_{t-1}\right)\right] & if \quad x_{t_c} > x_{t_c-1} \\ \quad x_t > x_{t_{top}} \\ \quad x_{t-1} < x_{t_{top}} \\ b\sum_{t=t_{top}+1}^{t_c} \gamma^{t-\left(t_{top}+1\right)}\left(x_t - x_{t-1}\right) & if \quad x_{t_c} < x_{t_c-1} \\ bR\left(\boldsymbol{x}_{t_c-1}\right) & if \quad x_{t_c} = x_{t_c-1} \end{cases}$$

$$= bR\left(\boldsymbol{x}_{t_c}\right).$$

Translation invariance For all $d \in \mathbb{R}$, $R\left(\boldsymbol{x}''_{t_c}\right) = R\left(\boldsymbol{x}_{t_c}\right)$ where $\boldsymbol{x}''_{t_c} = \left(x_{t_{bottom}} + d, x_{t_{bottom}+1} + d, \ldots, x_{t_c} + d; x_{t_{top}} + d\right)$. This result depends on the fact that the measure is based on differences between the stream values.

Proof.

$$R\left(\boldsymbol{x}''_{t_c}\right) = \begin{cases} \sum_{\substack{t=t_{bottom}+1 \\ x_t+d \le x_{ttop}+d}}^{t_c} \delta^{t-\left(t_{bottom}+1\right)}\left(x_t+d-x_{t-1}-d\right) + \alpha \sum_{\substack{t=t_{bottom}+1 \\ x_{t-1}+d \ge x_{ttop}+d}}^{t_c} \delta^{t-\left(t_{bottom}+1\right)}\left(x_t+d-x_{t-1}-d\right) + \\ \quad + \sum_{\substack{t=t_{bottom}+1 \\ x_t+d > x_{ttop}+d \\ x_{t-1}+d < x_{ttop}+d}}^{t_c} \delta^{t-\left(t_{bottom}+1\right)}\left[\alpha\left(x_t+d-x_{t-1}-d\right)+\left(x_{ttop}+d-x_{t-1}-d\right)\right] & \text{if } x_{t_c}+d > x_{t_c-1}+d \\ \sum_{t=t_{top}+1}^{t_c} \gamma^{t-\left(t_{top}+1\right)}\left(x_t+d-x_{t-1}-d\right) & \text{if } x_{t_c}+d < x_{t_c-1}+d \\ R\left(\boldsymbol{x}''_{t_c-1}\right) & \text{if } x_{t_c}+d = x_{t_c-1}+d \end{cases}$$
$$= R\left(\boldsymbol{x}_{t_c}\right).$$

Quasilinearity

$$R\left(\boldsymbol{x}_{t_c}\right) = R\left(\boldsymbol{x}_{t_c-1}\right) + F\left(x_{t_c}, x_{t_c-1}\right).$$

Proof.
The property is satisfied considering the function $F(x,y) : \mathbb{R}^2 \to \mathbb{R}$

$$F\left(x_{t_c}, x_{t_c-1}\right) = \begin{cases} \delta^{t_c-\left(t_{bottom}+1\right)}\left(x_{t_c}-x_{t_c-1}\right) & \text{if } x_{t_c} \le x_{t_{top}} \text{ and } x_{t_c} > x_{t_c-1} \\ \alpha\delta^{t_c-\left(t_{bottom}+1\right)}\left(x_{t_c}-x_{t_c-1}\right) & \text{if } x_{t_c-1} \ge x_{t_{top}} \text{ and } x_{t_c} > x_{t_c-1} \\ \delta^{t_c-\left(t_{bottom}+1\right)}\left[\alpha\left(x_{t_c}-x_{t_{top}}\right)+\left(x_{t_{top}}-x_{t_c-1}\right)\right] & \text{if } x_{t_c} > x_{t_{top}} ; x_{t_c-1} < x_{t_{top}} \text{ and } x_{t_c} > x_{t_c-1} \\ \gamma^{t_c-\left(t_{top}+1\right)}\left(x_{t_c}-x_{t_c-1}\right) & \text{if } x_{t_c} < x_{t_c-1} \\ 0 & \text{if } x_{t_c} = x_{t_c-1} \end{cases}$$

Moreover, if $t_c - 1 = t_{bottom}$ or $t_c - 1 = t_{top}$ then it means that there is only a point in time after the beginning of the recovery or the drop. Consequently, in this case $R\left(\boldsymbol{x}_{t_c-1}\right) = 0$ and

$$R\left(\boldsymbol{x}_{t_c}\right) = F\left(x_{t_c}, x_{t_c-1}\right).$$

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Data availability The data that support the findings of this study are available from the SOEP Research Data Center under restrictions. The code is available upon request.

Declarations

Data Reference Socio-Economic Panel (SOEP); data for years 1984–2020, SOEP-Core Version 37; EU Edition 2022; https://doi.org/10.5684/soep.core.v37eu.

Conflict of Interest The authors have no conflict of interests to declare related to this publication.

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References

Adger, W. N. (2000). Social and ecological resilience: Are they related? *Progress in Human Geography, 24*(3), 347–364.

Alessi, L., Benczur, P., Campolongo, F., Cariboni, J., Manca, A. R., Menyhert, B., & Pagano, A. (2020). The resilience of EU member states to the financial and economic crisis. *Social Indicators Research, 148*, 569–598. https://doi.org/10.1007/s11205-019-02200-1

André, C., Causa, O., Soldani, E., Sutherland, D., & Unsal, F. (2023). Promoting gender equality to strengthen economic growth and resilience. OECD Economics Department Working Papers 1776, OECD Publishing. https://doi.org/10.1787/54090c29-en

Asheim, G. B., Bossert, W., D'Ambrosio, C., & Vögele, C. (2020). The measurement of resilience. *Journal of Economic Theory, 189*, 105104.

Barrett, C. B., & Constas, M. A. (2014). Toward a theory of resilience for international development applications. *Proceedings of the National Academy of Sciences of the United States of America,111*(40), 14625–14630.

Becchetti, L., Bellucci, D., & Pisani, F. (2024). The fittest survive: Regional resilience and exposure to financial crisis. *International Review of Economics and Finance, 96*(103652), 1–21. https://doi.org/10.1016/j.iref.2024.103652

Benczur, P., Joossens, E., Manca, A. R., Menyhert, B, & Zec, S. (2020). How resilient are the European regions: Evidence from the societal response to the 2008 financial crisis. EUR 30352 EN, Publications Office of the European Union. https://doi.org/10.2760/383460, JRC121554.

Bertschek, I., Block, J., Kritikos, A. S., & Stiel, C. (2023). German financial state aid during COVID-19 pandemic: Higher impact among digitalized self-employed. *Entrepreneurship and Regional Development,36*(1–2), 76–97. https://doi.org/10.1080/08985626.2023.2196267

Bhamra, R., Dani, S., & Burnard, K. (2011). Resilience: The concept, a literature review and future directions. *International Journal of Production Research, 49*(18), 5375–5393.

Bossert, W., Clark, A. E., D'Ambrosio, C., & Lepinteur, A. (2023). Economic insecurity and political preferences. *Oxford Economic Papers, 75*(3), 802–825. https://doi.org/10.1093/oep/gpac037

Cissé, J. D., & Barrett, C. B. (2018). Estimating development resilience: A conditional moments-based approach. *Journal of Development Economics, 135*, 272–284.

Cullen, M. R., Baiocchi, M., Eggleston, K., Loftus, P., & Fuchs, V. R. (2016). The weaker sex? Vulnerable men and women's resilience to socio-economic disadvantage. *SSM - Population HealTh,2*, 512–524. https://doi.org/10.1016/j.ssmph.2016.06.006

ESPON (2014). ECR2. Economic Crisis: Resilience of Regions. Applied Research 2013/124/2012. (Draft) Scientific Report | Version 31/03/2014. https://archive.espon.eu/sites/default/files/attachments/Scientific_report.pdf

European Commission (2020). 2020 Strategic Foresight Report. Charting the course toward a more resilient Europe. https://commission.europa.eu/system/files/2021-04/strategic_foresight_report_2020_1_0.pdf

Ferrera, M. (2019). Welfare State. In D. Berg-Schlosser, B. Badie, & L. Morlino (Eds.), *The Sage Handbook of Political Science* (pp. 1179–1195). Oxford University Press.

Folke, C. (2006). Resilience: The emergence of a perspective for social-ecological systems analyses. *Global Environmental Change, 16*(3), 253–267.

Fritsch, M., Kritikos, A., & Sorgner, A. (2015). Why Did Self-Employment Increase so Strongly in Germany? IZA DP No. 8818, January 2015.

Gallo, A., Pacei, S., & Ferrante, M. R. (2024). A composite inter-temporal economic insecurity index. *Social Indicators Research, 175*, 517–543. https://doi.org/10.1007/s11205-024-03356-1

Giovannini, E., Benczur, P., Campolongo, F., Cariboni, J., & Manca, A. R. (2020). Time for transformative resilience: the COVID-19 emergency. EUR 30179 EN, Publications Office of the European Union. https://doi.org/10.2760/062495.

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., & Schupp, J. (2018). The German socio-economic panel study (SOEP). Jahrbücher Für Nationalökonomie und Statistik/journal of Economics and Statistics. https://doi.org/10.1515/jbnst-2018-0022

Grabka, M. M. (2022). SOEP-core v37- Codebook for the $PEQUIV file 1984–2020: CNEF variables with extended income information for the SOEP. SOEP Survey Papers Series D - Variable Descriptions and Coding. Retrieved January 8, 2025. https://www.diw.de/docum ents/publikationen/73/diw_01.c.836478.de/diw_ssp1082.pdf.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics, 4*, 1–23.

Holling, C. S. (1996). Engineering resilience versus ecological resilience. In P. Schulze (Ed.), *Engineering within Ecological Constraints* (pp. 31–43). National Academy Press.

Holling, C. S. (2001). Understanding the complexity of economic, ecological, and social systems. *Ecosystems, 4*, 390–405. https://doi.org/10.1007/s10021-001-0101-5

IFO (2024). ifo Economic Forecast for Eastern Germany and Saxony: East German Economy Growing More Strongly Than the West. Ifo Institute for Economic Research, Press release - 3 July 2024. https://www.ifo.de/en/press-release/2024-07-03/ifo-economic-forecast-eastern-germany-and-saxony-east-german-economy.

Joossens, E., Manca, A. R., & Zec, S. (2022). Measuring and understanding individual resilience across the EU. *European Commission, JRC Technical Report*. https://doi.org/10.2760/434622

Luthar, S. S., Cicchetti, D., & Becker, B. (2000). The construct of resilience: A critical evaluation and guidelines for future work. *Child Development, 71*, 543–562.

Martin, A. S., Distelberg, B., Palmer, B. W., & Jeste, D. V. (2015). Development of a new multidimensional individual and interpersonal resilience measure for older adults. *Aging & Mental Health, 19*(1), 32–45. https://doi.org/10.1080/13607863.2014.909383

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

Martin, R., & Sunley, P. (2007). Complexity thinking and evolutionary economic geography. *Journal of Economic Geography, 7*(5), 573–602.

Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: Conceptualization and explanation. *Journal of Economic Geography, 15*(1), 1–42. https://doi.org/10.1093/jeg/lbu015

Marulanda Fraume, M. C., Cardona, O. D., Marulanda Fraume, P., Carreño, L., & Barbat, A. H. (2020). Evaluating risk from a holistic perspective to improve resilience: The United Nations evaluation at global level. *Safety Science, 127*, 104739. https://doi.org/10.1016/j.ssci.2020.104739

McGlade, J., Murray, R., Baldwin, J., Ridgway, K., & Winder, B. (2006). Industrial Resilience and Decline: A Co-Evolutionary Framework. In Complexity and Co-Evolution, Edited by Elizabeth Garnsey and James McGlade, Edward Elgar Publishing Limited: Cheltenham, UK.

McKnight, A., & Rucci, M. (2020). The financial resilience of households: 22 country study with new estimates, breakdowns by household characteristics and a review of policy options. Centre for Analysis of Social Exclusion. London School of Economics. CASE/219, May 2020.

Myck, M. (2010). Wages and Ageing: Is There Evidence for the 'Inverse-U' Profile? *Oxford Bulletin of Economics and Statistics, 72*(3), 263–410. https://doi.org/10.1111/j.1468-0084.2009.00582.x

Nicholson, J. (2014). Supporting mothers living with mental illness in recovery. In N. Benders-Hadi & M. E. Barber (Eds.), *Motherhood, Mental Illness and Recovery: Stories of Hope* (pp. 3–18). Springer.

OECD, (2020). Women at the core of the fight against COVID-19 crisis. OECD Policy Responses to Coronavirus (COVID-19), OECD, Paris.

Pimm, S. L. (1984). The complexity and stability of ecosystems. *Nature, 307*, 321–326.

Ranci, C. (2010). *Social vulnerability in Europe. The new configuration of social risks*. Palgrave Macmillan.

Richardson, G. E. (2002). The metatheory of resilience and resiliency. *Journal of Clinical Psychology, 58*, 307–321.

Riera Mallol, G. (2023). On the Determinants of Individual Resilience: Results from Panel and Cross-Sectional Data [Doctoral thesis, Unilu - University of Luxembourg]. ORBilu-University of Luxembourg. https://hdl.handle.net/10993/57164

Sánchez, A., D'Agostino, A., Giusti, C., & Potsi, A. (2024). Measuring child vulnerability to poverty: Material and psychosocial deprivation. *Socio-Economic Planning Sciences, 91*, 101794. https://doi.org/10.1016/j.seps.2023.101794

Sánchez, A., & Jiménez-Fernández, E. (2023). European Union cohesion policy: Socio-economic vulnerability of the regions and the COVID-19 shock. *Applied Research in Quality of Life, 18*, 195–228. https://doi.org/10.1007/s11482-022-10116-1

Scarfe, R., Singleton, C., Sunmoni, A., & Telemo, P. (2023). The age-wage-productivity puzzle: Evidence from the careers of top earners. *Economic Inquiry*. https://doi.org/10.1111/ecin.13191

Stevenson, C., Costab, S., Wakefielda, J. R. H., Kellezia, B., & Stacka, R. J. (2020). Family identification facilitates coping with financial stress: A social identity approach to family financial resilience. *Journal of Economic Psychology, 78*, 102271. https://doi.org/10.1016/j.joep.2020.102271

Walker, B. H., Anderies, J. M., Kinzig, A. P., & Ryan, P. (2006). Exploring resilience in social-ecological systems through comparative studies and theory development: Introduction to the special issue. *Ecology and Society, 11*(1), 12.

Weick, K. E., & Sutcliffe, K. M. (2007). Managing the unexpected: Resilient performance in an age of uncertainty (Vol. 8). John Wiley & Sons.

Williams, R., & Druy, J. (2009). Psycological resilience and its influence on managing mass emergencies disasters. *Psychiatry, 8*(8), 293–296.

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