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Conceptualizing and measuring "industry resilience": Composite indicators for postshock industrial policy decision-making

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ABSTRACT

Can resilience be a relevant concept for industrial policy? Resilience is usually described as the ability of a socioeconomic system to recover from unexpected shocks. While this concept has caught the attention of regional economics researchers seeking to understand the different patterns behind regional recovery after a disruption, it is increasingly recognized that resilience can have policy-relevant conceptual applications in many other regards. In this paper, we apply it to industries and define the "industry resilience" concept and measurements. Our contribution is twofold. Theoretically, we frame industry resilience as a useful conceptual framework for policy-making to support the selection of industrial policy targets that are more capable of recovering after unexpected shocks. In addition, industry resilience can mitigate government failures by supporting decision-makers in promoting both economically and socially sustainable structural change. Methodologically, building on post-2008 U.S. data, we develop two composite indicators (CIs) to separately analyze quantitative and qualitative postshock variations in sectoral employment. Such CIs support policy-makers in visualizing sectoral performances dynamically and multidimensionally and can be used to compare each sector both to other sectors and to its counterfactual. Our results highlight that sectors react heterogeneously to shocks. This points to the relevance of tailoring vertical industrial policies according to sector features and the aims of industrial policy initiatives.

1. Introduction

The concept of resilience has acquired increasing prominence in many natural and social science disciplines [1–3] among researchers seeking to understand the different patterns shaping subject recovery after a shock. While the concept has also been widely used since 2008 in the field of management and economic studies [4–7], the role of resilience in relation to the postshock industrial structure has been less explored [8,9].

The topic is indeed relevant for policy-makers designing and implementing industrial policies, particularly considering that an increasing body of literature is challenging the mainstream definition of industrial policies as the way in which government promotes the competitiveness and productivity of industrial sectors through vertical policy initiatives [10,11] in favor of a broader view. Indeed, industrial policy is increasingly conceived of as a way to deal with a multiplicity of socioeconomic objectives through the implementation of a variety of tools aimed at modifying industrial sectors [12–19]. In particular, recent contributions have stressed how industrial policy can be interpreted as a set of tools to govern structural change [20,21], defined as the relative proportions between sectors of the economy. In line with other spheres of public decision-making [22–25], industrial policies also need to be supported through novel methodologies to accomplish such complex and multifaceted tasks, particularly in times of uncertainty.

The capacity of industrial policy to manage structural change should be considered particularly relevant given that growth and development imply a process of continuous structural transformation and face endogenous or exogenous unexpected shocks. Moreover, structural changes can produce economically and socially unsustainable outcomes, which could arise from a plurality of interconnected processes, such as ecological, economic and social dynamics. Such outcomes can emerge either from the process of continuous structural transformation that

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economic development implies (e.g., the adoption of ICT and automation in manufacturing) or from unexpected shocks. Especially when these shocks are particularly severe and unpredicted (e.g., the 2008 global crisis and the COVID-19 pandemic), they can shake social and economic arrangements and endanger the sustainability of structural change [7,26,27]. Shocks of these kinds in fact might rapidly lead to the collapse of companies, sectors, and territories. The velocity of these unexpected disruptions undermines the socioeconomic system as a whole and its capacity to govern and promote the future path of desirable structural change.

In this paper, we are focused specifically on this last aspect – i.e., threats to structural change sustainability coming from unexpected shocks. In this context, industrial policy becomes an essential tool to promote socially sustainable structural change [20] as a process that occurs without causing the collapse of the entire socioeconomic system and possibly promoting an improvement in the life of communities in the long term [28,29]. While we also recognize that sustainability entails a plurality of intertwined dimensions, our contribution specifically concerns social sustainability, which is a rather overlooked aspect relative to other pillars of the sustainability debate [30].

Once industrial policy is conceptualized as a tool to promote the sustainability of structural change, the choice of *which industries* policy-makers target through industrial policy is particularly relevant, since different sectors can display substantially different capacities to promote sustainable structural change [31,32]. In particular, industrial sectors can react very differently to shocks, absorbing them and adapting to the new environment, therefore displaying different resilience capacities [8,9]. From the perspective of this paper, the ability not to collapse in the immediate aftermath of a shock is a desirable goal in the attempt to ensure future paths of sustainable structural change. Nevertheless, it is also necessary to clarify that resilience capacity might have different sources working for, or even against, structural change. For instance, it is true that companies, or entire sectors, might be resilient because they are capable of undertaking virtuous processes of internal structural transformation based on investments, R&D and innovation. In contrast, it is also true that they might appear resilient only because they are effective in capturing protection through the action of regressive coalitions.

Therefore, being able to carefully study the nature of *postshock industry resilience* should be considered crucial to support policy-making in selecting sectors able to foster sustainable structural change.

This paper specifically addresses this last point and is a first step in this direction. In particular, we offer a novel methodology to examine postshock industry resilience and the different degrees to which industries react to shocks to support the design of selective industrial policies. From this perspective, in this contribution, we purposefully focus on industries as units of analysis. This choice is grounded in real-world evidence and recent literature. First, while production organizations can have various configurations (such as vertically integrated chains, interdependent networks and territorial agglomerations; see Refs. [33–36]; and [37]; among others), industries and sectors still represent one of the objects that most frequently draws attention in industrial policy measures, as testified by many industrial policy experiences worldwide and observed in several contributions (see, for example, [12,20,28,38,39]. Given that our proposition is to build and test a novel methodology to assess postshock industry resilience, our first empirical exercise relates to such widespread industrial policy targets.

Second, industry is a particularly relevant level of analysis from a political economy perspective. Indeed, industrial sectors have always been considered to represent sociopolitical aggregations of interests [34,40,41,42], with clear implications for policy formulation and implementation and for economic dynamics [43,44].

We make a first empirical application of our methodology by using data on U.S. industries from the post-2008 downturn, with an additional focus on manufacturing, given the increasing prominence that the sector has assumed in policy initiatives since the 2008 crisis.

Our contribution is threefold. First, we look at various dimensions of the change in employment within industrial sectors during and after a crisis. In particular, by developing a tailored index, we observe a) a measure of the quantity and b) a measure of the quality of the jobs preserved. Second, we move a step forward relative to previous studies by modeling industry resilience, looking at the behavior of these variables *across the whole crisis-and-recovery period* and against a hypothetical counterfactual trend, rather than simply accounting for pre-to postcrisis differences. Finally, we use this modeling to develop two composite indices (one for employment quantity and one for employment quality), allowing us to rank industrial sectors according to their performance. To assess the overall postshock industry resilience of sectors, such composite indices are also analyzed jointly, potentially enabling policy-makers to tailor relevant policy choices accordingly.

The remainder of the paper is as follows: the next section analyses relevant literature contributions on resilience and sets our research in the debate about structural change and social sustainability. Section 3 develops the methodology and describes the data. Section 4 shows the empirical application in the U.S. case, together with some methodological robustness checks. Concluding remarks, policy implications and future research lines are included in section 5.

2. A review of the literature

Over the past decades, the concept of resilience has attracted considerable attention from different disciplinary fields [1,2,3] and has been applied to different units of analysis, stages of the life course and spatial scales [7,45].

The concept of resilience originates from early studies in physics,[1] math and engineering [46,47], where it measures the "*speed at which the system returns to the stable point or trajectory following a perturbation*" [48].

More recent applications in ecology [49–53], psychology [54–56], management and decision-making [57][58] [59,60]; and economic studies [6,7,9,61–64]; to cite only some) have departed from such a *return-to-equilibrium* interpretation and broadly define resilience as the ability to absorb changes and adapt to emerging circumstances [27,65]. In these studies, therefore, resilience accounts for systems' endurance and renewal [66–68], stressing, particularly for social systems, the ability of humans to learn and adapt [3,69].

The 2008 economic downturn has contributed to intensifying research on and applications of the concept in economic studies. First, regional economics and economic geography have used it as a lens to explain why territories behave heterogeneously in the face of disruptive recessionary shocks, stressing that regions' adaptability to economic crises depends upon place-specific features [4,70–75].

More recently, however, other stands of literature have acknowledged the need to also look at sector-specific patterns of response and adaptation to shocks [9,76]. Indeed, industries react heterogeneously to a crisis, given that economic activities experience different degrees of fluctuation over the business cycle. In other words, *crises impact firms and workers differently depending on their industry* [9]. In this view, postshock industry resilience might become a relevant framework for informing and orienting policy initiatives targeting sectors. However, the few studies that have attempted to assess the resilience of industries are, on the one hand, based mostly on anecdotal evidence and case studies [77,78]; on the other hand, they have primarily focused only on specific aspects characterizing resilience, such as the degree of supply chain susceptibility to disruptive events [78], the overall risks associated with supply–customer relationships [79], and industries' inner features affecting their capacities to withstand a crisis [9].

To the best of our knowledge, only [8] have proposed a measure for

[1] See, for instance, Merriam-Webster Dictionary Online at http://www.merriamwebster.com.

industry resilience that allows ranking of sectors based on their resilience, thus offering policy-makers informative insights into how to enhance less resilient industries. Specifically, their study examined industry resilience in terms of sectoral output changes occurring across EU countries over the 2008–09 downturn, revealing considerable cross-sectoral differences. As the authors suggest, extending this work by exploring other sector-specific features would contribute to supporting decision-makers targeting sectoral interventions. In view of this, we believe that such a research avenue could be pursued and complemented by looking at industry resilience through the lens of structural change.

2.1. Industry resilience from the perspective of sustainable structural change

Structural change refers to the open-ended process of adjustment of the economic system, characterized by shifts in the relative proportions of productive sectors and by a transformation of underlying social features [80–82]. It entails a process of continuous conflict and negotiation among actors within and across sectors, with the consequence that some sectors seek expansion and capture higher shares of employment and value-added while others aim at preserving themselves from potential downsizing [81,83,84]. This approach crucially sheds light on employment dynamics across sectors, including potential intra- and intersectoral employment shifts, and opens up a range of possible reconfigurations of the economic system.

While structural change entails phases of adjustment of economic structures [84–88], it also modifies the shape of the underlying society [89–92]. Specifically, such transformations change the living conditions of individuals and communities. They induce radical changes in individual and social behaviors and in people's needs and demand for goods, services and rights [28]. This might lead to the exacerbation of inequalities and social conflicts and to decreasing social cohesion [21,31,93], thus exposing the process of structural change to dynamics that in many respects may not be sustainable. However, even when the sustainability of structural change appears to be granted, severe and unexpected shocks can drastically challenge the socioeconomic system and its desirable dynamic transformations [7,26,27].

Social sustainability, in particular, has been interpreted, on the one hand, as a condition in which societies are able to maintain and reproduce their social conditions [94,95]. In this sense, socially sustainable structural change processes are those that happen without endangering the vitality of social systems [20]. On the other hand, some studies assert that social sustainability also emphasizes an improvement in the conditions of people and communities, thus entailing, for example, social justice and equity, poverty alleviation or the expansion of opportunities and capabilities [28–30,96–98].

In this framework, for the purpose of this paper, written to investigate the relationship between shocks and structural change sustainability, it seems to us particularly relevant to focus on employment dynamics. In doing so, we begin to explore the social dimension of this sustainability. We decided to study the aftershock variation in jobs from both quantitative and qualitative perspectives. This is consistent with the growing attention in international debates to the relevance of decent employment opportunities [99], particularly the creation of good jobs. Such jobs are interpreted as those entailing stable contracts, adequate wages and social protections and allowing individuals to cultivate life, dignity, and, in general, a sense of fulfilment [31,100,101]. While the contribution of good jobs to the improvement in people's life conditions is apparent, from a societal standpoint, such jobs also entail improvements in social cohesion and the mitigation of social conflicts [93,101]. The exacerbation of labor market dualism brought about by the current transformations of productive structures (e.g., through the use of nonstandard forms of employment that deteriorate wages and working conditions in general [102–104]; might indeed fragment countries' social fabric and trigger social conflicts, undermining economic prosperity in the long run and affecting the sustainability of the process of structural change [105]. In this view, understanding how each sector withstands a downturn and the subsequent recovery in terms of both employment quantity and quality becomes a crucial feature for industrial policies seeking to govern structural change dynamics by orienting them toward a sustainable path.

3. Data and methodology

Previous studies on resilience in the field of economic geography and regional economics have measured resilience mainly in terms of post-shock changes in the regional/county employment rate [4,6,74,75,106–108] or the ratio of the employment drop to the rebound [109]. To a lesser extent, such changes in employment after a crisis have been coupled with changes in other key economic variables, such as GDP [6,63], productivity [63], and volumes of trade flows [110].

Few attempts have been made to observe the behavior of the economic variables across the whole drop-and-recovery period. In this regard, to the best of our knowledge, only Han and Goetz ([109] and especially [111]) have proposed the design of an index that can offer empirical insights into how a shock is experienced over time in different regions, taking into consideration how quickly and to what extent employment drops and recovers, counterfactual trends, and the duration of both phenomena.

We start from these previous methodological steps to develop our methodology, which is based on observation of the behavior of our variables of interest across the whole crisis-and-recovery period. In our view, this allows us to have a better grasp of the amplitude, duration and velocity of employment changes, particularly for policy purposes.

Methodologically, we follow four steps. First, we select the variables that allow us to measure employment levels and employment quality by sector (section 3.1). We use data on U.S. employment retrieved from various sources and build an original database. In particular, for employment quality, we consider different variables and build an index to take into account job stability and salaries (Good Jobs Index, section 3.1.2). Second, we depart from the existing methods – mainly used in regional studies – that analyze resilience as pre-vs. postcrisis employment variation to model the phenomenon looking at the behaviors of the curves of the variables under scrutiny (section 3.2). We sum up such variations into a composite indicator, and we apply this methodology to the employment level and the Good Jobs Index and obtain two composite indicators (section 3.3).

3.1. Data selection and description

3.1.1. Employment quantity

The first data source that we used is U.S. Department of Labor Bureau of Labor Statistics (BLS) data, which include monthly data on employment for 15 two-digit NAICS sectors.[2] We selected the number of employees per sector as a proxy for employment quantity, and to correctly identify the time span to measure the crisis and the recovery, we first observed the trend of the business cycle related to the 2008 crisis. A business cycle is usually identified by two local points [109,112]:

- a peak, which indicates the local maximum of the economic cycle, with the economic downturn starting the month after the economy – or sector – records its peak; and
- a trough, which indicates the local minimum of the economic cycle, after which the economic recovery begins.

[2] In our paper, by "industry," we mean the sphere of economic activities that have the same "common market" and areas of productions [135,167]. We therefore look at all economic activities rather than only at manufacturing.

Table 1
Peaks and troughs by sector.

Sector	Peak Month	Trough Month	Peak to Trough (Months)
Mining	September 2008	October 2009	13
Construction	March 2007	January 2011	46
Manufacturing	December 2007	February 2010	26
Wholesale trade	December 2007	May 2010	29
Transportation and warehousing	April 2008	December 2009	20
Finance and insurance	July 2008	August 2010	37
Real estate and rental and leasing	June 2008	January 2011	31
Information	March 2008	August 2011	41
Accommodation and food services	July 2008	February 2010	19
Retail trade	March 2008	December 2009	21
Arts, entertainment and recreation	February 2008	March 2010	25
Professional and business services	November 2008	May 2010	18
Utilities	No peaks observed		
Educational services	No peaks observed		
Health care and social assistance	No peaks observed		

Sources: Authors' elaboration based on BLS data

According to the National Bureau of Economic Research calculation of the U.S. Business Cycle Expansions and Contractions,[3] the U.S. economy entered a recession in January 2008, following the peak in December 2007, and the cycle reached its trough after 18 months. To observe the sectoral business cycles, in a similar fashion to other studies (see, e.g., Ref. [109]; for the case of U.S. counties), we allowed a ± 12 month deviation from the overall economic trend to identify each sector's peak. Therefore, we first observed each sector's employment trend starting from January 2007 to January 2009.

Table 1 reports the peaks and troughs for the 15 initial sectors. The data show substantial heterogeneity with respect to the peak month and the fall duration. According to the BLS data, the first sector to enter the crisis was construction (March 2007), followed by manufacturing and wholesale trade, whose peak corresponded with that of the general economic cycle. The last sector to fall into crisis was professional and business services in November 2008. The distance between the peak and trough months of each sector also vary greatly, ranging from a minimum of 13 months for mining to a maximum of 46 months for construction. In addition, we found three sectors – utilities, educational services and health care and social assistance – for which we could not identify clear peak and trough months. Therefore, we excluded them from the analysis, leaving us with 12 sectors.

In addition to analyzing all sectors, we focused on manufacturing subsectors and selected the 17 NAICS subsectors for which BLS data are available and for which we could explicitly identify a peak between January 2007 and December 2008.[4] A table reporting peaks, troughs and peak-to-trough duration for the manufacturing subsectors is available in the appendix (Table A1); in this case as well, we find substantial cross-subsector variation.

Such cross-sector heterogeneity leads us, consistent with previous studies (see, e.g. Ref. [109], to consider different starting and end periods of the economic downturn for each industry as follows: for each industry *j*, the starting period ($t_{0,j}$) is the month after the employment peak ($X_{peak,j}$).

3.1.2. Employment quality: building a Good Jobs Index

Together with the observation of how postshock industry resilience performs on the quantity side, we aim to describe to what extent industries are also able to recover from the employment quality side, that is, through the creation or recovery of good jobs, after a shock. To address this dimension, building on the literature that we have explored previously (see section 2.1), we took into account the salary aspect and the contractual aspect and summarized them in an index that we call the *Good Jobs Index*, whose increase (decrease) should indicate an increase (decrease) in the quality of the jobs created by each sector.

For earnings, we collected BLS data for the monthly average hourly earnings of all employees for each sector *j* (AVG_W_j). Regarding the contractual component, we wished to measure the intensity to which standard forms of employment (full-time permanent employment) were used in the sector [113]. identifies four types of nonstandard employment: temporary employment, part-time work, temporary agency work and other forms of employment involving multiple parties, disguised employment and dependent self-employment. To the best of our knowledge, however, there are no available data on the distinct use of standard versus nonstandard forms of employment by sector for the time span that we consider. Therefore, we decided to proxy this aspect as the percent deviation between the actual number of workers employed in an industry and the full-time equivalent (for a similar approach, see Ref. [114].

We retrieved data from the U.S. Bureau of Economic Analysis (BEA) and used full-time and part-time employees by industry (*FTE&PTE*) to measure the actual employees in each sector and full-time equivalent employees by industry (*FTEE*).[5] The closer the actual number of workers to the full-time equivalent, the greater is the use of standard forms of employment; conversely, the larger the distance between the actual number of workers and the full-time equivalent, the higher is the number of workers hired with part-time or temporary (of less than 1 year) contracts. The contractual part of the index, for each sector *j*, is therefore represented by the reciprocal of the percent deviation of the *FTE&PTE* from *FTEE* ($FTEE_j/(FTE\&PTE_i\text{-}FTEE_j)*100$), a measure that grows when the distance between actual and full-time equivalent workers tends to zero.[6]

The final *Good Jobs Index GJI* is the product of the salary component (monthly average hourly earnings of all employees for each sector *j*) and the contractual component, normalized via *minmax* normalization to allow variation between 0 and 1.

$$GJI = NORM\left(AVG\_W_J * \frac{FTEE_j}{(FTE\&PTE_j - FTEE_j)*100}\right). \quad (1)$$

[3] https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions. Last retrieved on 8 October 2021.

[4] Specifically, we study the following manufacturing subsectors: wood products, nonmetallic mineral products, primary metals, fabricated metal products, machinery, computer and electronic products, electrical equipment and appliances and components, transportation equipment, furniture and related products, other miscellaneous durable manufacturing, textile mills and textile products mills, paper and paper products, printing and related support activities, petroleum and coal products, chemicals, plastic and rubber products, food and beverage and tobacco products. We exclude apparel and leather and allied products since we found no peaks during the period under analysis.

[5] These data are available only on an annual rather than monthly basis. In the final quality index, therefore, the monthly variation across each year is ensured by the wage component, while the contractual component is constant for each year.

[6] For the cases in which *FTE&PTE* and *FTEE* are equal, the measure is not defined. This happens in only one subsector of manufacturing (petroleum and coal) and for two years (2011 and 2014). In these two cases, we substituted the missing value with the average value of the two years before and after.

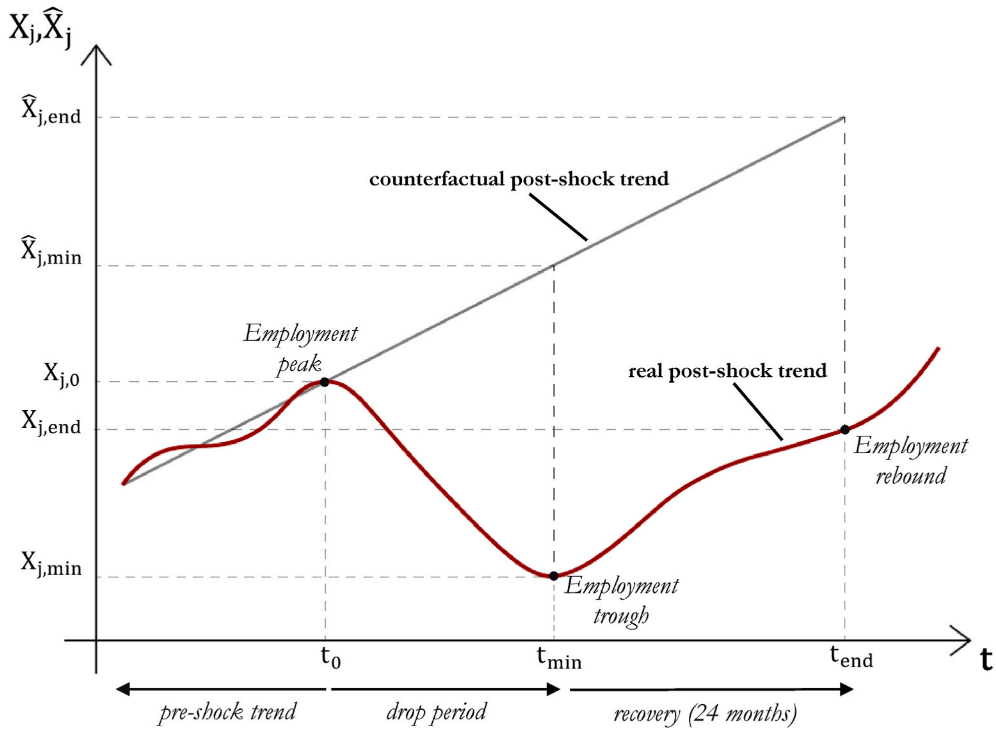

Fig. 1. Modeling industry resilience.
Source: Authors' elaboration

3.2. Modeling industry resilience

Many contributions, given the complexity of measuring all the dimensions of resilience, resolve the measurement issue by taking the simple difference between pre- and postshock employment levels (see, e.g., Refs. [6,74,115]. However, others have underlined that resilience should also take into account different elements: in addition to differences in levels, the velocity of the drop to the minimum and of the rebound and the counterfactual behavior that the region would have shown in absence of the shock should be examined [109,116,117]. We follow this second approach, which allows us to account for and analyze various dimensions of the change. We draw from the work by Ref. [111] to develop a model taking into account drops, rebounds, velocity, and counterfactual measures related to the variables that we use to look at industry resilience.

We synthetize the industry resilience modeling in Fig. 1. The figure represents the trend of employment in industry j before and after a shock. At t_0, sector j experiences the employment *peak*, whereupon the recession starts. At t_{min}, sector j experiences the employment *trough*, after which the sector recovers.

The employment peak and trough represent the local minimum and maximum and allow us to define the behavior of the curve and to identify the two major dimensions of industry resilience, i.e., the employment *drop* and the employment *rebound*. The employment *drop* is the vertical distance between the employment *peak* and the employment *trough*. After the employment *trough*, we can observe the employment *rebound*, and the change in employment for each sector after a certain period t_{end} from the *trough*. We set the ending period ($t_{end,j}$) to 24 months after the employment trough ($X_{min,j}$) to allow an observable trajectory for each sector to be clearly defined.[7] In developing their measure of resilience [111], also take into account the velocity of the recession and of the rebound as the time spent by the variable to reach the *trough* level and the time spent to reach the *rebound* level. We build upon this approach to compose our first three indicators to be included in the final industry resilience composite index:

1. **Industry Rebound** $IR_j = X_{j,end} - X_{j,min}$, which represents the change in the employment level from the trough over the 2 years after the employment trough. It measures the extent of the recovery of an industry over a given period in absolute terms.
2. **Industry Drop Velocity** $IDV_j = \frac{X_{j,min} - X_{j,0}}{t_{j,min} - t_{j,0}}$, which is the slope of the employment drop from t_0 to t_{min} and measures the velocity of the employment decline.
3. **Industry Recovery Velocity** $IRV_j = \frac{X_{j,end} - X_{j,min}}{t_{j,end} - t_{j,min}}$, which is the slope of the employment recovery from t_{min} to t_{end} and measures the velocity of the employment rise.

Finally, Han and Goetz ([109,111]); measure the drop at the trough as the distance between the expected value of employment $\widehat{X}$, using a compound growth rate over the 36 months before the peak and the value

[7] The choices on the time span for measuring the recovery differ greatly across the contributions looking at resilience. For instance Refs. [109,111], set t_{end} to 6 months after the trough. Other studies, such as [63]; look at long-term resilience, analyzing the capability of a sector to recover over a 7-year period. We chose an intermediate range to allow the sector to clearly reveal an observable trajectory and smooth short-term volatility effects. At the same time, we wish to avoid excessively long time spans, which might be influenced by other factors independent of the shock and that are more relevant when we are looking at the resilience of industries rather than of territories (such as long-term technological change).

at the trough. In our context, the inclusion of the counterfactual dimension is relevant in a cross-sector comparative perspective, given that a similar variation in employment in different sectors might imply very different dynamics according to their precrisis trends. Consequently, based on available data, we compute the expected value of employment if the shock had not happened, both for the trough and for the rebound. Based on a steady-state growth path, we use a compound growth rate over the 36 months before the peak for employment quantity and 12 months before the peak for employment quality.[8] In this way, we are able to develop indicators 4 and 5:

4. **Rebound-Counterfactual Difference Ratio** $RCD_j = \frac{X_{j,end} - X_{j,0}}{\widetilde{X}_{j,end} - X_{j,0}}$, which is the ratio between the actual rebound–peak difference and the one that we would have observed in the absence of the shock (counterfactual).
5. **Trough–Counterfactual Difference Ratio** $TCD_j = \frac{X_{j,min} - X_{j,0}}{\widetilde{X}_{j,min} - X_{j,0}}$, which is the ratio between the actual trough–peak difference and the one that we would have observed in the absence of the shock (counterfactual).
6. Finally, we include **Industrial Average Employment** $\overline{X}_j = \frac{\sum_{t=0}^{T} X_{j,t}}{n}$, calculated as the average of the variable over the peak–rebound period.

To allow for comparability among the sectors, which can vary greatly in terms of size, the minimum and the rebound values are calculated as the percentage deviation from the peak value (=100) for each sector. The six measures described above are computed accordingly.

3.3. Composite indicators of industry resilience and an evaluation matrix

To assess industry resilience in a synthetic measure encompassing its multifaceted dimensions, we use composite indicators (CIs).

CIs are frequently used to capture and assess phenomena that are difficult to observe and measure. They have been frequently used to compare cross-sectional performances and statuses in a variety of realms that, in the socioeconomic sphere, include competitiveness, degree of openness, and socioeconomic and political characteristics (see, e.g., Refs. [32,63,118,119]. Composite indicators are used to build performance-based rankings among observations and are widely diffused among policy-makers, international organizations and other bodies to inform decision-makers, governments, citizens and investors about trends and changes in country rankings over time (a few examples of these are [120]; and previous years [121]; and [122].

In the same spirit, we built two CIs ranking the J sectors on the basis of $K = 6$ indicators capturing the behavior of the curve. We proceeded as follows: for each sector, we calculated the K indicators described previously (section 3.2) for both employment quantity (i.e., the number of people employed in the sector) and employment quality (i.e., the *Good Jobs Index*).[9] These K indicators were then integrated into two CIs, one for quantity (*CI_QUANT*) and one for quality (*CI_QUAL*).

Composite indicator building involves three major steps: a) normalization to make the variables comparable, b) indicator weighting, and c) aggregation [123].

[8] The shorter time span of the period to calculate the compound growth rate of employment quality is due to salary data availability.

[9] For the peak, the trough and the rebound months for each sector, we always use those related to employment quantity as the reference. This is justified by the fact that crisis and recovery periods are generally defined by looking at quantity measures, while there is no guarantee that quality measures follow a cyclical trend, which is necessary for identifying peaks and troughs. Therefore, the CI for the Good Job Index measures the resilience properties of the quality dimension over the time span of the quantity dimension.

Table 2
Summary of variables for measuring quantity and quality.

Variable	Component	Measured as	Source
QUANTITY DIMENSION			
Employment	*(only one variable)*	Number of workers, thousands	BLS
QUALITY DIMENSION			
Good Jobs Index	Salary (AVG_W$_j$)	Average hourly earnings of all employees (in U.S. $)	BLS
	Contracts *(FTEE$_j$/(FTE&PTE$_i$-FTEE$_j$))*	Percent deviation of the sum of full-time and part-time workers (number of workers) from the full-time equivalent (in FTE).	BEA

Source: Authors' elaboration

For the first step of normalization, considering the nature of our data, we resorted to rank transformation, which is a robust method that neatly addresses outliers and skewed variables [124]:

$$I_{kj} = Rank\left(x_{kj}\right) \tag{2}$$

where I_{kj} represents the normalized value of individual indicator k for sector j.

Ranks are defined so that the lowest indicator value has a rank of 1, the second lowest a rank of 2, and so on [124].

For the weights, we attached the same weight to all variables. This choice was made following general practice in composite indicator building, where uniform distributions are often assigned to the input factors [125,123,126].

As an aggregation method, we used an equally weighted geometric mean, which uses the product of the indicators as follows. For each sector j:

$$gM_j = \left(\prod_{i=1}^{k} I_j^{w_k}\right)^{1/\sum_{i=1}^{k} w_k} \tag{3}$$

where I_j is the rank-normalized indicator and w_k is the corresponding weight. Compared to other standard aggregation procedures, the geometric mean is more robust to outliers and allows for nonsubstitutability of the single indicators [123,124]. We found that the latter property is particularly desirable for our case. In fact, our methodology is innovative in that it uses indicators aimed at capturing different dimensions of the behavior of the sectors. Indeed, we aimed to combine aspects such as velocities, trends and sizes that, according to our theoretical framework, all contribute to providing pieces of information on industry resilience that are not mutually substitutable.

In the robustness checks, we test the equal weighting scheme adopted in our CIs against weights randomly perturbated by a specified noise factor to control for alternative weighting schemes [124].

The final CIs were obtained from ordering in descending order the geometric mean values and assigning higher rankings to higher values, which correspond to an overall better performance. The results consist of two rank-based CIs, one for quantity (*CI_QUANT*) and the other for quality (*CI_QUAL*).

When these CIs are analyzed individually, they provide information about the relative performance of each sector during and after the crisis in terms either of employment level or of job quality. They can also be analyzed jointly to assess whether sectors react to a crisis consistently in both dimensions.

4. Results

This section consists of an illustrative application of the CIs in the case of the U.S. post-2008 crisis. It has the main objective of highlighting the nature of the information and results that the methodology that we developed can give to policy- and decision-makers. Nevertheless, this

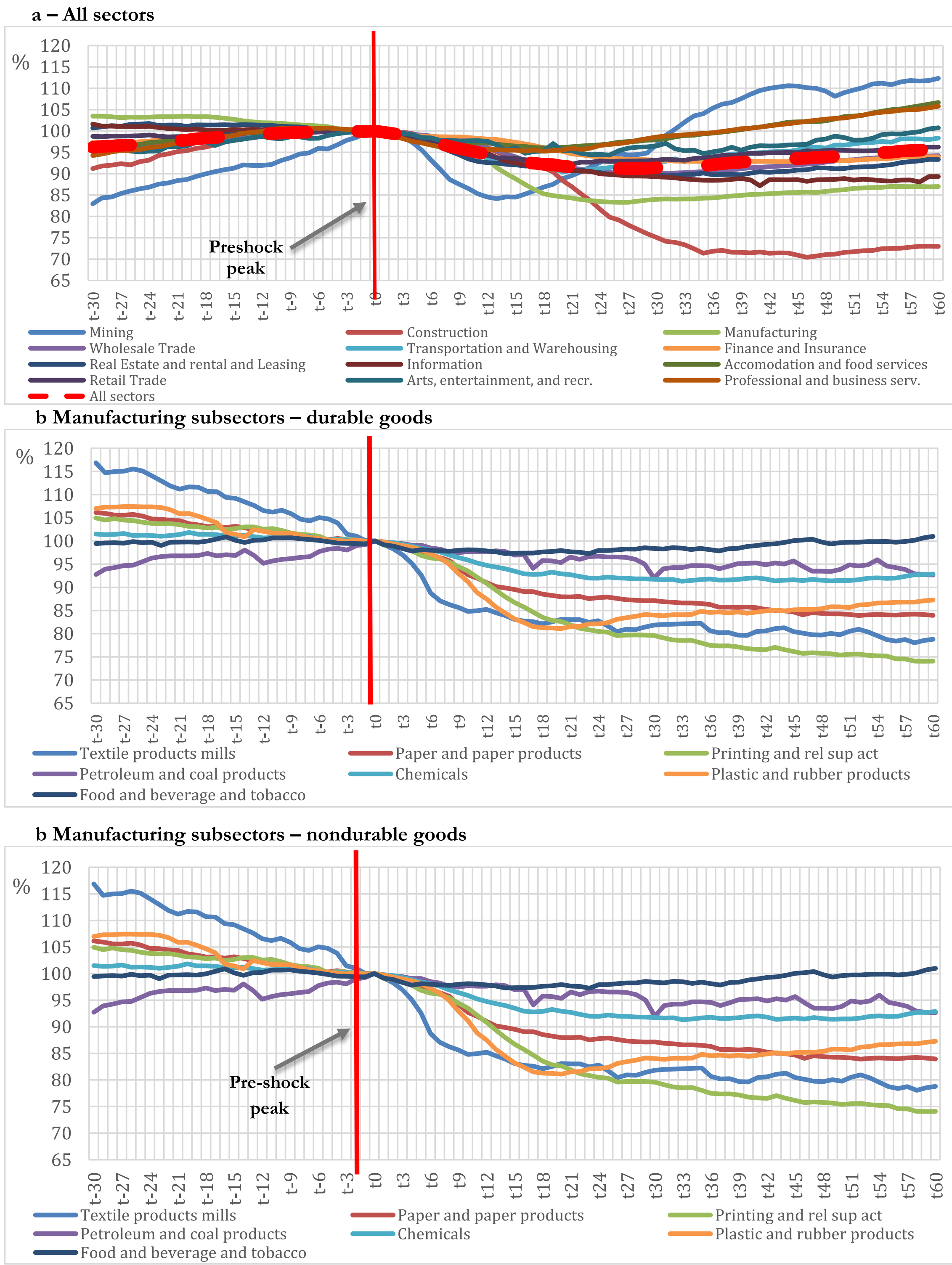

Fig. 2. Employment trends for U.S. sectors during the 2008 recession (preshock peak value = 100).
Source: Authors' elaborations on BLS dataNote: All variations are measured as the percentage change with respect to the preshock peak value of each sector

Table 3
Quantitative resilience: Building *CI_QUANT* – all sectors.

Sector	A												B	
	IR		*IDV*		*IRV*		*RCD*		*TCD*		$\overline{X}$		*gM*	*CI_QUANT*
	Value	*I*	Value	*I*	Value	*I*	Value	*I*	Value	*I*	Value	*I*		
Mining	22.15	12	−1.44	1	0.944	12	0.223	9	−1.74	7	93.4	6	**6.16**	**4**
Construction	4.14	7	−0.8	2	0.137	7	−1.19	3	−2.18	6	80.49	1	**3.48**	**11**
Manufacturing	2.961	5	−0.8	2	0.119	6	2.182	11	5.023	11	88.37	2	**5.28**	**7**
Wholesale trade	3.655	6	−0.42	5	0.159	8	−0.75	6	−2.21	5	93.34	5	**5.75**	**5**
Transportation and warehousing	4.836	9	−0.51	4	0.211	9	−0.8	5	−3.6	2	94.18	7	**5.32**	**6**
Finance and insurance	1.31	1	−0.22	11	0.056	2	−1.15	4	−2.33	4	94.93	9	**3.83**	**10**
Real estate and rental and leasing	2.594	3	−0.34	7	0.106	4	−7.41	1	−17.5	1	92.08	4	**2.64**	**12**
Information	1.854	2	−0.31	8	0.054	1	4.774	12	9.067	12	91.1	3	**4.36**	**8**
Accommodation and food services	5.584	10	−0.21	12	0.231	10	0.234	10	−1.13	8	98.14	12	**10.24**	**1**
Retail trade	2.653	4	−0.39	6	0.114	5	−1.26	2	−3.07	3	94.63	8	**4.23**	**9**
Arts, entertainment, and recreation	4.445	8	−0.23	10	0.094	3	−0.11	7	−1.09	10	96.67	10	**7.43**	**3**
Professional and business services	5.925	11	−0.24	9	0.258	11	0.114	8	−1.11	9	97.59	11	**9.76**	**2**

Notes: IR= Industry Rebound; IDV= Industry Drop Velocity; IRV= Industry Recovery Velocity; RCD = Rebound-Counterfactual Difference Ratio; TCD = Trough-Counterfactual Difference Ratio; $\overline{X}$ = Industrial Average Employment gM = geometric mean.
Source: Authors' elaboration based on BLS data

Table 4
Qualitative resilience: Building CI_QUAL – all sectors.

Sector	A												B	
	IR		*IDV*		*IRV*		*RCD*		*TCD*		$\overline{X}$		*gM*	*CI_QUAL*
	Value	*I*	Value	*I*	Value	*I*	Value	*I*	Value	*I*	Value	*I*		
Mining	−15.74	1	−1.81	2	−1.73	1	−0.10	6	−0.29	4	88.15	4	2.40	12
Construction	14.14	9	−0.90	5	0.27	8	−0.03	7	−0.23	5	85.38	3	5.79	7
Manufacturing	3.07	6	−1.06	4	0.39	9	1.20	12	5.23	12	84.14	2	6.29	6
Wholesale trade	3.87	8	0.14	11	0.06	6	−0.17	4	−0.07	7	100.90	11	7.39	3
Transportation and warehousing	3.81	7	−1.07	3	0.03	3	−0.28	3	−1.06	3	91.07	6	3.88	10
Finance and insurance	15.64	10	0.13	10	0.75	10	0.49	11	0.42	10	108.01	12	10.47	1
Real estate and rental and leasing	18.53	11	−0.32	8	0.75	11	0.11	9	−0.10	6	91.09	7	8.46	2
Information	−1.34	4	0.09	9	0.04	4	−0.66	2	−2.29	2	100.56	10	4.23	8
Accommodation and food services	98.98	12	−5.49	1	3.74	12	−0.12	5	−37.09	1	30.14	1	2.99	11
Retail trade	−2.46	3	−0.80	6	0.20	7	0.48	10	1.43	11	90.32	5	6.41	5
Arts. entertainment. and recreation	−1.08	5	−0.33	7	0.05	5	0.06	8	0.22	9	97.23	8	6.82	4
Professional and business services	−8.44	2	0.15	12	−0.37	2	−12.07	1	0.11	8	98.00	9	3.89	9

Notes: IR= Industry Rebound; IDV= Industry Drop Velocity; IRV= Industry Recovery Velocity; RCD = Rebound-Counterfactual Difference Ratio; TCD = Trough-Counterfactual Difference Ratio; $\overline{X}$ = Industrial Average Employment; gM = geometric mean.
Source: Authors' elaboration based on BLS data.

first elaboration also gives some insightful suggestions on how the relation between quantitative and qualitative resilience can work in some cases, which can also be relevant in terms of policy implications.

First, to summarize the information given in the data section, in Table 2, we summarize the variables and the sources used to build the two dimensions (quantity and quality) on which we measure resilience. In the appendix (Table A2), we report some summary statistics.

Before proceeding with the index calculations and graphical representation, after having made the theoretical case in Fig. 1, we report in Fig. 2 the actual trends of employment quantity by sector across the crisis period.[10] For the calculation of the CIs, for all sectors, t_0 is the month in which the employment trend experiences the last peak before the recession. Given the differences among previous trends, the peak can be more or less visible: for example, the mining sector (Fig. 2a) and primary metal subsectors (Fig. 2b) show a clear growing preshock trend and a noticeable decrease after the peak; other sectors or subsectors, such as nonmetallic mineral products (Fig. 2b) or chemicals (2.c), display a smoother curve. After the shock, the local minimum happens for different sectors at different points in time, sometimes very distant from one another (compare, for instance, the cases of mining, manufacturing, and construction in Fig. 2.a or the cases of primary metals, wood products and furniture in Fig. 2b). More generally, from this descriptive evidence, it appears that sectors reacted very differently to the shocks, with some of them recovering and improving with respect to precrisis periods and others experiencing long-run stagnation with virtually no recovery. This also gave rise in some cases to among-sector divergent trends that appear to be persistent over time.

Table 3 reports the first transformation for quantitative resilience, measured as the variation in employment quantity. In the first section (A), the table reports, for each sector, the value and the ranking *I* of the six individual indicators capturing the behavior of the curve, where the higher the value is, the higher the position in the relative ranking. A first result is that each sector displays different behaviors in relation to each of the six measures capturing industry resilience, thereby validating the choice of measuring different aspects of the curve and including all of them in the final index. In the second section of table (B), we report for each sector the geographic mean *gM* of the six individual indicators and the associated final ranking (*CI_QUANT*).

The construction of the composite indicator related to quality

[10] For the sake of readability, due to the high number of subsectors in manufacturing, we report durable and nondurable sectors separately in Fig. 2b and 2 c, respectively.

Table 5
CI_QUANT and *CI_QUAL* – all sectors.

Sector	*CI_QUANT*	*CI_QUAL*
Mining	**4**	**12**
Construction	**11**	**7**
Manufacturing	**7**	**6**
Wholesale trade	**5**	**3**
Transportation and warehousing	**6**	**10**
Finance and insurance	**10**	**1**
Real estate and rental and leasing	**12**	**2**
Information	**8**	**8**
Accommodation and food services	**1**	**11**
Retail trade	**9**	**5**
Arts, entertainment, and recreation	**3**	**4**
Professional and business services	**2**	**9**

Source: Authors' elaboration based on BLS and BEA data

resilience *CI_QUAL* is the same as that used for *CI_QUANT*, and the results are reported in Table 4. Each sector is assigned a partial rank for each variable. Such ranks are summarized in the geometric mean *gM* and ranked accordingly.

Table 5 summarizes the results for both *CI_QUANT* and *CI_QUAL*, while Fig. 3a reports the matrix representing quantitative and qualitative resilience jointly. The main result emerging from the analysis, which is useful in terms of policy implications, is that sectors can behave heterogeneously in terms of both employment quantity and quality. In other words, different sectors show different industry resilience capacities. For the specific case of the U.S. 2008 crisis under analysis, this heterogeneity takes the form of a trade-off between the quantitative and the qualitative aspects of employment: the majority of the sectors are located either in the second quadrant (four sectors) or in the fourth quadrant (five sectors) of the matrix. The negative relation between *CI_QUANT* and *CI_QUAL* is also confirmed by Spearman's ρ, which is negative and significant at 10% (ρ_s = *-0.57**). Since manufacturing includes a large variety of subsectors and given the increasing role that manufacturing and related policy initiatives have acquired, particularly in the aftermath of the 2008 crisis [16,127–130], we offer a specific focus on it to explore how its subsectors perform in terms of industry resilience.

Table 6 and Fig. 3b apply our methodology to the 17 manufacturing subsectors. In this case, the heterogeneity among subsectors is even more pronounced than before, as the point cloud is scattered among the four quadrants with no clear observable trend. Indeed, contrary to the previous case, the quality and quantity indicators for manufacturing subsectors do not seem to show a specific relation, as also indicated by the low and nonsignificant Spearman's ρ (ρ s = - 0.05).

Interpreting the motivations behind the heterogeneous reactions to

Table 6
CI_QUANT and CI_QUAL – manufacturing subsectors.

Sector	CI_QUANT	CI_QUAL
Wood products	10	2
Nonmetallic mineral products	11	10
Primary metals	9	1
Fabricated metal products	15	4
Machinery	14	15
Computer and electronic products	5	12
Electrical equipment and appliances	1	3
Transportation equipment	6	13
Furniture and related products	13	14
Other miscellaneous durable manufacturing	2	6
Textile products mills	16	9
Paper and paper products	12	8
Printing and related support activities	17	5
Petroleum and coal products	8	17
Chemicals	4	7
Plastic and rubber products	3	16
Food and beverage and tobacco products	7	11

Source: Authors' elaboration based on BLS and BEA data

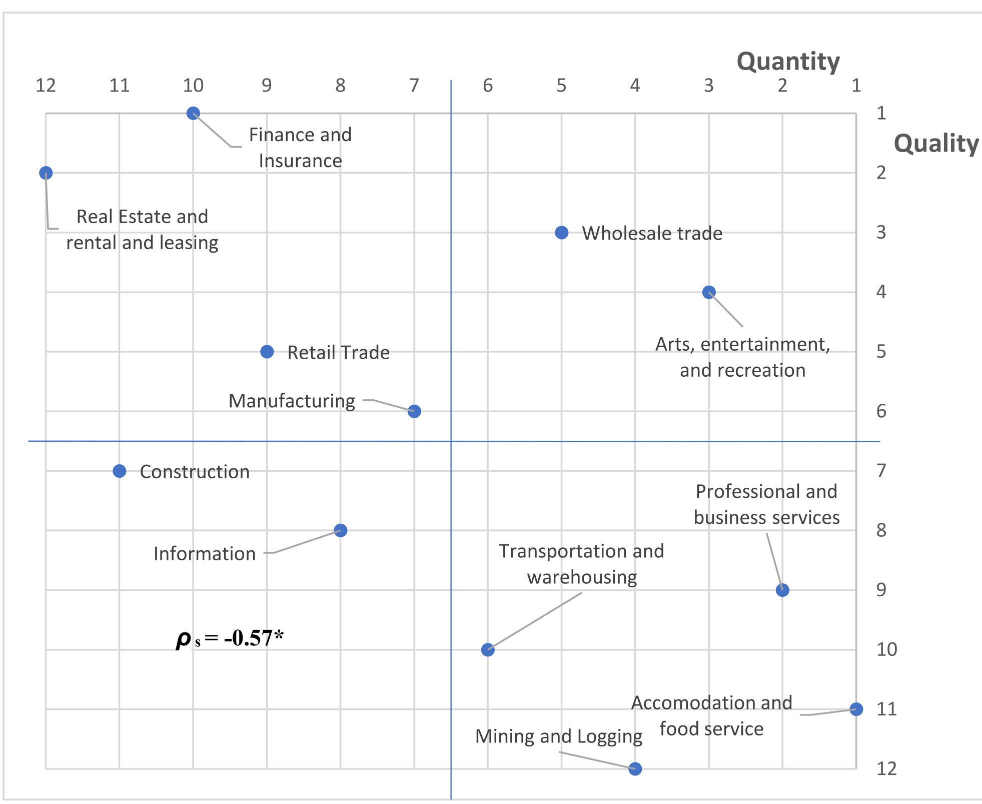

Fig. 3a. Matrix – all sectors.
Source: Authors' elaboration based on BLS and BEA data

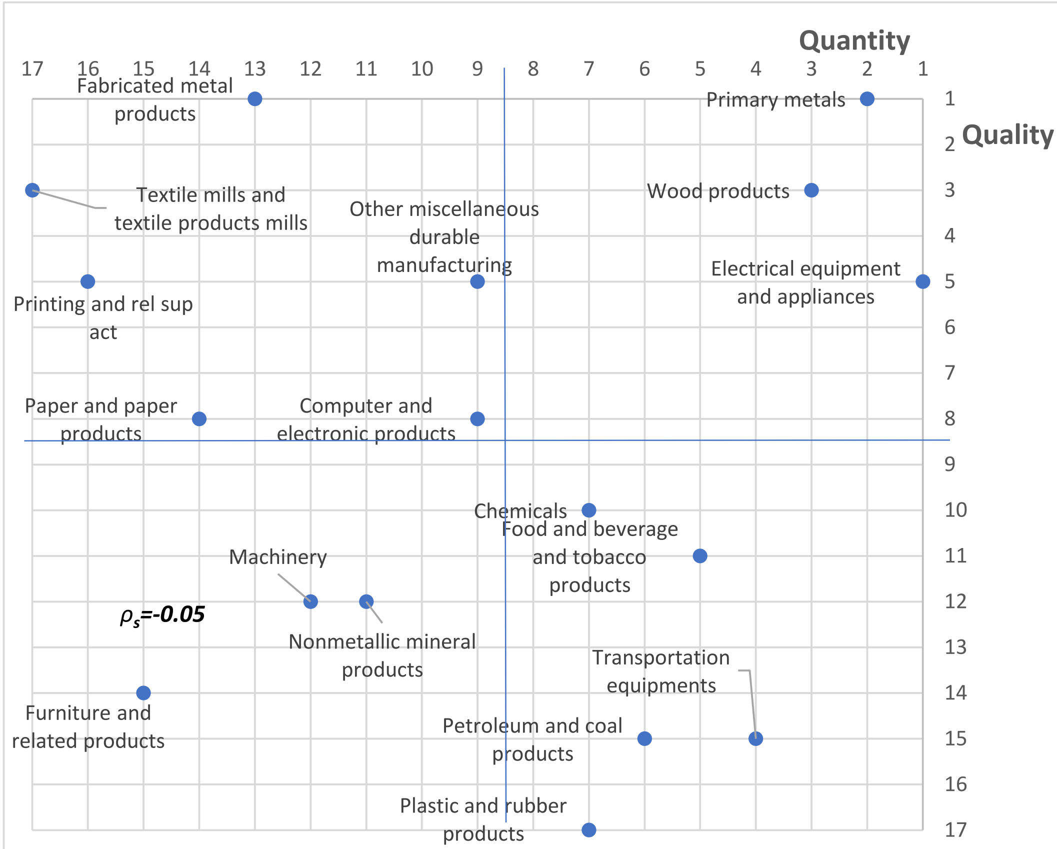

Fig. 3b. Matrix – manufacturing subsectors.
Source: Authors' elaboration based on BLS and BEA data

the shock of the different sectors is beyond the scope of this paper. What we want to stress here is that the results obtained using the CIs measuring industry resilience represent a preparatory dashboard that can inform decision-makers about the ability of industries to react to shocks. Such a dashboard, displaying industries' different degrees of resilience, provides policy-makers with informative insights enabling them to decide which sectors to focus on for policy purposes. Starting from this basis, decision-makers might decide to follow up and take further actions to identify which factors characterize high-resilience sectors in comparison to others and whether such features can be adopted in other industrial contexts to strengthen their resilience. For instance, stronger industry resilience might be related to, among others, sectoral technological endowments and productive capacity [31, 131–134], the type of backward and forward linkages connecting sectors [135,77,78], market volatility [31,136], the scale of market competition [133,137], and the structure and diffusion of industrial relations [138–140]. The assessment of industry resilience, as depicted by the dashboard developed and presented in this study, represents a preparatory phase for the investigation of such aspects.

4.1. Robustness checks

4.1.1. Uncertainty analysis

Composite indicators, like any model, have associated uncertainties. In particular, the results that they generate might be dependent on the choices related to their design. To address this issue, we resort to *uncertainty analysis*, which "focuses on how uncertainty in the input factors propagates through the structure of the composite indicator and affects the composite indicator value" [123]. Specifically, uncertainty analysis is a Monte Carlo simulation–based procedure applied to the formula defining the composite indicator, which each time randomly varies the uncertain parameters identified to estimate the output distributions.

In general, uncertainty analysis helps gauge the robustness of composite indicators and improves the transparency of how they are built [124–126,141]. In our framework, we use uncertainty analysis to test the robustness of the sector rankings based on the two composite indicators that we built (*CI_QUANT* and *CI_QUAL*).

In our case, we assume that key uncertainties could primarily arise from the weights used, which are commonly considered a major source of uncertainty [126,142].

Concerning the weights, our main results rely on equal weighting, following the construction choice of most composite indicators [143]. However, a few studies on composite indicator building contend that an inherent degree of uncertainty often surrounds weight values [63]; JRC-EC, 2008; [144].[11] To take this aspect into account, in our robustness check, we randomly perturb weights by a specified noise factor.

Following [124]; for each replication of the composite indicator, a random value is attributed to each weight ω_i', following the form:

$$\omega_i' = \omega_i + \varepsilon_i, \varepsilon_i \sim U[-\varphi\omega_i, \varphi\omega_i] \quad (4)$$

[11] The existing contributions offer some alternative weighting methods. For instance, statistical models such as principal components analysis (PCA) allow the endogenous determination of weights ([123, 168–170]; and many more); other methods to establish weights include participatory procedures involving various stakeholders – experts, citizens and politicians [171]. Unfortunately, neither technique fits our framework. Specifically, few correlations exist among the indicators that we use, which is a relevant precondition for the application of PCA; in addition, the limited sample size does not suggest the need to further compress information using PCA. On the other hand, the novelty of our methodology does not allow us to elicit the weights based on stakeholder information.

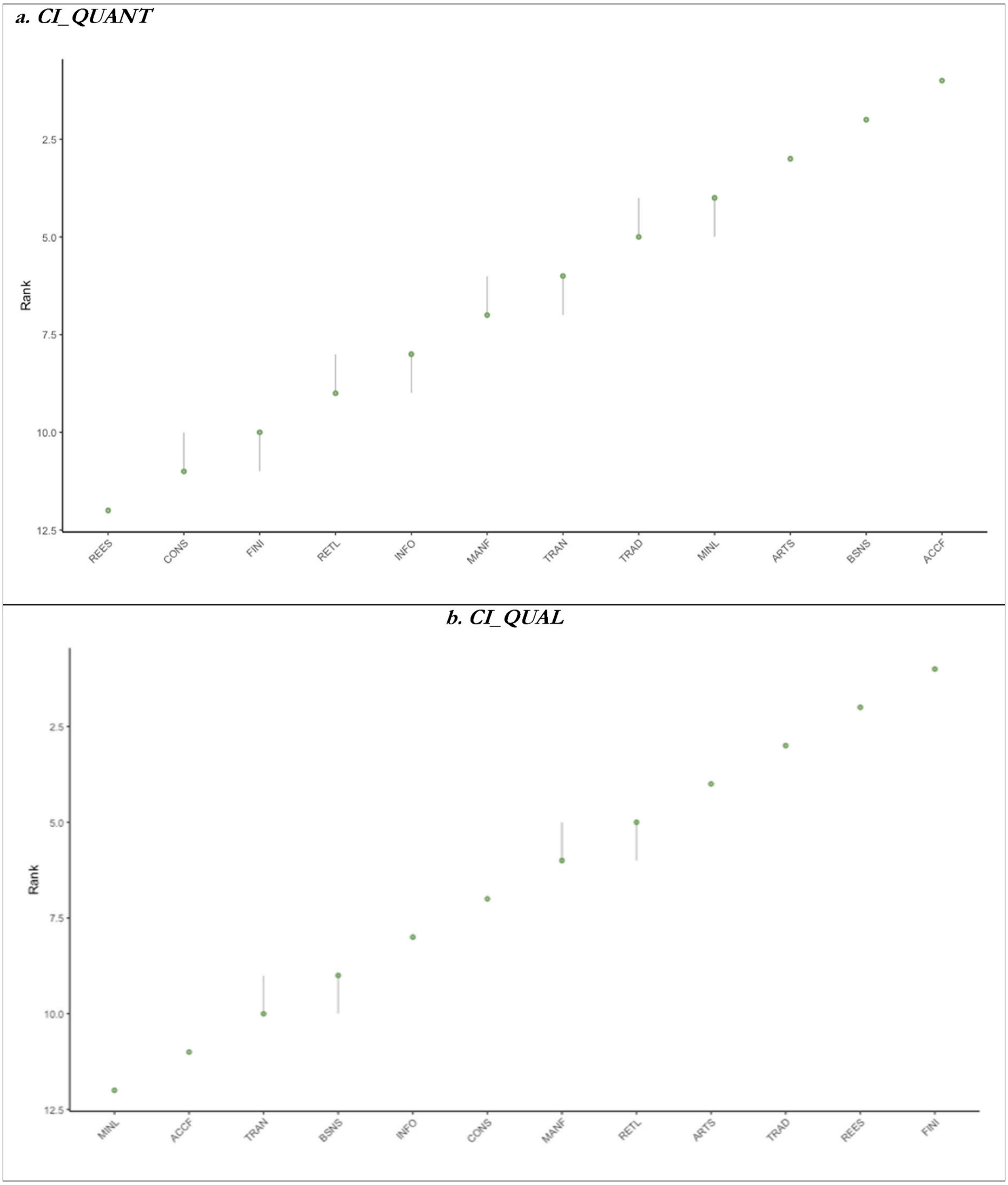

Fig. 4. Uncertainty analysis on all sectors.
Source: Authors' elaborationNote: The results show the median (green dot) and the corresponding 5th and 95th percentiles (bounds) of the distribution of sectors. Uncertain input factor: weights. Sector coding: ACCF – accommodation and food services; ARTS – arts, entertainment, and recreation; BSNS – professional and business services; CONS – construction; FINI – finance and insurance; INFO – information; MANF – manufacturing; MINL – mining; REES – real estate and rental and releasing; RETL – retail trade; TRAD – wholesale trade; TRAN – transportation and warehousing

where ω_i is the nominal weight, ε_i is the added noise, and φ is a "noise factor". In our case, we use $\varphi = 0.25$, meaning that we let ω_i' vary between $\pm$ 25% of its nominal value, following a uniform distribution.

To perform the uncertainty analysis, we use the R software package COINr [124]. We apply 10,000 Monte Carlo simulations on our composite indicators to combine alternative input values. COINr assumes equal probability for all alternatives, i.e., uniform distributions [124].

The results of the uncertainty analysis are reported in Figs. 4 and 5. Each graph shows the sector rankings with their related uncertainty bounds, which limit the rank uncertainty distribution between its 5th and 95th percentiles. A narrow uncertainty interval means that the ranking is more robust because it depends only to a limited extent on the selection of a particular set of weights. Conversely, a wider interval indicates a higher volatility of the sector's ranking, which markedly depends on the specific design of the composite indicator [126].

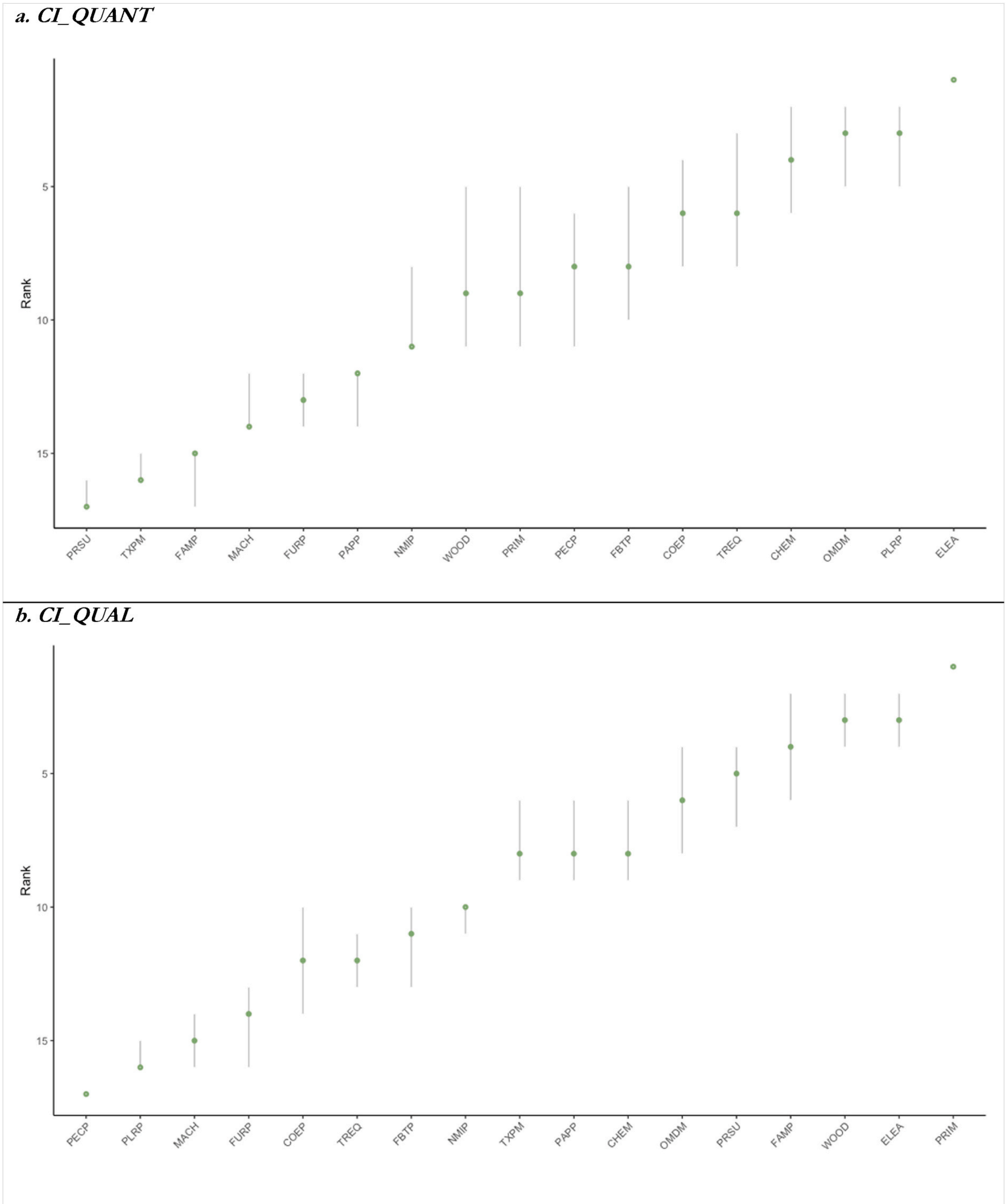

Fig. 5. Uncertainty analysis on manufacturing.
Source: Authors' elaborationNote: The results show the median (green dot) and the corresponding 5th and 95th percentiles (bounds) of the distribution of sectors. Uncertain input factor: weights. Sector coding: CHEM – chemicals; COEP – computer and electronic products; ELEA – electrical equipment and appliances; FAMP – fabricated metal products; FBTP – food and beverage and tobacco products; FURP – furniture and related products; MACH – machinery; NMIP – nonmetallic mineral products; OMDM – other miscellaneous durable manufacturing; PAPP – paper and paper products; PECP – petroleum and coal products; PLRP – plastic and rubber products; PRIM – primary metals; PRSU – printing and rel sup act; TREQ – transportation equipment; TXPM – textile products mills; WOOD – wood products

For the analysis of all sectors (Fig. 4), both *CI_QUANT* and *CI_QUAL* are robust to the weight perturbances. For both cases, the head and the tail of the rankings are highly stable. For the intermediate positions, the confidence intervals tend to be generally narrow, with a maximum possible variation of only one position.

The results related to manufacturing subsectors (Fig. 5), limited to the quantity dimension *CI_QUANT* (5.a), are sufficiently robust. The related confidence intervals are wider, although the possible ranking variation is above 4 positions only for 5 out of 17 subsectors. Regarding *CI_QUAL* (5.b), the main results are confirmed: only computers and

Table 7
Using average share to build CI_QUANT: Rankings compared.

Sector	*CI_QUANT (using* $\overline{X_j}$*)*	*CI_QUANT (using* $\overline{X(s)_j}$*)*
Accommodation and food services	1	1
Professional and business services	2	2
Arts, entertainment, and recreation	3	5
Mining	4	9
Wholesale trade	5	4
Transportation and warehousing	6	6
Manufacturing	7	3
Information	8	8
Retail trade	9	10
Finance and insurance	10	11
Construction	11	7
Real estate and rental and leasing	12	12

Source: Authors' elaboration

electronic products, fabricated metal products and other miscellaneous durable manufacturing display wider confidence intervals. Overall, the inclusion of a simulations-based uncertainty analysis represents a further useful element for policy-makers to gain insights into the heterogeneous behaviors of sectors facing unexpected shocks.

4.1.2. *Units of measurement*

A second robustness check is related to the unit of measurement that we use. In our main results, we computed the dimensions that make up our CIs (Section 3.2) by using *absolute values* of employment, in line with previous studies [109,111].

Indeed, by using employment levels, we have been able to identify relevant peaks, troughs and rebounds related to sectoral business cycles and leverage these elements to build the few dimensions on which our CIs are based (see also [145–147]; on the use of employment as a business cycle indicator). This methodology has allowed us to study the behavior of each sector over time and to rank sectors based on their performance over the shock period. A possible way to enrich the analysis is to integrate some information about the *relative weight* that each sector accounts for in the economy and how its relative weight changes during and after the crisis. To take a first step in this direction, we modify the *CI_QUANT* index by substituting the indicator corresponding to sector *j's* average employment level over the whole period ($\overline{X_j}$) with the sector's average *employment share* over the total employment over the period:

$$\overline{X(s)}_j = \frac{\sum_{i=0}^{n} \frac{X_{j,i}}{\sum_j X_{j,i}} *100}{n} \tag{5}$$

The resulting index and matrix are reported below for all sectors. Compared with the original ranking of *CI_QUANT*, the new index gives a few different results, as shown in Table 7. In particular, the performance seems particularly different for manufacturing and mining, given that the index formulated in this way is more sensitive to the relative size of the sector, independent of how well it performs following a shock. The other sectors, instead, do not move up (or down) more than two positions. This is reflected in the matrix where the information about *CI_QUANT* and *CI_QUAL* are analyzed jointly: apart from manufacturing, which moves to the first quadrant, and mining, which moves to the third quadrant, the other modifications in the ranking do not affect in which of the four quadrants each sector is placed (Fig. 6).

The results obtained through this robustness check can complement the main results in providing additional informative insights related to the relative size of sectors to policy-makers seeking to understand postshock sectoral performance.

5. Concluding remarks and policy implications

In this study, we have elaborated on the concept of *postshock industry resilience* in the context of socially sustainable structural change and offered a methodology to measure it. In this view, the application of the CIs to the U.S. case has to be considered as an illustrative exercise. We choose not to interpret the internal sectoral dynamics at this stage or the specific causal linkages with the 2008 shock. Rather, we intend this

Fig. 6. Using average share to build CI_QUANT: Matrix between CI_QUANT and CI_QUAL.
Source: Authors' elaboration

exercise as a demonstration of a *modus operandi* [20] that can be used for and by governments designing and implementing industrial policies.

From the perspective of structural change sustainability, postshock industry resilience can work as a valuable indicator to inform decision-makers on which sectors are able to couple employment retention with good-quality jobs and to warn of the possible interrelation between the two aspects of job quantity and job quality. The general evidence that we find is that the different industries react heterogeneously to shocks; i.e., they display different degrees of postshock industry resilience. This reinforces the idea that policy-makers should be aware of such differences, especially given that industrial policy de facto, whether explicitly or not, targets specific sectors. Sector resilience matters because it might reinforce the overall socioeconomic system's resilience during a severe shock. From the perspective that we discussed in this paper, this might mean preventing the collapse of the system and, in this way, contributing to the future sustainability of structural change.

However, it is also important to specify that recognizing different industry resilience capacities is a first necessary step demanding further understanding of the real determinants of these differences. As we anticipated, industry resilience can be the result of the virtuous reactions of firms, territories and industries that are genuinely better at reorganizing themselves after the shock. In these cases, industrial policy should be able to recognize such capacities and act accordingly. However, resilience capacities can also be the result of less virtuous actions: lobbying and capturing with the aim of opposing structural change and desirable future transformation. In these cases, again but from the opposite perspective, industrial policy should intervene properly. With this paper, we hope to stimulate further research on the relationship between industry resilience and structural change sustainability.

This line of reasoning seems particularly timely given the increasing importance and use of industrial policy interventions as a tool to react to the global long-term downturns since the 2008 global crisis [14,15,32,148–151], which indeed calls for solutions to strengthen the capability of governments to design and implement policy interventions effectively and efficiently. This is even more true for selective industrial policies, which can be exposed to a variety of potential issues regarding government failures [14,152–158]. In this view, therefore, industry resilience represents a conceptual and methodological instrument that, on the one hand, supports policy-makers in selecting and prioritizing policy targets and, on the other hand, increases transparency about such a selection process and its accountability to citizens and social stakeholders.

Industry resilience, of course, represents *one among many* possible criteria that could be chosen by policy-makers. In addition, this methodology does not prescribe *which sectors* are to be promoted by industrial policies. This is a choice that ultimately lies in the hands of policy-makers, who might choose among different strategies. For instance, policy-makers might want to "pick the winner" among sectors according to their resilience capability or support weaker sectors to achieve higher degrees of resilience or even target a mix of the two.

A few words of caution on this study are then needed. First, for the current application, our methodology has produced results that can provide specific indications of postshock industry resilience in the context of the 2008 financial crisis. In this sense, it can inform on how the same or similar sectors could react to shocks displaying analogous features. Further research could expand on this evidence by exploring the industry resilience of sectors facing shocks of a different nature and with different transmission mechanisms. This could lead to the creation of a taxonomy linking sectors and postshock industry resilience by types of shocks. Second, we also wish to clarify that the results that we obtain, in terms of heterogeneity, are also related to the time span that we have considered to assess resilience: further studies might encompass a longer time span to complement our evidence with additional information [159–161].

Our study also opens additional research avenues. First, our methodology can be tested in settings with other countries, groups of countries or lower-level geographical units.

A second possible research path arises from the fact that we find a potential trade-off between quality and quantity dimensions in the all-sector case while this evidence does not seem to hold in the case of manufacturing subsectors. This might suggest that working on more fine-grained industrial aggregation levels could yield different results with respect to the more general ones. Such a hypothesis could be tested in future studies.

Third, in this paper, we chose industries as units of observation for the reasons explained in the introduction. Nonetheless, we acknowledge that several production configurations other than sectors exist, e.g., clusters, districts, networks, groups, and value chains [33,35,37,162,163]; and many more), which might also be relevant from the policy-making point of view. In light of this, further investigations might explore the adaptability of our methodology to other policy-relevant typologies of production organization.

Moreover, while we have offered a contribution on how to measure postshock industry resilience, future studies are needed to identify the industry-level determinants of resilience, which could depend upon a number of factors, including the organization of production, the structure of the production network, and technological endowments [9,164,165].

Finally, we believe that the industry resilience perspective could strengthen the evidence on regional resilience produced by regional economics and economic geography studies [166]. In particular, relevant insights could be generated by studying how regional resilience relates to the local industrial mix and its industry resilience profile.

Author statement

Marco R. Di Tommaso: Conceptualization; Writing - Original Draft; Writing – Review & Editing; Supervision **Elena Prodi:** Methodology, Investigation; Formal Analysis; Writing - Original Draft; Writing – Review & Editing; **Chiara Pollio:** Methodology, Writing - Original Draft; Writing – Review & Editing; Visualization; **Elisa Barbieri:** Conceptualization; Writing – Review & Editing.

Data availability

The data used in this study are openly available at U.S. Department of Labor Bureau of Labor Statistics (BLS) and U.S. Bureau of Economic Analysis (BEA).

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Appendix

Table A1
Peaks and troughs by sector, manufacturing

Sector	Peak Month	Trough Month	Peak to Trough (Months)
Wood products	July 2007	July 2011	48
Nonmetallic mineral products	January 2008	January 2011	36
Primary metals	September 2008	October 2009	14
Fabricated metal products	May 2008	February 2010	21
Machinery	July 2008	January 2010	18
Computer and electronic products	March 2008	April 2010	25
Electrical equipment and appliances	May 2008	January 2010	20
Transportation equipment	February 2008	June 2009	16
Furniture and related products	April 2007	March 2011	47
Other miscellaneous durable manufacturing	December 2007	June 2010	38
Textile products mills	September 2008	January 2012	40
Paper and paper products	April 2008	February 2012	46
Printing and rel sup act	January 2008	November 2011	46
Petroleum and coal products	July 2008	January 2011	30
Chemicals	April 2008	January 2011	33
Plastic and rubber products	February 2008	October 2009	20
Food and beverage and tobacco products	November 2008	October 2010	23

Table A2
Summary statistics

	Obs	Mean	St dev	Min	Max
ALL SECTORS					
Employment (thousands)	626	6123.72	4093.54	1883	15535
Average hourly wage	626	23.40	5.34	11.96	32.96
Full-time and part-time workers (thousands)	66	7054.89	5160.56	639	18080
Full-time-equivalent workers (thousands)	66	6493.08	4715.25	630	16773
MANUFACTURING					
Employment (thousands)	480	0.04	0.02	0.01	0.15
Average hourly wage	480	19.46	14.65	1.74	88.07
Full-time and part-time workers (thousands)	480	840.13	8730.62	0.04	131469
Full-time-equivalent workers (thousands)	224	2863.65	1969.22	657.89	10947.90

Note: While data for employment and average hourly wage are measured monthly, data on part-time, full-time, and full-time equivalent workers are measured yearly. See also section 3.1 for more details.
Source: Authors' elaboration

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