

An index of static resilience in interindustry economics

4th of July 4, 2023

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Abstract: We introduce a novel static indicator of economy-wide resilience that captures the ability of an economy to adjust and recover from a negative shock from either the demand or the supply side. The metric is counterfactual and reveals by simulation the extent of the adjustments that would keep total income at least at the initial pre-shock level while maintaining the initial economic structure. The larger the scale of the needed adjustments in response to the shock, the smaller is the resilience of the economic system. The methodology we propose for this evaluation uses the concept of constrained input-output multipliers which in turn are incorporated within a linear programming problem. We show the applicability of this approach by calculating and comparing demand and supply resilience indices for a group of ten large *OECD* economies. For all these economies, the results show that manufacturing industries are more resilient than services sectors and that economic resilience regarding negative supply shocks is higher than demand shocks.

Keywords: demand resilience, supply resilience, static economic resilience, constrained input-output multipliers, endogenous scaling.

JEL codes: C67, D57, O57

Highlights:

We introduce a novel resilience metric that uses publicly available data.

The methodology allows the classification of industries and countries according to resilience.

The resilience metric unveils the role of the underlying economic structure.

The index may be useful in designing response policies to unexpected events.

1. Introduction

In recent years, any analysis of the impact of the pandemic derived from COVID-19 has highlighted how important is economic resilience and its measurement (*OECD*, 2021b; Linkov *et al.* 2021a; Linkov *et al.* 2021b; Hynes *et al.* 2022; Trump *et al.*, 2020; among others. The analysis of economic resilience dates back to the 70's. The idea of resilience was firstly used for the study of ecological systems (Holling, 1973). In this regard, resilience is a concept that transcends economics. It describes the ability of physical, biological, or social systems to withstand an external negative shock (Haimes, 2009; Serfilippi and Ramnath, 2018). Nowadays, the concept of resilience is applied in a broad range of interdisciplinary studies that are concerned with the interactions between people and nature. Furthermore, resilience is jointly used with the concept of "adaptive capacity", another term with multiple meanings (Carpenter *et al.*, 2001).

Generally speaking, resilience can be defined in several ways (Cumming *et al.*, 2005): the amount of change that a system can undergo maintaining the same controls on structure and function; the system's ability to self-organize; and the degree of learning and adaptation of the system. Therefore, as pointed out by Béné *et al.* (2012), resilience relates to three different types of capacities: absorptive, adaptive, and transformative capacity (*OECD*, 2014).

More specifically, in the field of economics and according to the existing literature, there exist several definitions of economic resilience. These definitions strongly depend on the context of each analysis, i.e., economic resilience derived from the response and recovery from earthquakes (Tierney, 1997), from society behavior and disaster hazard analysis (Rose 2004, 2009), among others. Although the definition of economic resilience still requires some concision (Rose, 2009), we can define economic resilience as the capacity of households, institutions, regions and countries to absorb and recover from shocks, while positively adapting and transforming their structures and means for living in the face of short- or long-term stresses, change and uncertainty (Mitchell, 2013). For instance, in the analysis of Pant *et al.* (2014), economic resilience is defined as the capacity of the economic system that allows the recovery of economic productivity from a disruptive event, in a specific period of time and with appropriate costs. Following Rose and Liao (2005), economic resilience, instead, refers to the

"inherent ability and adaptive response that enables firms and regions to avoid maximum potential losses".

From these general conceptualizations, we may define economic resilience, in short, as the ability of an economy to adjust and recover from external shocks. The external shock may be the result of the ordinary course of events (i.e., a fall in demand for exports, say) or a disruption following an unexpected event (i.e., a fall in demand from a pandemic, say). In both these cases, we associate resilience to what Rose (2007) defines as static resilience. It relates to the in-built ability of the economic system to counteract the negative shock via resource reallocation of economic flows. Hence, it is aligned with the well-known problem in economics of efficient allocation of resources. According to Rose (2007) this interpretation is static in the sense that the adjustments in the economy do not require changes in technology or factor endowments.

Dynamic resilience, on the other hand, has to do with disruptions affecting physical or human capital stocks mostly observed after some unexpected major disasters (i.e., an earthquake, a terrorist attack, etc.). Common features for dynamic economic resilience given by Rose (2007) are the speed and stability of a system, related to its capacity of recovery from a severe shock. In short, resilience can be classified as static (Rose, 2004, 2007), which measures the capacity or robustness of a system to offset maximum impacts, and as dynamic (Pant *et al*, 2014), which has to do with the speed of the system to recover from a shock.

From the perspective of measuring the inherent economic resilience of a system, we will focus on the concept of static or short-term resilience since we aim at unveiling some intrinsic properties of the economic system in its normal course of events. This has the advantage that standard mitigation policies by the government, for example, can be more easily conceptualized and eventually programmed (Briguglio *et al*, 2009). The intensity of the government's mitigation or intervention would reveal the response-needs of the system to offset the negative shock. In fact, all we need is the counterfactual response regardless of the actual feasibility of the policy implementation. The degree of this counterfactual response indicates the state of the system when facing the shock.

High system fragility measured in terms of acute reactions to shocks would therefore suggest low system resilience. Therefore, one possible and simple way of revealing the economic resilience of the system when facing a negative shock would be measuring

the minimal countervailing needs that, outside the subsystem receiving the shock, would eliminate its detrimental effects. The larger the compensation needs, the more fragile would be the economy in the face of a shock and the lower would be its resilience and, thus, the higher its vulnerability. In this regard, as in Klein *et al.* (2004), we assume that "a system is vulnerable because it is not resilient, and it is not resilient because it is vulnerable". In fact, existing empirical evidence reveals that an economy's vulnerability is linked to its structural fragility (Díaz, 2020).

Summing up, in our approach the degree of resilience of an economy is associated with the volume of resources that would have to be mobilized in order to restore, in our case, the pre-shock income level generated by this economy while technology does not change, and the sectoral structure of demand (supply) remains similar to the pre-shock equilibrium. It is true that economic resilience, as already mentioned, is a multifaceted concept and thus, single metrics that address one resilience coordinate will provide only limited information (Haimes, 2009). However, limited information is always better than no information and any metric, no matter its simplicity, helps to reveal part of the underlying structure that is not directly and easily observable, and this always contributes to a better understanding of the system's ability to adjust to changes.

Unlike major disaster disruptions that may have huge but discontinuous effects, we can model economic flows using a continuous function, which yields a computational procedure that allows us to measure intrinsic economic resilience in its static variety. Since resilience is both sector specific and network related, a variety of general equilibrium models have been used to analyze the effects of disruptions. The reason is that the general equilibrium approach offers the most convenient modelling platform for this type of analysis since it integrates the receipt and the transmission of external shocks and feedbacks. We can broadly classify these approaches in two groups, namely, computational general equilibrium (CGE) models (Shoven and Whalley, 1984) and input-output (I-O) models (Leontief, 1986).

In this regard, within the group of CGE models, it is worth mentioning the recent works of Wu *et al.* (2021) and Walmsley *et al.* (2023). The former uses a static CGE to evaluate the impact of the COVID-19 pandemic on both the demand and supply side of the Chinese economy. The latter, instead, applies a dynamic CGE to estimate the impact of the recent pandemic and its recovery for the USA economy. Within the second group (I-O models), Han (2022) explores the structural changes in the Chinese economy

derived from the COVID-19 pandemic using the information provided by the technical I-O coefficient matrix whereas Pichler and Farmer (2022) use I-O data for the German, Italian and Spanish economies to evaluate domestic demand and supply shocks. In a different methodological line, Temel and Phumpiu (2021) use a novel graph-theoretical method to a group of developed and developing economies that helps to identify the top priority sectors that should be targeted to mitigate the effects of COVID-19 on unemployment.

The possibilities and limitations of the interindustry I-O model are well known. On the one hand, the model is transparent in the nature of its network interdependencies, computationally operational, easily interpretable and—last but not least—we usually have the necessary data available (Miller and Blair, 2009). In this regard, it offers the possibility of measuring what we call total static economic resilience, or economy-wide resilience, since I-O models allows capturing the existing direct and indirect interdependencies between production activities. On the other hand, the classical interindustry model has limited behavioral reactions and we should interpret its results as short- or medium-term responses prior to price adjustments (Rose and Liao, 2005). In addition, and in contrast to CGE models and non-linear macroeconometric approaches, I-O models only capture either quantity effects or price effects but not both at the same time (Rose, 2004). However, the linearity of the model makes it amenable to ready integration into a linear programming framework (Intriligator, 2002; Graham, 2016).

Therefore, as a combined result, what we propose to do here is to use a computational mechanism that allows us to identify the minimal recovery changes in the system, i.e., changes in the demand or in the supply structure as well as the minimal volume of resources mobilized in response to negative shocks received by economic sectors. As stated before, the higher the volume of resources mobilized, the lower the degree of resilience (higher vulnerability) of the economic system. Different to the previous contributions, which are all ex-post analyses of disruptions, our approach is ex-ante.

The paper is organized as follows. Section 2 shows the economic framework used to incorporate the measurement of intrinsic static economic resilience laying the basic properties of the interindustry model, whereas Section 3 extends the concept of constrained multipliers to develop a static economic resilience index based on I-O relationships. In section 4 we apply the proposed methodology using domestic industry-

by-industry I-O data from a group of *OECD* economies for the year 2018 and present the numerical results we obtain in relation to both demand and supply resilience indicators. Section 5 concludes the paper.

2. Economic framework: a generalization of the demand driven total multiplier model.

A modern economy operates through a network of interconnected industries and institutional agents. When an external shock affects a certain industry, the effects that fall directly on that industry have repercussions in the form of a cascade through the network of industrial interconnections and end up affecting the functioning of the entire economy. Interindustry economics (Leontief, 1986; Miller and Blair, 2009) provides an adequate framework for the quantitative measure of these ripple effects. An interindustry economy is composed of n distinguished industries. Each industry labeled $j=1, 2, \dots, n$ acts both as a demander and a supplier of goods. Industry j demands goods from the rest of the industries that it then uses as inputs in its production process and these intermediate demand flows are used by industry j in fixed proportions. The industry's output, in turn, satisfies the intermediate demand of other industries that use good j as input in their production activities as well as final demand by households, the public sector, the external sector, etc. The economy is in balance when total supply equals total demand in each and all of the n industries.

In its simplest possible form, the balance condition in an I-O Leontief system is given by the expression:

$$\mathbf{x} = \mathbf{A} \cdot \mathbf{x} + \mathbf{y} \tag{1}$$

with $\mathbf{x} = (x_i)$ being a column vector representing total production or industries' gross output, $\mathbf{y}=(y_i)$ being the non-negative column vector of final demand. The non-negative matrix $\mathbf{A} = (a_{ij})$ describes the technical I-O coefficients. Each coefficient a_{ij} indicates the quantity of the output of industry i needed as input in the production of one unit of the output of industry j . The model in expression (1) is solvable under some regularity conditions¹ with non-negative solution given by:

¹ If matrix \mathbf{A} is non-negative, constant and its maximal eigenvalue is less than 1, the system of equations (1) is non-negatively solvable. See Nikaido (1972).

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1} \cdot \mathbf{y} = \mathbf{M} \cdot \mathbf{y} \quad (2)$$

with the inverse matrix \mathbf{M} denoting the so-called Leontief inverse of total (direct plus indirect) multipliers. We can also write the equilibrium system of equations (2) in differential terms. In this regard, we can either consider exogenous changes in final demand that lead to direct and indirect variations in industries' gross output:

$$\Delta \mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1} \cdot \Delta \mathbf{y} = \mathbf{M} \cdot \Delta \mathbf{y} \quad (3)$$

Alternatively, we can also consider exogenous changes in industries' gross output that lead to endogenous variations in final demand:

$$\Delta \mathbf{y} = (\mathbf{I} - \mathbf{A}) \cdot \Delta \mathbf{x} = \mathbf{M}^{-1} \cdot \Delta \mathbf{x} \quad (4)$$

A vector $\Delta \mathbf{x}$ endogenously calculated from (3) will indicate the required changes in the production of all industries that are necessary to accommodate the exogenous change $\Delta \mathbf{y}$ in the final demand originated in a specific industry k or, more generally, in a subset of industries. Focusing first on the effects originated from a unitary change in the final demand of industry k , $\Delta \mathbf{y}'_{(k)} = (0, 0, \dots, 1, \dots, 0)$, with a 1 in the k -th position², we can quickly calculate the total demand-induced change using the multiplier matrix \mathbf{M} as:

$$\mu_k^y = \sum_{i=1}^n m_{ik} \quad (5)$$

We can easily extend the quantification of the multiplier effects defined in (5) to non-unitary changes of any sign in final demand, say $\Delta \mathbf{y}'_{(k)} = (0, 0, \dots, \delta_k^y, \dots, 0)$ with δ_k^y positive or negative in the k -th position. In this case, and by the linearity implied by the constancy of matrix \mathbf{A} , the aggregate output multiplier value associated to a δ_k^y change in final demand of industry k will be:

$$\mu_k^y(\delta_k^y) = \sum_{i=1}^n \delta_k^y \cdot m_{ik} = \delta_k^y \cdot \sum_{i=1}^n m_{ik} \quad (6)$$

² For notational convenience, $\Delta \mathbf{y}'_{(k)}$ is the row vector version of the corresponding column vector.

The k demand-induced multiplier $\mu_k^y(\delta_k^y)$ in (6) will be positive if $\delta_k^y > 0$ or negative if $\delta_k^y < 0$. In the first case, we have positive demand shocks, in the second one negative demand shocks.

Similarly, vector $\Delta \mathbf{y}$ in (4) captures the direct and indirect endogenous variations in final demand of all industries when there are exogenous changes in the gross output of industry k or in a subset of industries. In this case, the supply-induced effects of a change $\Delta \mathbf{x}'_{(k)} = (0, 0, \dots, \delta_k^x, \dots, 0)$ in the output of industry k on final demand would be:

$$\mu_k^x(\delta_k^x) = \delta_k^x - \sum_{i=1}^n \delta_k^x \cdot a_{ik} = \delta_k^x \cdot \left(1 - \sum_{i=1}^n a_{ik} \right) \quad (7)$$

Therefore, the k supply-induced multiplier $\mu_k^x(\delta_k^x)$ in (7) will identify a positive supply shock if $\delta_k^x > 0$ or a negative one if $\delta_k^x < 0$.

3. A measure of demand and supply static economic resilience within the input-output framework.

The multiplier matrix \mathbf{M} measures the unrestricted effects of external unitary shocks affecting the economy via its final demand. In the same vein, the information contained in matrix \mathbf{M}^{-1} provides the unrestricted effects in final demand derived from external unitary supply shocks. When a negative demand shock, such as a decline in investment flows, falls on industry k the ripple effects expand over the network and reduce overall production by a magnitude that we can approximate using the multiplier matrix \mathbf{M} and the accounting from expression (6). Similarly, if the shock takes place constraining the supply, as would be the case under the scarcity or unavailability of some specific input, matrix \mathbf{M}^{-1} working through expression (7) would provide now an evaluation of the implications on final demand. Consequently, one possible way to estimate the economy's ability to recover from a negative demand or supply shock falling on industry k would be to calculate the minimum volume of resources that should be mobilized in the remaining $i \neq k$ industries that would counteract the shock on k and keep the economy at least at the initial level of gross domestic product (*GDP*).

Therefore, what we propose here is to use an adaptation of the Leontief I-O model in which the multipliers are able to capture the level of compensating changes that would

be necessary following a shock. To calculate these economy-wide resilience indices for the economy, we isolate and measure the economic strength in the non-impacted industries $i \neq k$ that offsets the shock in impacted industry k . Taken together, this simulation would provide us with a quantification of the economy's ability to withstand the shock (falling on industry k) and adjust to it (from counterfactual changes in all $i \neq k$). Since we can sequentially simulate the shock and counterfactuals across all industries, this strategy would identify the strength associated with unaffected industries that, together with the initial negative shock, would offset total *GDP* in aggregate terms for each and all industries.

We begin first with a description of the method used to construct the resilience indicator induced by shocks on the demand side. Our proposed way to implement this approach is through the concept of restricted multipliers developed by Guerra and Sancho (2011) to examine government spending policies under budget constraints.

Suppose that a shock of magnitude $\delta_k^y < 0$ falls on the final demand in industry k . We can calculate the countervailing values $\delta_i^y > 0$ for $i \neq k$ that would keep aggregate final demand constant and do so with the least deviation from the initial final demand structure:

$$\begin{cases} \delta_i^y = \delta_k^y & (i = k) \\ \delta_i^y = -\delta_k^y \cdot \frac{y_i}{\sum_{j \neq k} y_j} & (i \neq k) \end{cases} \quad (8)$$

Indeed, the changes in final demand in vector $\delta^y = (\delta_i^y)$ have two properties. Firstly, from the definition in expression (8) we verify:

$$\sum_{i=1}^n \delta_i^y = \delta_k^y + \sum_{i \neq k} \left(-\delta_k^y \cdot \frac{y_i}{\sum_{j \neq k} y_j} \right) = \delta_k^y - \delta_k^y \cdot \left(\frac{\sum_{i \neq k} y_i}{\sum_{j \neq k} y_j} \right) = 0 \quad (9)$$

Thus, total aggregate final demand remains unchanged (i.e., neutral scaling). Secondly, the changes in the non-shocked industries $i \neq k$ are set to be proportional to initial demand levels to keep the final demand structure in the non-shocked industries as close as possible to the initial pre-shock structure. As stated in the introduction, this later condition is in line with static or short-term economic resilience.

Consequently, the negative shock δ_k^y reduces gross output according to (6). On the other hand, the $n-1$ positive shocks would counteract this fall through its aggregation over the $n-1$ industries. The overall result takes both forces, negative and positive, into account and thus the restricted multiplier associated to the neutral shift in final demand takes value:

$$\hat{\mu}_k^y(\delta_k^y) = \mu_k^y(\delta_k^y) + \sum_{i=1}^n \sum_{j \neq k} \delta_i^y \cdot m_{ij} \quad (10)$$

Under the type of negative shock and positive countervailing compensation we examine, the first term of this summation is always negative and captures the standard unrestricted multiplier $\mu_k^y(\delta_k^y)$ from expression (6) whereas the second one is always positive. The composite result is that the restricted multipliers $\hat{\mu}_k^y(\delta_k^y)$ defined in expression (10), unlike the always-negative standard multipliers $\mu_k^y(\delta_k^y)$ stemming from a negative shock $\delta_k^y < 0$, can now have any sign.

The neutral scaling defined in expression (8) would change "post-shock" final demands from y_i to $\tilde{y}_i = y_i + \delta_i^y$. This scaling, however, does not guarantee that total output in the economy is going to be preserved. In fact, in general, total output \mathbf{x} under demand scheme \mathbf{y} will be different from total output $\tilde{\mathbf{x}}$ under demand scheme $\tilde{\mathbf{y}}$ both industry wise and economy wide (Guerra and Sancho, 2011).

The same type of discrepancy will occur regarding *GDP*. If the n -th vector $\mathbf{v} = (v_j)$ denotes value-added per unit of j -th industrial output, income *GDP* can be calculated as the dot product:

$$GDP = \mathbf{v}' \cdot \mathbf{x} = \sum_{j=1}^n v_j \cdot x_j \quad (11)$$

As before, *GDP* under demand scheme \mathbf{y} will be different from *GDP* under demand scheme $\tilde{\mathbf{y}}$ through the changes taking place from \mathbf{x} to $\tilde{\mathbf{x}}$. Nonetheless, for any demand shock δ_k^y we can refine the scaling in (8) to determine the minimal value ρ_k^y that would re-scale the neutral coefficients δ_i^y for $i \neq k$ and has the additional property that *GDP* remains at least at the initial level after the shock δ_k^y , i.e., $GDP = GDP$. With this adjustment, we guarantee that the economy would recover from the external shock, at least in terms of *GDP* measured by its total aggregate value added, i.e., the adjustment would be costless for the economy.

In other words, given a demand shock δ_k^y impacting industry k find the re-scaling value ρ_k^y that solves the linear programming problem:

$$\begin{aligned} & \text{Min } \rho_k^y \text{ subject to} \\ & \left\{ \begin{array}{l} (12.1) \quad \tilde{\delta}_i^y = \delta_k^y \quad \text{if } i = k \quad \text{and} \quad \tilde{\delta}_i^y = \rho_k^y \cdot -\delta_k^y \cdot \frac{y_i}{\sum_{j \neq k} y_j} \quad \text{if } i \neq k \\ (12.2) \quad \tilde{y}_i = y_i + \tilde{\delta}_i^y \\ (12.3) \quad \tilde{x}_i = \sum_{j=1}^n a_{ij} \cdot \tilde{x}_j + \tilde{y}_i \\ (12.4) \quad \sum_{i=1}^n v_i \cdot x_i \leq \sum_{i=1}^n v_i \cdot \tilde{x}_i \end{array} \right. \quad (12) \end{aligned}$$

Equation (12.1) indicates the re-scaling adjustment over the neutral one. Equation (12.2) indicates the new level of final demand after the re-scaling whereas equation (12.3) is the Leontief equilibrium condition between total output and total demand. Finally, equation (12.4) is the recovery provision for total value-added, i.e., *GDP*.

The optimal solution ρ_k^y of system (12) is the magnitude that approximates the degree of system-wide economic resilience associated to industry k when facing a negative demand shock δ_k^y . The smaller the re-scaling value ρ_k^y , the smaller the compensatory adjustments needed in the economy and, therefore, the more resilient the economy's response to the negative shock. A small value of ρ_k^y implies that the productive technology and final demand structure of the economy prior to the shock are capable of offering a better adaptive response to offset the shock.

If the solution of (12) yields $\rho_k^y=1$, the neutral scaling defined in (8) would be sufficient to counteract the losses in *GDP* from the negative shock. In other words, a unitary decline in the domestic final demand of sector k is automatically counteracted by increases in the domestic final demand in the remaining $i \neq k$ sectors that at the aggregate would keep the initial level of final demand. On the other hand, whenever $\rho_k^y > 1$ the neutral adjustment would be insufficient to counteract the induced losses in *GDP*. Hence, the larger the negative distance $1 - \rho_k^y$, the larger the recovery effort and the smaller the adaptability or resilience, in our terminology. Then, we define $1 - \rho_k^y$ as the net demand resilience coefficient. Lastly, if $\rho_k^y < 1$, the neutral adjustment would be more than sufficient to compensate the economic losses from the negative shock in sector k . As a result, the volume of resources that should be mobilized to offset the

perverse effects of the shock would be lower, which means a high degree of resilience in sector k .

Similarly, we can also construct supply-induced resilience coefficients and indices. In this case, the negative shocks on supply generate shocks in final demand according to expression (4). Using the supply-induced multiplier defined in equation (7) we can replicate the analysis and obtain the resilience indices from a supply perspective. We omit the details here, but they can be looked up in Appendix 1 at the end of the paper.

4. Calibration and results.

For the calculation of the demand and supply resilience indices, we have used the industry-by-industry domestic I-O tables regularly compiled by the *OECD* statistical database (*OECD*, 2021a). From this data set, we have selected the domestic I-O tables that correspond to ten of the largest *OECD* economies. We include Australia, Canada, Colombia, Germany, France, Italy, Mexico, Spain, the United Kingdom, and the United States of America. The industry breakdown includes 44 industries (see details in Appendix 2). The monetary flows of the domestic I-O tables are expressed in US millions of dollars and refer to the year 2018 which is the last version available at the moment.

We have evaluated both the demand and supply resilience indicators solving the demand and supply linear programming problems specified in (12) and (A4-Appendix 1), respectively, using the linear solver *BDMLP* available in *GAMS* (2021). We introduce a negative shock in each of the 44 industries in each economy and solve the 44 linear programming problems sequentially via a loop. In order to ease the interpretation of the results, the negative shock refers to a unitary decline in the domestic demand (supply) of a specific industry³. Once the negative shock is introduced within the linear programming problem in (12) (and in supply system (A4) in Appendix 1), the domestic demand (supply) flows of the remaining industries optimally adjust to compensate the decline in *GDP*. Consequently, if the net demand resilience coefficient $1 - \rho_k^y$ is positive and large, the degree of resilience of the economy to a potential unexpected shock in industry k will be high: less public resource mobilization is

³ Recall that under the standard I-O approach with constant returns to scale and zero substitution elasticities average multipliers equal marginal multipliers. Hence, the magnitude of the evaluated shock does not affect the evaluated resilience indexes (Guerra and Sancho, 2014).

necessary to counteract the negative effect in sector k . On the other side of the spectrum, if the net demand resilience coefficient turns out to be negative and large, the degree of resilience of the economy regarding industry k will be low. The interpretation for the net supply resilience coefficient $1 - \rho_k^x$ is similar (see Appendix 1 for details).

4.1. Static demand-induced resilience indices.

In order to have a general overview of the degree of demand resilience by country, we have calculated the average demand resilience index for each of the ten selected *OECD* countries. We also provide the range and the standard deviation to summarize their distribution. In Table 1, we review the stylized facts by country sorted from the highest to the lowest average net demand resilience coefficient.

Table 1: Net demand-induced resilience indices by country. Distribution Parameters.				
Country	Average Index	Maximum Index Value	Minimum Index Value	St.Deviation
United Kingdom	0.0763	0.7314	-0.1687	0.9773
France	0.0752	0.6538	-0.2193	1.3497
Canada	0.0596	0.5032	-0.1790	0.9149
Spain	0.0593	0.7193	-0.2195	1.3147
Australia	0.0518	0.2444	-0.0968	0.3143
Italy	0.0483	0.6083	-0.2256	1.1612
Colombia	0.0463	0.3911	-0.1529	0.6880
Germany	0.0455	0.5680	-0.2057	1.0319
United States	0.0347	0.2633	-0.0631	0.2352
Mexico	-0.0049	0.5017	-0.2585	1.2404

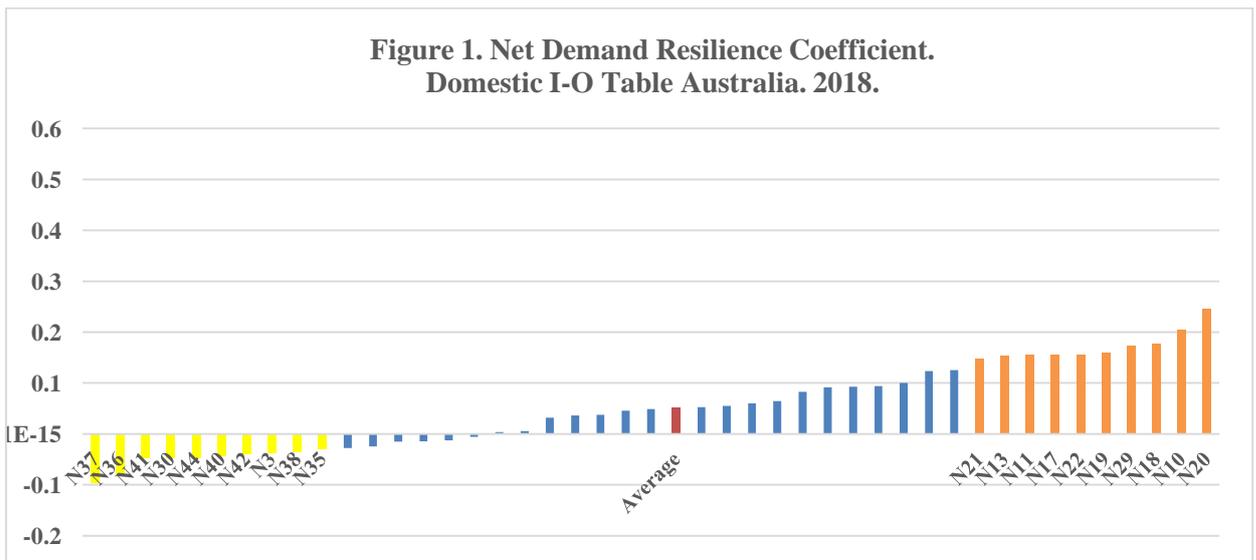
Source: our model using *OECD* I-O data for 2018

Figures 1-10 depict, for every industry and for each of the ten *OECD* selected economies, the results of the net demand resilience coefficients previously defined. These figures present the industries' net demand resilience coefficient $1 - \rho_k^y$ sorted by size, i.e., from the least resilient industry to the most resilient one. To facilitate the presentation of the results, in these figures we highlight only the ten most demand resilient sectors as well as the ten least demand resilient sectors out of the total 44 sectors included in the database.

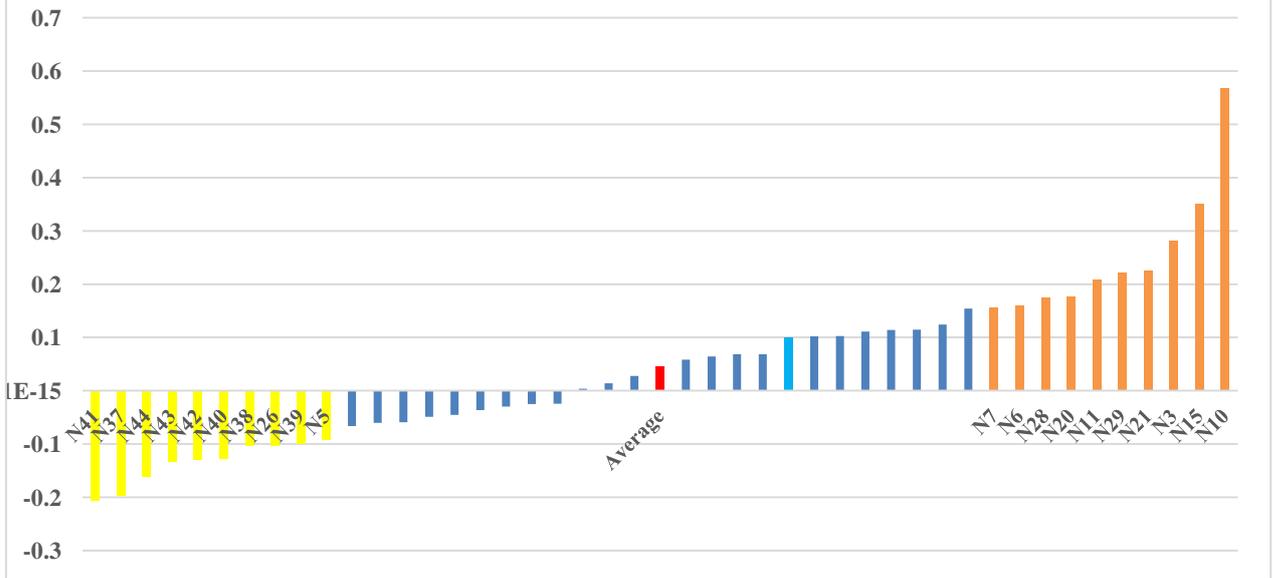
In line with the definition of the static demand resilience coefficient in (12), the United Kingdom (Figure 6) turns out to be the most demand resilient economy with an average

net demand resilience coefficient of 0.0763 among the ten selected *OECD* countries. An alternative interpretation of this net demand resilience index is the following: in the United Kingdom, on average, the volume of resources needed to compensate the negative demand shock in sector k to restore the initial *GDP* is less than proportional to the initial negative shock i.e., -1 US millions of dollars, thus 7.63 percent below the initial negative shock. On these grounds, United Kingdom is closely followed by France, which has an average net demand resilience coefficient of 0.0752.

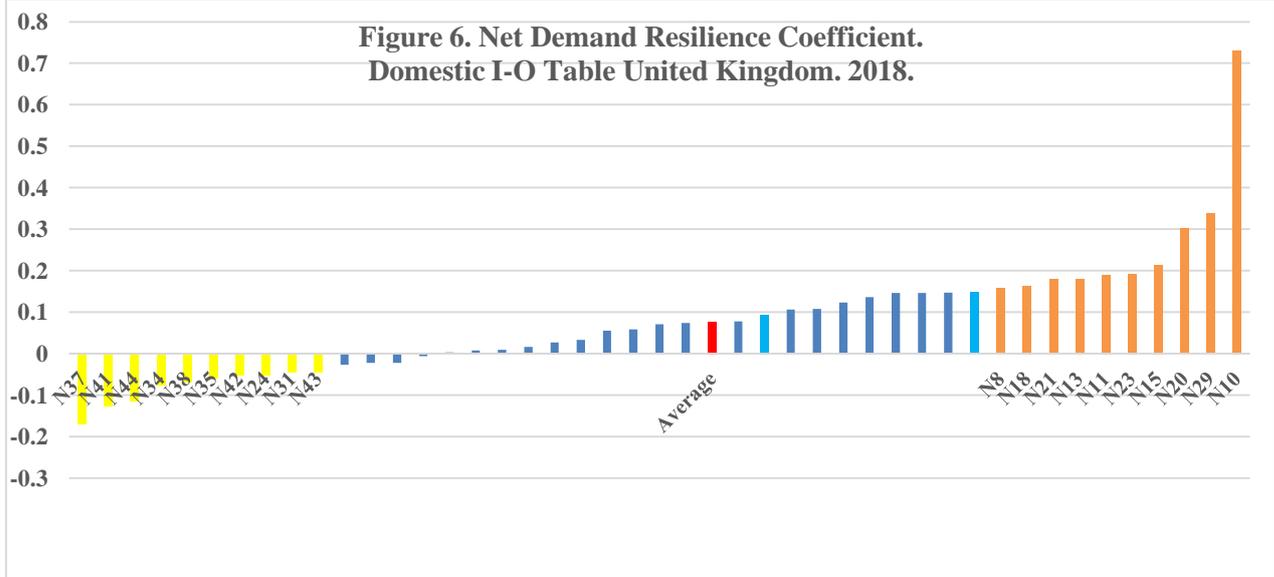
Despite the average similarity between these two *OECD* economies, notice that France (Figure 4) presents the highest standard deviation among these ten selected *OECD* economies, with a value of 1.3143. Therefore, in great contrast to United States (figure 7) or Australia (Figure 1), which have the lowest standard deviation, in the case of France, the degree of demand resilience varies remarkably from one sector to another.



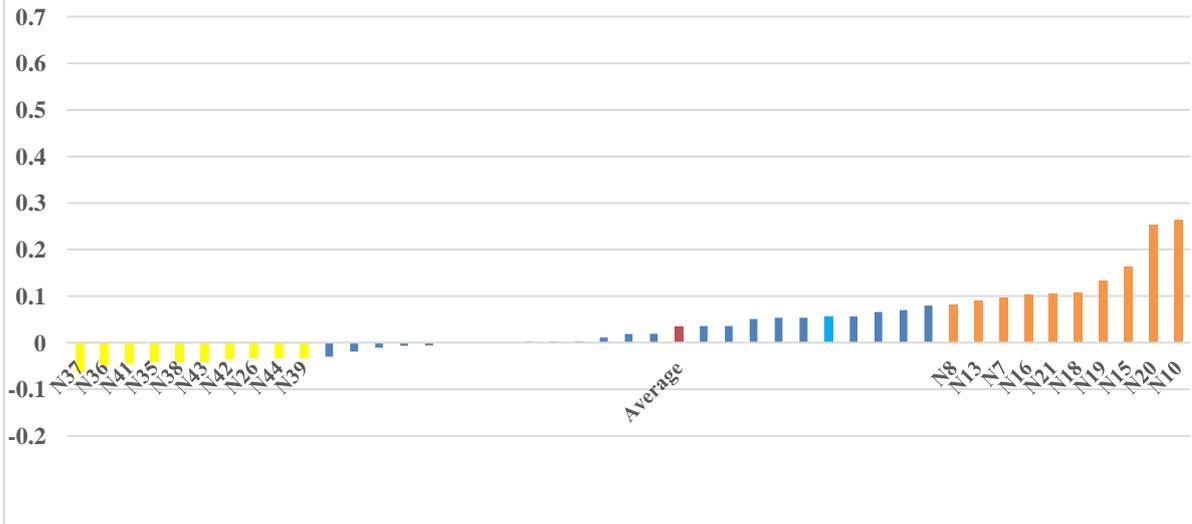
**Figure 5. Net Demand Resilience Coefficient.
Domestic I-O Table Germany. 2018.**



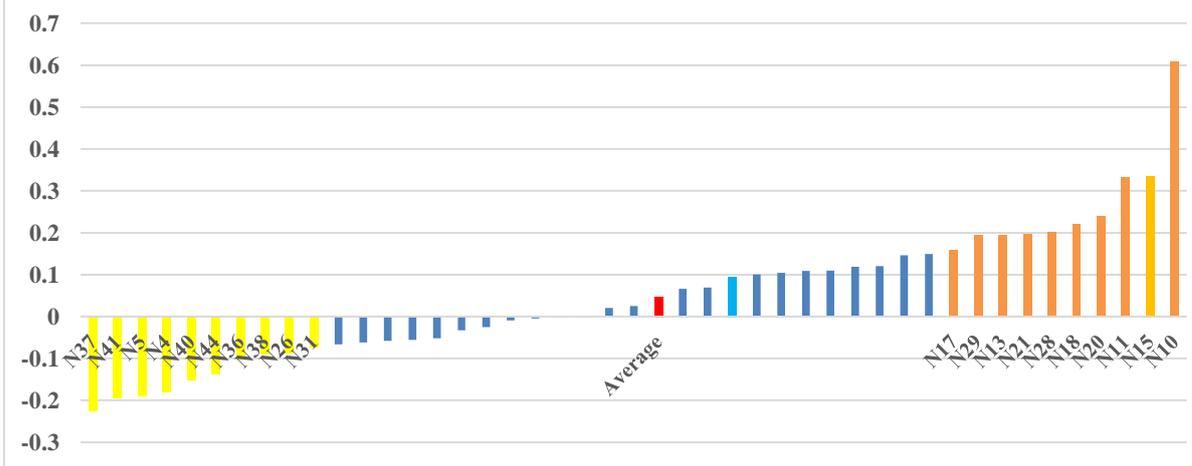
**Figure 6. Net Demand Resilience Coefficient.
Domestic I-O Table United Kingdom. 2018.**



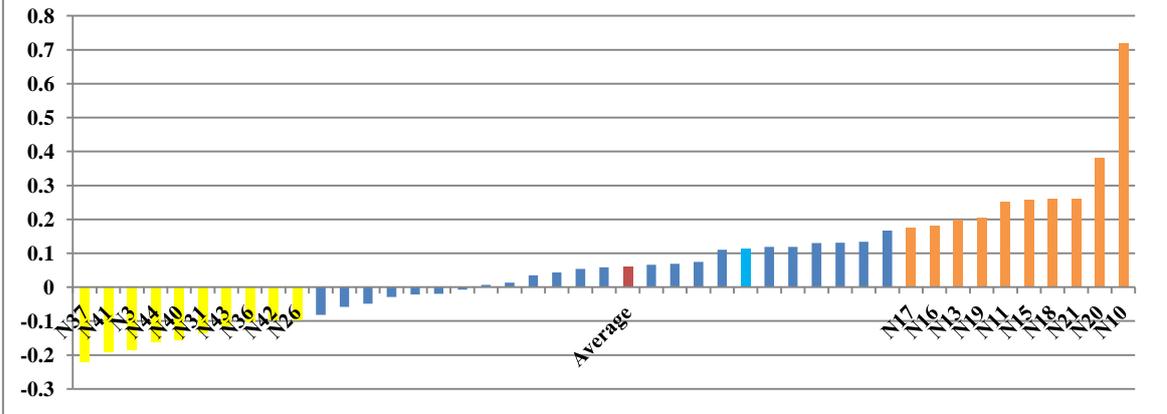
**Figure 7. Net Demand Resilience Coefficient.
Domestic I-O Table United States. 2018.**



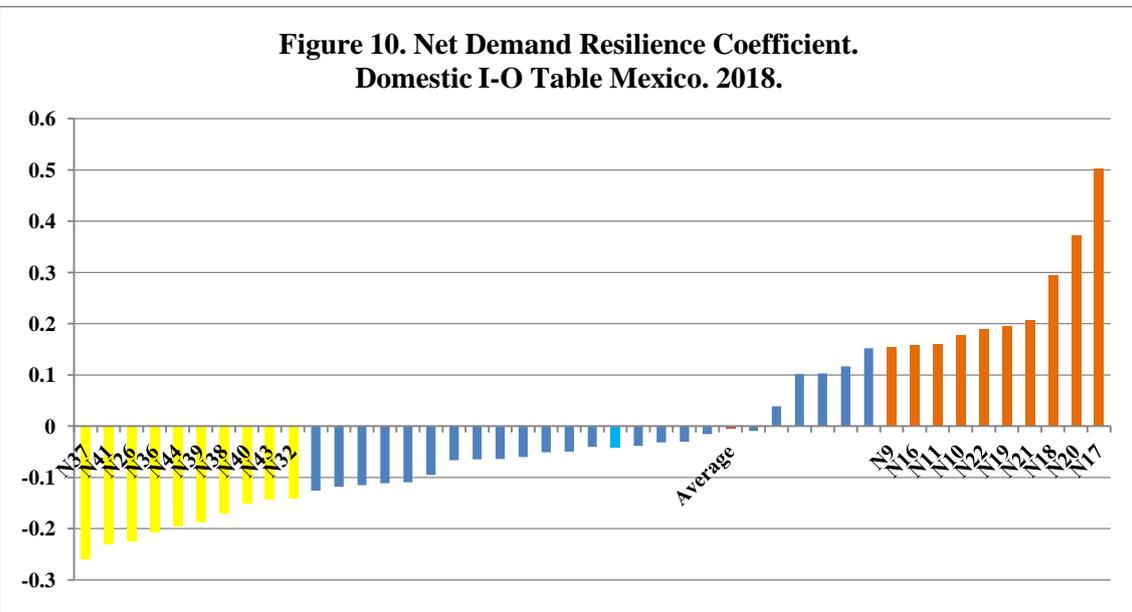
**Figure 8. Net Demand Resilience Coefficient.
Domestic I-O Table Italy 2018**



**Figure 9. Net Demand Resilience Coefficient.
Domestic I-O Table Spain. 2018.**



**Figure 10. Net Demand Resilience Coefficient.
Domestic I-O Table Mexico. 2018.**



At the other end of the ranking, we find Mexico (Figure 10) followed by the United States (Figure 7). According to our criteria, Mexico turns out to be the least resilient economy with an average net demand resilience coefficient of -0.0049. This figure, though quite close to zero, i.e., close to the neutral adjustment mentioned in section 3, is negative. Hence, this figure informs that, on average and in that economy, the volume of resources necessary to restore the initial *GDP* level after receiving a negative demand shock is more than proportional to that initial shock. In other words, in the case of the Mexican economy, on average, the volume of mobilized resources to counteract the negative final demand shocks account to 0.49 per cent above the negative shock.

If we now focus on the most demand resilient economy among the ones considered in our analysis, the United Kingdom, the ten industries that present the highest net demand resilience coefficient are the following (sectors on the right-hand side of Figure 6): *Coke and refined petroleum products* industry (N_10), *Air transport* industry(N_29), *Motor vehicles, trailers and semi-trailers* industry (N_20), *Basic metals* industry (N_15), *Electricity, Gas, Steam and Air Conditioning* industry (N_23), *Chemical and Chemical products* industry (N_11), *Rubber and Plastic products* industry (N_13), *Other Transport Equipment* industry (N_21), *Electrical Equipment* industry (N_18) and *Wood and Products of Wood and Cork* (N_8) industry.

According to the interpretation of this coefficient, this implies that if any of these industries undergoes a negative final demand shock i.e., a decline in exports, a sharp reduction in final consumption or investment flows, little mobilization of alternative resources should be necessary in order to counteract the derived decline in income.

Table 2: Country Frequency of the First Ten Highest Demand Resilient Industries			
Sector Code	Country ISO 3166-1 alpha 3 Code	Sector Code	Country ISO 3166-1 alpha 3 Code
N_1		N_23	UK
N_2		N_24	
N_3	GER	N_25	
N_4		N_26	
N_5		N_27	
N_6	GER	N_28	FRA,GER,ITA
N_7	CAN,FRA,GER,USA	N_29	AUS,COL,FRA,GER,UK,ITA
N_8	UK,USA	N_30	
N_9	COL,MEX	N_31	

N_10	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA,MEX	N_32	
N_11	AUS,CAN,COL,FRA,GER,UK,ITA,SPA,MEX	N_33	
N_12		N_34	
N_13	AUS,CAN,COL,UK,USA,ITA,SPA	N_35	
N_14		N_36	
N_15	CAN,FRA,GER,UK,USA,ITA,SPA	N_37	
N_16	USA,SPA,MEX	N_38	
N_17	AUS,CAN,COL,ITA,SPA,MEX	N_39	
N_18	AUS,CAN,COL,FRA,UK,USA,ITA,SPA,MEX	N_40	
N_19	AUS,CAN,COL,FRA,USA,SPA,MEX	N_41	
N_20	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA, MEX	N_42	
N_21	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA,MEX	N_43	
N_22	AUS,MEX	N_44	

Do the remaining countries present common patterns in terms of the most demand resilient industries identified in United Kingdom? For most of the ten selected economies (Table 2), as in the case of United Kingdom, the majority of the industries that are classified as common high demand resilient industries pertain to the industrial sector i.e., *Motor vehicles, trailers, and Semi-trailers* industry (N_20) and the *Other Transport Equipment* (N_21) and some energy-related sectors such as *Coke and Refined Petroleum products* industry (N_10). As it can be asserted from Table 2, these industries are identified as high demand resilient sectors in all the selected *OECD* economies. Similarly occurs in the case of *Electrical Equipment* industry (N_18) with the exception of the United States. The *Rubber and Plastic Products* industry (N_13) and the *Basic Metal* industry (N_15) are also quite common high demand resilient sectors. These two sectors are classified as high demand resilient sectors in seven out of the ten *OECD* economies analyzed here. Within the service industries, it is worth mentioning the case of the *Air Transport Service* Industry (N_29).

If we now move to comment on the results of the least demand resilient economy, Mexico, the industries that present the lowest net demand resilience coefficient are the following (sectors on the left-hand side of Figure 10): *Real Estate Services* industry (N_37), *Education Services* industry (N_41), *Wholesale and Retail Trade, repair of motor vehicles* industry (N_26), *Financial and Insurance activities* industry (N_36), *Other Service Activities* industry (N_44), *Administrative and Support Services* industry (N_39), *Professional, scientific and technical activities* industry (N_38), *Public Administration and Defense, Compulsory Social Security* industry (N_40), *Arts,*

Entertainment and Recreation activities industry (N_43) and Accommodation and Food services activities industry (N_32).

Table 3: Country Frequency of the First Ten Lowest Demand Resilient Industries			
Sector Code	Country ISO 3166-1 alfa 3 code	Sector Code	Country ISO 3166-1 alfa 3 code
N_1		N_23	CAN
N_2		N_24	UK
N_3	AUS, FRA, SPA	N_25	
N_4	COL, ITA	N_26	CAN,GER, USA, ITA,SPA, MEX
N_5	FRA,GER,ITA	N_27	
N_6		N_28	
N_7		N_29	
N_8		N_30	AUS
N_9		N_31	FRA,UK,ITA, SPA
N_10		N_32	MEX
N_11		N_33	
N_12		N_34	UK
N_13		N_35	AUS,CAN,COL,FRA, UK,USA
N_14		N_36	AUS, CAN, COL,USA,ITA, SPA, MEX
N_15		N_37	AUS,CAN, COL,FRA, GER, UK,USA,ITA, SPA, MEX
N_16		N_38	AUS, CAN, COL,GER, UK,USA, ITA, MEX
N_17		N_39	CAN,COL,FRA, GER,USA,MEX
N_18		N_40	AUS,CAN,COL,FRA,GER, ITA,SPA, MEX
N_19		N_41	AUS, CAN,COL,FRA,GER,UK,USA,ITA, SPA,MEX
N_20		N_42	AUS,CAN,FRA, GER,UK,USA,SPA
N_21		N_43	COL,GER,UK,USA,SPA,MEX
N_22		N_44	AUS,COL,FRA,GER,UK,USA,ITA,SPA,MEX

In replicating the previous exercise (Table 3), the bulk of industries that are common low demand resilient industries belong, in this case, to the service sectors. This is, for instance, the case of the *Real Estate activities* industry (N_37) and *Education service* industry (N_41) that stand out as low demand resilient industries in all ten *OECD* selected economies. In the same vein, it is worth mentioning the case of the *Other service activities* (N_44) that are identified as “key” low demand resilient industries in nine out of ten economies (with the exception of Canada). The *Public Administration and Defense, Compulsory Social Security* service industry (N_40) and *Professional, Scientific and Technical activities* service industry (N_38) are low demand resilient

service industries in eight out of the ten *OECD* economies selected for this analysis. *The Financial and Insurance Activities* industry (N_37) is also a common low demand resilient sector across these countries. It is identified as such in seven out of the ten selected economies. Lastly, outside the service sectors, we can highlight the extractive industries: *Mining and Quarrying, energy producing products* industry (N_3), *Mining and Quarrying, non-energy producing products* industry (N_4) and *Mining Support Service Activities* industry (N_5).

4.2. Static supply-induced resilience indices.

In Table 4 we report, for each of the ten *OECD* countries, the resilience coefficients induced from the supply side sorted again from highest to lowest average index. In this case, none of the ten economies presents a negative index. Notice that when we compare the results in Table 4 with those depicted in Table 1, on average, the supply resilience indices are higher compared with the demand resilience indices. This informs us that, at short-term and according to the assumptions of our approach, the volume of resources that have to be mobilized to compensate negative supply shocks are much lower compared to negative demand shocks. In addition, some economies stand out as being resilient both from the demand and supply sides. This is the case of the United Kingdom and France. At the other end, among the least demand and supply resilient economies, we find the case of Mexico.

Coming back to the results reported in Table 4, Australia (Figure 11) with an average coefficient of 0.1342 ranks first as having the most resilient economy to negative supply shocks, while Italy (Figure 18) with 0.0789 ranks last. Furthermore, notice that Italy presents the highest sectorial variability as measured by the standard deviation. Hence, in the case of Italy, there exists a great heterogeneity in the negative effects of supply shocks across industries. We can also observe that the United Kingdom, in the second position of the ranking with a coefficient of 0.1303, is quite similar in results to Australia both in average and standard deviation values. France with a value of 0.1192 takes the third place in the ranking but, unlike Australia and the United Kingdom, the variability in France is almost twice as large and is the second largest one after Italy. Recall that we already detected that France had the largest variability when we examined the demand-induced resilience indices. Germany, the United States and

Mexico, on the other hand, present quite similar average indices but, again, their variability turns out to be quite dissimilar.

Table 4: Net supply-induced resilience indices by country. Distribution Parameters.				
Country	Average Index	Maximum Index Value	Minimum Index Value	St.Deviation
Australia	0.1342	0.7813	-0.4664	3.8833
United Kingdom	0.1303	0.8258	-0.6051	3.8848
France	0.1192	0.8140	-0.7867	6.9363
Spain	0.1125	0.8384	-0.7756	6.2033
Canada	0.1053	0.6786	-0.5133	3.5557
Germany	0.0931	0.8419	-0.6082	4.7160
United States	0.0930	0.6230	-0.3994	2.7599
Mexico	0.0910	0.7144	-0.6830	6.3113
Colombia	0.0884	0.7070	-0.8148	4.7663
Italy	0.0789	0.8731	-0.9929	8.0682

Source: our model using *OECD* I-O data for 2018

In Figures 11-20 we can observe the detail of the results by industry sorted by size from the lowest to the highest supply resilience index. As before, we highlight the ten lowest and ten highest industries in each of the Figures.

For the economy with the highest supply resilience index, Australia, the top ten supply resilient sectors, in descending order, are (sectors on the right-hand side of Figure 11): *Basic metals* industry (N_15), *Coke and refined petroleum products* industry (N_10), *Food products, beverages and tobacco* industry (N_6), *Other transport equipment* industry (N_21), *Construction* industry (N_25), *Chemical products* industry (N_11), *Rubber and plastic products* industry (N_13), *Motor vehicles, trailers and semitrailers* industry (N_20), *Paper products and printing* industry (N_9), and *Wood and products of wood and cork* industry (N_8). Any supply shock falling on one of these sectors would require smaller positive supply adjustments in the rest of the industries to compensate for the negative shock. Notice that all these sectors belong mostly to the set of industrial sectors.

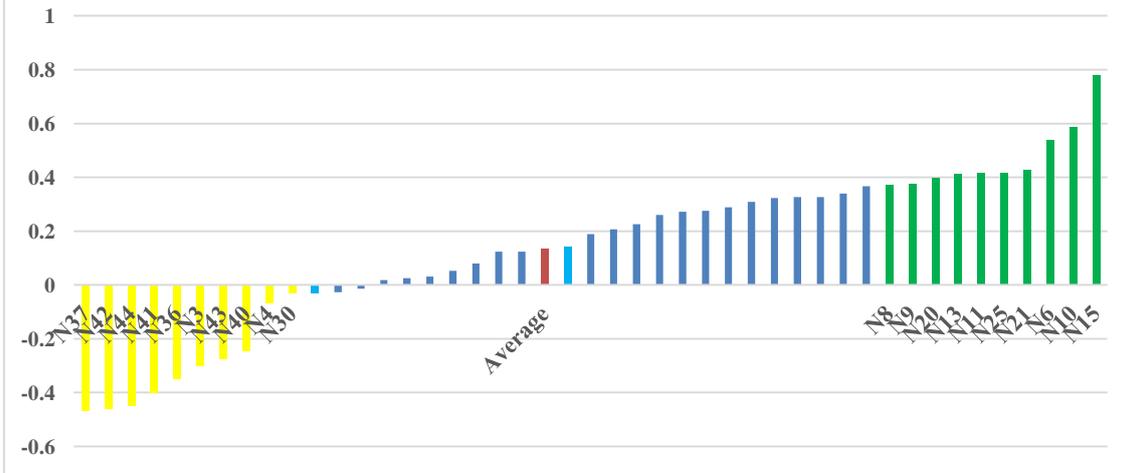
In Table 5 we report the frequency of the shared most resilient-supply industries of Australia with the rest of countries. We can observe that with the exception of *Construction* (N_25) and for most countries, there is a strong similarity in the subset of

industrial sectors across countries. In all of the ten countries, *Coke and refined petroleum products* industry (N_10) and *Motor vehicles, trailers and semitrailers* industry (N_20) are in the top ten supply resilient sectors, followed by *Food products, beverages and tobacco* industry (N_6), *Chemical products* industry (N_11), and *Basic metals* industry (N_15) with nine shared industries altogether. Furthermore, some of these manufacturing industries are also classified as being high demand resilient industries (See section 4.1), i.e., *Coke and refined petroleum products* industry (N_10) and *Motor vehicles, trailers and semitrailers* industry (N_20).

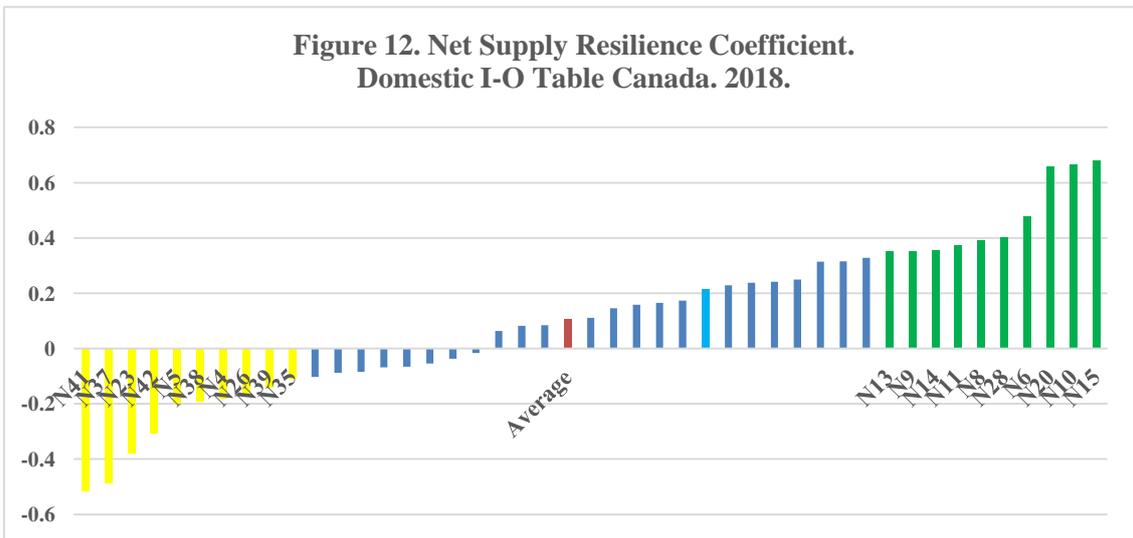
At the other side of the classification, we find that the least ten supply resilient industries in the least supply resilient economy, Italy (Figure 18) as mentioned before, happen to be: *Real Estate activities* industry (N_37), *Mining support services* industry (N_5), *Mining and quarrying* (N_4), *Education* industry (N_41), *Other services activities* industry (N_44), *Professional, scientific, and technical activities* industry (N_38), *Human health and social work activities* industry (N_42), *Agriculture* industry (N_1), and *Financial and insurance activities* industry (N_36). As in the case of the demand resilience, most of the least supply resilient industries belong to the general services category, with the exception of agriculture activities and two of the mining activities.

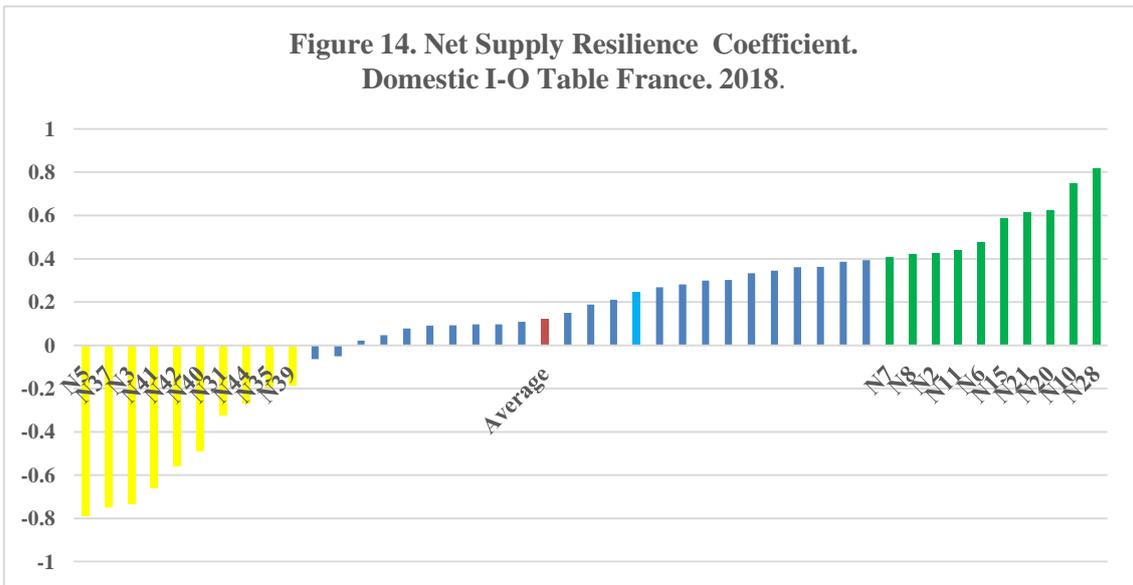
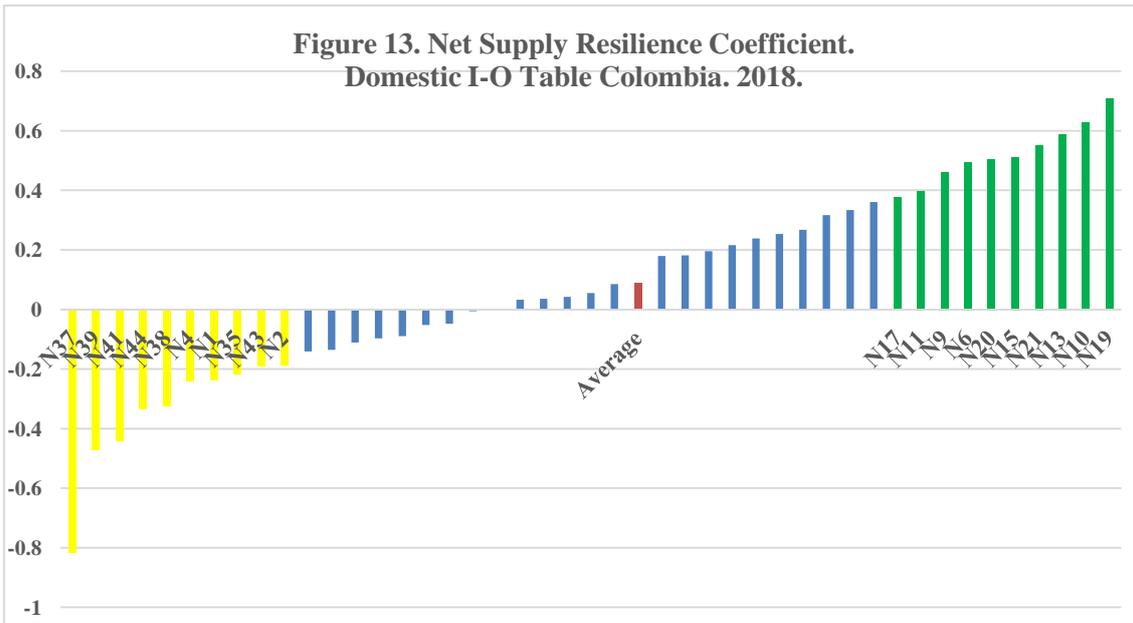
When we look at Table 6 we find the frequency of the shared least supply resilient industries. *Agriculture* (N_1) seems to be an outlier since only Colombia shares the classification for this sector. All ten countries share *Real Estate activities* industry (N_37) and *Education services industry* (N_41) in the subset of least resilient industries followed by *Human health and social work activities* (N_42) and *Other services activities* (N_44) with eight shared industries. As was the case with the least demand resilient industries, we find once again a majority of industries belonging to the services sector in this classification of least supply resilient industries. Notice that, some sectors such as *Real Estate activities* industry (N_37), *Education service* industry (N_41) and *Other services* industry (N_44) are also identified as being low demand resilient industries (See section 4.1).

**Figure 11. Net Supply Resilience Coefficient.
Domestic I-O Table Australia. 2018.**

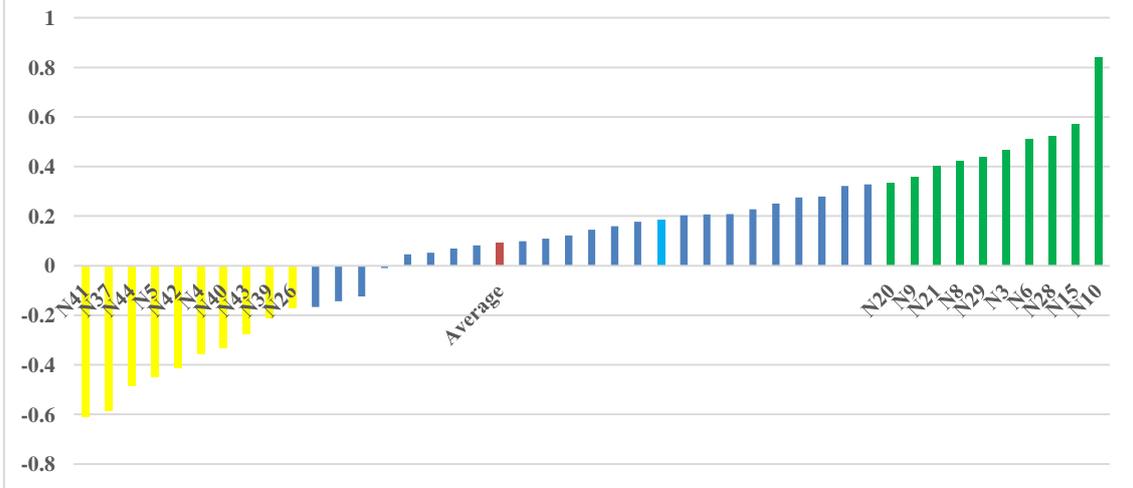


**Figure 12. Net Supply Resilience Coefficient.
Domestic I-O Table Canada. 2018.**

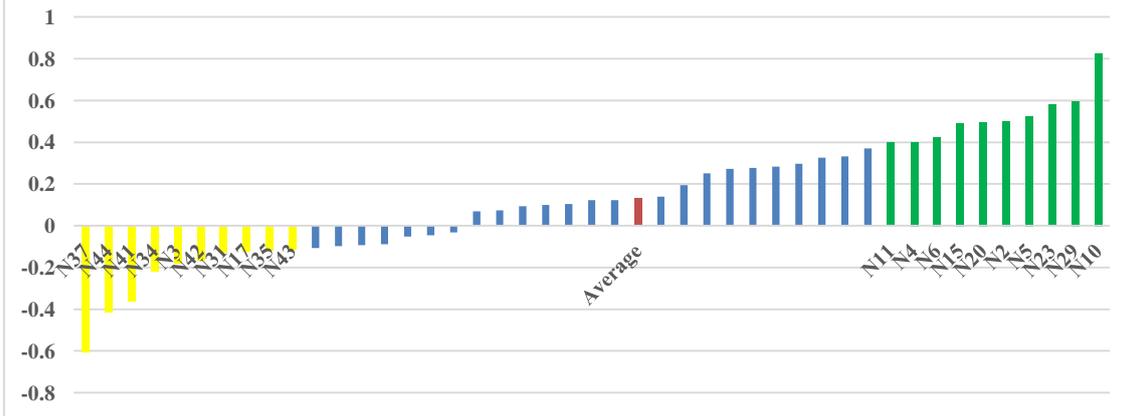




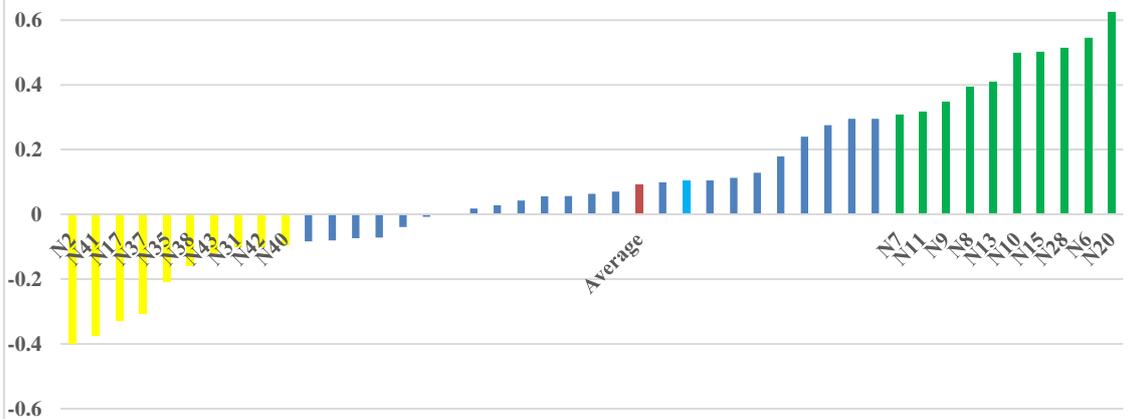
**Figure 15. Net Supply Resilience Coefficient.
Domestic I-O Table Germany. 2018.**



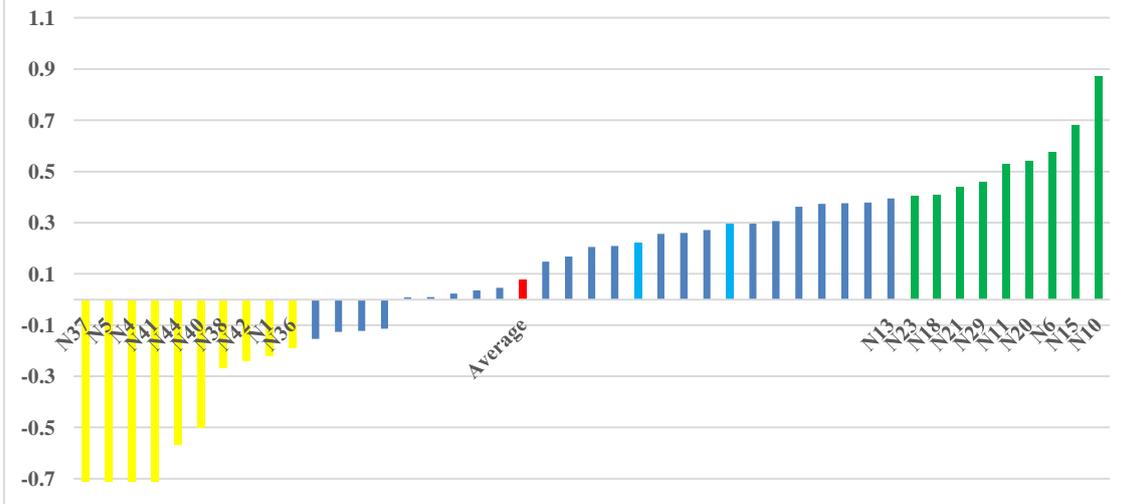
**Figure 16. Net Supply Resilience Coefficient.
Domestic I-O Table United Kingdom. 2018.**



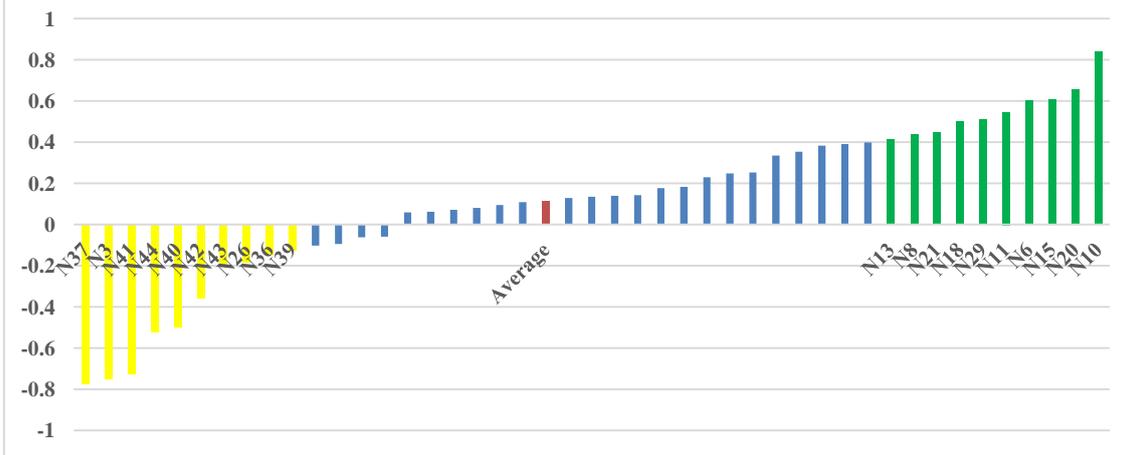
**Figure 17. Net Supply Resilience Coefficient.
Domestic I-O Table United States. 2018.**



**Figure 18. Net Supply Resilience Coefficient.
Domestic I-O Table Italy. 2018.**



**Figure 19. Net Supply Resilience Coefficient.
Domestic I-O Table Spain. 2018.**



**Figure 20. Net Supply Resilience Coefficient.
Domestic I-O Table Mexico. 2018.**

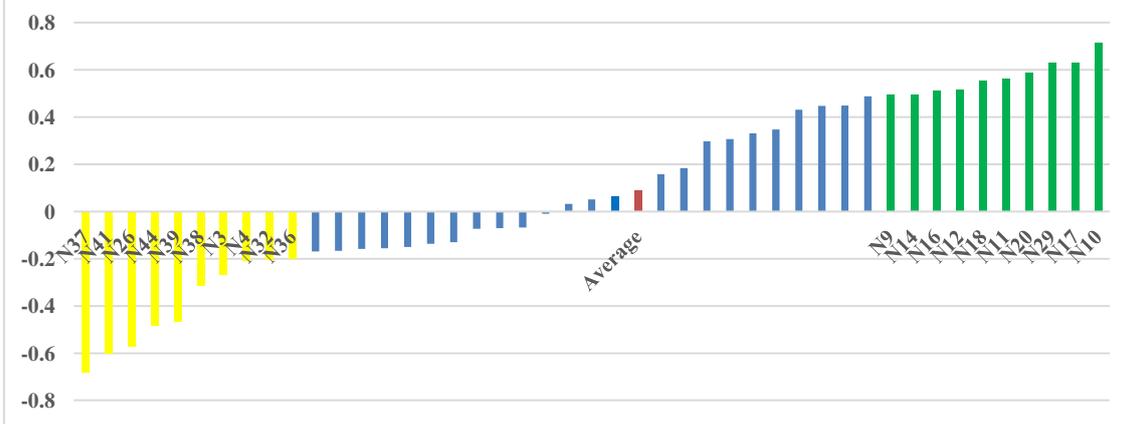


Table 5: Country Frequency of the First Ten Highest Supply Resilient Industries			
Sector Code	Country ISO 3166-1 alfa 3 code	Sector Code	Country ISO 3166-1 alfa 3 code
N_1		N_23	UK,ITA
N_2	Fra,UK	N_24	
N_3	GER	N_25	AUS
N_4	UK	N_26	
N_5	UK	N_27	
N_6	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA	N_28	CAN,FRA,GER,USA
N_7	FRA,USA	N_29	GER,UK,ITA,SPA,MEX
N_8	AUS,CAN,FRA,GER,USA,SPA	N_30	
N_9	AUS,CAN,COL,GER,USA,MEX	N_31	
N_10	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA,MEX	N_32	
N_11	AUS,CAN,COL,FRA,UK,USA,ITA,SPA,MEX	N_33	
N_12	MEX	N_34	
N_13	AUS,CAN,COL,USA,ITA,SPA	N_35	
N_14	CAN,MEX	N_36	
N_15	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA	N_37	
N_16	MEX	N_38	
N_17	COL,MEX	N_39	
N_18	ITA,SPA,MEX	N_40	
N_19	COL	N_41	
N_20	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA,MEX	N_42	
N_21	AUS,COL,FRA,GER,ITA,SPA	N_43	
N_22		N_44	

Table 6: Country Frequency of the First Ten Lowest Supply Resilient Industries			
Sector Code	Country ISO 3166-1 alfa 3 code	Sector Code	Country ISO 3166-1 alfa 3 code
N_1	COL,ITA	N_23	CAN
N_2	COL,USA	N_24	
N_3	AUS,FRA,UK,SPA,MEX	N_25	
N_4	AUS,CAN,COL,GER,ITA,MEX	N_26	CAN,GER,SPA,MEX
N_5	CAN,FRA,GER,ITA	N_27	
N_6		N_28	
N_7		N_29	
N_8		N_30	AUS,USA
N_9		N_31	FRA,UK
N_10		N_32	MEX
N_11		N_33	
N_12		N_34	UK

N_13		N_35	CAN,COL,FRA,UK,USA
N_14		N_36	AUS,ITA,SPA,MEX
N_15		N_37	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA,MEX
N_16		N_38	CAN,COL,USA,ITA,MEX
N_17		N_39	CAN,COL,FRA,GER, SPA,MEX
N_18	UK,USA	N_40	AUS,FRA,GER,USA,ITA,SPA
N_19		N_41	AUS,CAN,COL,FRA,GER,UK,USA,ITA,SPA, MEX
N_20		N_42	AUS,CAN,FRA,GER,UK,USA,ITA,SPA
N_21		N_43	AUS,COL,GER,UK,USA,SPA
N_22		N_44	AUS,COL,FRA,GER,UK,ITA,SPA,MEX

5. Conclusions and discussion of the main results.

This work has a double objective: methodological and empirical. On the one hand, we introduce a new methodological criterion of static resilience that can be calculated from the available I-O data of an economy. In previous research, the degree of resilience of an economy has been approximated through the size of the economic consequences of negative shocks, whether on the demand side, the supply side, or both simultaneously (Wu et al. 2021; Pichler and Farmer, 2022; Han, 2022). Our work differs from previous ones in that we offer an alternative criterion of economic resilience based on the concept of restricted multipliers. This allows a numerical estimate of the degree of adjustment to a negative external shock in terms of the volume of resources that should be mobilized to restore the initial levels of *GDP*. Our proposed indicators are counterfactual, reveal intrinsic properties of the economy and provide information previous to the presence of an actual shock, i.e., ex-ante. To this effect, they take into account that the production structure should remain constant whereas the adjustments in demand, or in supply, should respect as much as possible their initial structure. From here, the larger the efforts in terms or resources needed to counteract a shock and recover *GDP* levels, the lower the degree of resilience. This is relevant from a policy perspective as it allows anticipating the effects of a disruption before they materialize and thus facilitates the design of response policies. For instance, the efforts could be orientated to increase the digitalization of specific services sectors, a factor that is closely linked to the degree of economic resilience (Copestake *et al*, 2022). Additionally, our novel approach makes it possible to rank economies and sectors not in terms of the size of the derived effects from the negative shocks but, instead, in terms of the size of the mobilized resources

that would compensate those effects. Therefore, in our view, our criterion is more compatible with a genuine definition of static economic resilience (Rose, 2004).

On the other hand, we use our conceptual proposal to empirically evaluate demand and supply resilience for a set of ten *OECD* countries. We use the homogenized I-O dataset elaborated in the *OECD* using the most recent available data for 2018. This data has the advantage of distinguishing I-O intermediate data separating domestic inputs from imported inputs. The numerical results show, in general terms, that high demand and supply resilience tend to be associated with industrial sectors. This is specially the case of the *Motor vehicles, trailers and semi-trailers* industry (N_20) and *Coke and refined petroleum products* industry (N_10). In contrast, the least demand and supply resilience sectors are mostly associated with the general services sectors. *Real Estate activities* industry (N_37) along with *Education services* industry (N_41) and *Other services* industries (N_44) are common low demand and supply resilient sectors across countries. This is the type of characteristic that we observe it in all of the ten selected *OECD* countries. In addition, and in line with our results, these economies appear to be less resilient regarding negative demand shocks compared to those originated in the supply side of the economy. The United Kingdom and France present the most resilient economic structures to demand shocks; with The United States and Mexico being the least resilient of the ten countries. On the supply side, Australia and the United Kingdom are the most resilient economies whereas Colombia and Italy take the bottom places in the ranking.

As stated before, in our calculations we impose the condition that the adjustments must preserve initial *GDP*, the target that we select as the measuring yardstick. Other and different targets than *GDP* preservation are of course possible. For instance, we plan to examine restrictions on employment levels in our future work. Lastly, we only control for domestic demand and supply shocks. However, external supply chain constraints also affect economic performance, and thus a possible extension of our analysis could examine their role in defining the value of resilience indicators for industries and for economies.

Disclosure statement

The authors declare no potential conflict of interest.

Acknowledgements

We gratefully acknowledge the support from grant PID2020-116771GB-100 funded by MCIN/AEI/10.13039/501100011033. The first and second authors also thank the financial support of the Junta de Andalucía (PAIDI 2020, grant number P20.00691) and the Programa Operativo FEDER de Andalucía 2014-2020 (grant number B-SEJ-544-UGR20).

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References

- Béné, C., Godfrey Wood, R., Newsham, A., and Davies, M. (2012), “Resilience: New Utopia or New Tyranny? Reflection about the Potentials and Limits of the Concept of Resilience in Relation to Vulnerability Reduction Programmes”, *Institute for Development Studies Working Paper* 405.
- Briguglio, L., Cordina, G., Farrugia, N. and Vella, S. (2009), “Economic vulnerability and resilience: concepts and measurements”, *Oxford Development Studies*, 37(3), pp. 229-247.
- Copestake, A., Estefania Flores, J., and Furceri, D. (2022). Digitalization and Resilience. IMF Working paper No 2022/210.
- Carpenter, S., Walker, B., Anderies, J.M, and Abel, N.(2001), “From Metaphor to Measurement: Resilience of What to What?”, *Ecosystems* 4, pp. 765–781.
- Cumming, G.S., Barnes, G., Perz, S., Schmink, M., Sieving, K.E., Southworth, J., Binford, M., Holt, R.D., Stickler, C. and Van Holft, T.(2005), “An Exploratory Framework for the Empirical Measurement of Resilience”, *Ecosystems* 8, pp. 975–987.
- Díaz, H., Cerezo, V. and Hernández, I. (2020), “Structural vulnerability of the Mexican economy before the crisis induced by the COVID-19 pandemic”. *Contaduría y Administración*, 65(5) *Especial COVID-19*, pp. 1-14.
- GAMS (2021), **General Algebraic Modeling System**, GAMS Development Corporation, Fairfax, VA, USA.
- Graham, D. (2016), “Input-output and linear programming”, in **Modern economic thought**, chapter 6, (S. Weientraub, ed.), University of Pennsylvania Press, Philadelphia.
- Guerra, A. I. and Sancho, F. (2011), “Budget constrained expenditure multipliers”, *Applied Economic Letters*, 18(13), pp. 1259-1262.
- Guerra, A. I., and Sancho, F. (2014). “An operational, nonlinear input–output System”. *Economic Modelling*, 41, pp. 99-108.
- Haimes, Y.Y. (2009), “On the definition of resilience in systems”, *Risk Analysis*, 29(4), pp. 498-501.
- Han, Y. (2022). “The impact of the COVID-19 pandemic on China's economic structure: An input–output approach”. *Structural Change and Economic Dynamics*, 63, pp. 181-195.HA
- Holling, C. S. (1973), “Resilience and Stability of Ecological Systems”. *Annual Review of Ecology and Systematics*, 4, 1–23.

- Hynes, W., Trump, B.D., Kirman, A. *et al.* (2022), “Systemic resilience in economics”, *Nature Physics*, 18, pp. 381–384.
- Intriligator, M. (2002), **Mathematical optimization and economic theory**, chapter 9, *Classics in Applied Mathematics*, edited by the Society for Industrial and Applied Mathematics.
- Klein, R., Nicholls, R. and Thomalla, F. (2004), “Resilience to natural hazards: How useful is this concept?”. *Environmental Hazards*. 5. Pp. 35-45.
- Leontief, W. (1986), **Input-output economics**, second edition, Oxford University Press, New York.
- Linkov, I., Keenan, J. and Trump, B. D. (2021a), **COVID-19: Systemic Risk and Resilience**. Springer.
- Linkov, I., Trump, B. D., Golan, M. and Keisler, J. (2021b). “Enhancing resilience in post-COVID societies: by design or by intervention?”, *Environmental, Science and Technology*, 55, pp. 4202–4204.
- Miller, R.E. and Blair P.D. (2009), **Input-output analysis: Foundations and extensions**, Cambridge University Press, New York.
- Mitchell, A. (2013), “Risk and resilience: From good idea to good practice”, *OECD Development Cooperation Working Papers*, 13, *OECD Publishing*, Paris.
- Nikaido, H. (1972), **Introduction to sets and mappings in modern economics**, Amsterdam, North-Holland.
- OECD* (2014), **Guidelines for resilience systems analysis**, *OECD Publishing*.
- OECD*, (2021a), Input-Output Tables. Available at:
<https://www.OECD.org/sti/ind/input-outputtables.htm>
- OECD* (2021b), **Strengthening Economic Resilience Following the COVID-19 Crisis: A Firm and Industry Perspective**, *OECD Publishing*, Paris.
- Pant, R., Barker, K., and Zobel, C. (2014), “Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors”, *Reliability Engineering and System Safety*, 125, pp. 92–102.
- Pichler, A., and Farmer, J. D. (2022). “Simultaneous supply and demand constraints in input–output networks: the case of Covid-19 in Germany, Italy, and Spain”. *Economic Systems Research*, 34, pp. 273-293.
- Rose, A. and Liao, S. (2005), “Modeling regional economic resilience to disasters. A computable general equilibrium analysis of water services disruptions”, *Journal of Regional Science*, 45(1), pp. 75-112.
- Rose, A. (2004), “Defining and measuring economic resilience to disasters”, *Disaster Prevention and Management*, 13(4), pp. 307-314.

- Rose, A. (2007), “Economic resilience to natural and man-made disasters: multidisciplinary origins and contextual dimensions”, *Environmental Hazard*, 7, pp. 383-398.
- Rose, A. (2009), “Economic Resilience to Disasters”, *Published Articles & Papers*, 75, *CARRI Research Report 8*.
- Serfilippi, E, and Ramnath, G. (2018), “Resilience measurement and conceptual frameworks: a review of the literature”, *Annals of Public and Cooperative Economics*, 89, pp. 645-664.
- Shoven, J. B., and Whalley, J. (1984). “Applied general-equilibrium models of taxation and international trade: an introduction and survey”. *Journal of Economic literature*, 22, pp. 1007-1051.
- Temel, T., and Phumpiu, P. (2021). “Pathways to recovery from COVID-19: characterizing input–output linkages of a targeted sector”. *Journal of Economic Structures*, 10, pp.29.
- Tierney, K., (1997), “Impacts of recent disasters on businesses: the 1993 midwest floods and the 1994 Northridge Earthquake”, in Jones, B. (Ed.), *Economic Consequences of Earthquakes: Preparing for the Unexpected*. **National Center for Earthquake Engineering Research**, Buffalo, NY, pp. 189–222.
- Trump, B. T., Linkov, I. and Hynes, W. (2020), “Combine efficiency and resilience in post-COVID societies”, *Nature* 588, 220.
- Walmsley, T., Rose, A., John, R., Wei, D., Hlávka, J. P., Machado, J., and Byrd, K. (2023). “Macroeconomic consequences of the COVID-19 pandemic”. *Economic Modelling*, 120, pp. 106147.
- Wu, F., Liu, G., Guo, N., Li, Z., and Deng, X. (2021). “The impact of COVID-19 on China’s regional economies and industries”. *Journal of Geographical Sciences*, 31, pp. 565-583.

Appendix 1: Supply-induced Resilience Indicators.

Suppose a shock of magnitude $\delta_k^x < 0$ falls on the gross output of industry k . We can calculate the countervailing values $\delta_i^x > 0$ for $i \neq k$ that would keep aggregate value-added, or GDP , at least at the initial level with the least deviation from the initial final demand pattern. We first define the neutral scaling:

$$\begin{cases} \delta_i^x = \delta_k^x & (i = k) \\ \delta_i^x = -\delta_k^x \cdot \frac{x_i}{\sum_{j \neq k} x_j} & (i \neq k) \end{cases} \quad (A1)$$

As in the case of the demand-induced resilience indicator, the changes in gross output also fulfill the following condition:

$$\sum_{i=1}^n \delta_i^x = \delta_k^x + \sum_{i \neq k} \left(-\delta_k^x \cdot \frac{x_i}{\sum_{j \neq k} x_j} \right) = \delta_k^x - \delta_k^x \cdot \left(\frac{\sum_{i \neq k} x_i}{\sum_{j \neq k} x_j} \right) = 0 \quad (A2)$$

Hence, the restricted output induced multiplier reads as:

$$\hat{\mu}_k^x(\delta_k^x) = \mu_k^x(\delta_k^x) + \sum_{i=1}^n \sum_{j \neq k} \delta_i^x \cdot (1 - a_{ij}) \quad (A3)$$

For the case of the supply-induced resilience index, given a negative shock δ_k^x find the re-scaling value ρ_k^x that solves the linear programming problem:

$$\begin{cases} \text{Min } \rho_k^x \text{ subject to} \\ \tilde{x}_i = x_i + \delta_i^x \\ \tilde{y}_i = \tilde{x}_i - \sum_{j=1}^n a_{ij} \cdot \tilde{x}_j \\ \sum_{i=1}^n y_i = \sum_{i=1}^n v_i \cdot x_i \leq \sum_{i=1}^n v_i \cdot \tilde{x}_i = \sum_{i=1}^n \tilde{y}_i \\ \tilde{\delta}_i^x = \delta_k^x \text{ if } i = k \text{ and } \tilde{\delta}_i^x = \rho_k^x \cdot -\delta_k^x \cdot \frac{x_i}{\sum_{j \neq k} x_j} \text{ if } i \neq k \end{cases} \quad (A4)$$

Therefore, similarly to the interpretation of the net demand resilience coefficient, the most resilient industry sector from a supply side perspective would be then the one that presents the highest positive net supply resilience coefficient $1 - \rho_k^x$.

Appendix 2: Industry Classification *OECD* Input-Output Tables

Industry-Code	ISIC 4 Division	Industry Description
N_1	01, 02	Agriculture, hunting, forestry
N_2	3	Fishing and aquaculture
N_3	05, 06	Mining and quarrying, energy producing products
N_4	07, 08	Mining and quarrying, non-energy producing products
N_5	9	Mining support service activities
N_6	10, 11, 12	Food products, beverages, and tobacco
N_7	13, 14, 15	Textiles, textile products, leather, and footwear
N_8	16	Wood and products of wood and cork
N_9	17, 18	Paper products and printing
N_10	19	Coke and refined petroleum products
N_11	20	Chemical and chemical products
N_12	21	Pharmaceuticals, medicinal chemical, and botanical products
N_13	22	Rubber and plastics products
N_14	23	Other non-metallic mineral products
N_15	24	Basic metals
N_16	25	Fabricated metal products
N_17	26	Computer, electronic and optical equipment
N_18	27	Electrical equipment
N_19	28	Machinery and equipment, nec
N_20	29	Motor vehicles, trailers, and semi-trailers
N_21	30	Other transport equipment
N_22	31, 32, 33	Manufacturing nec; repair and installation of machinery and
N_23	35	Electricity, gas, steam, and air conditioning supply
N_24	36, 37, 38, 39	Water supply; sewerage, waste management and remediation activities
N_25	41, 42, 43	Construction
N_26	45, 46, 47	Wholesale and retail trade; repair of motor vehicles
N_27	49	Land transport and transport via pipelines
N_28	50	Water transport
N_29	51	Air transport
N_30	52	Warehousing and support activities for transportation
N_31	53	Postal and courier activities
N_32	55, 56	Accommodation and food service activities
N_33	58, 59, 60	Publishing, audiovisual and broadcasting activities
N_34	61	Telecommunications
N_35	62, 63	IT and other information services
N_36	64, 65, 66	Financial and insurance activities

N_37	68	Real estate activities
N_38	69 to 75	Professional, scientific, and technical activities
N_39	77 to 82	Administrative and support services
N_40	84	Public administration and defense; compulsory social security
N_41	85	Education
N_42	86, 87, 88	Human health and social work activities
N_43	90, 91, 92, 93	Arts, entertainment, and recreation
N_44	94, 95, 96, 97, 98	Other services activities, activities of households as employers; undifferentiated goods and services production activities of households for own use