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Measuring structural resilience of economies Globalization or deglobalization?

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Abstract

The discussion about the role and effects of international trade has begun to intensify recently. On the one hand, we know that specialization and participation in the international division of labor results in more efficient production structures that bring welfare gains. On the other hand, the resulting strong interconnectedness of countries allows for rapid spread of shocks and a more volatile and vulnerable system. Overall, neither full self-sufficiency nor an extremely globalized production structure seems to be sustainable nowadays. However, the responsiveness of countries to shocks might depend on the resilience of the countries. A system's (economy's) level of resilience derives from two structural properties: redundancy and efficiency. An efficient system has only a few mutual relationships, which indicates strong specialized trade flows and corresponds to highly globalized production processes of a country. In contrast, a redundant system has many more similarly weak connections signaling a less specialized and embedded position of elements within the system, corresponding to a lower level of involvement within the international division of labor. While it is clear that extreme efficiency and extreme redundancy are not optimal arrangements, finding the optimal combination in between is challenging. Putting this framework of system resilience into international trade and production networks, may indicate the optimal trade-off between self-sufficiency (more redundant systems) and specialization within international trade (more efficient systems). In this paper we use methods from Ecological Network Analysis (ENA) to capture the countries' structural resilience building on sector level input-output data. The cross-country analysis shows that countries are heterogeneous in terms of resilience, and the structure of the countries has become more effective and globalized between 2000 and 2014. Using econometrics tools, we find a strong and significant association between redundancy/efficiency and the level of international trade, confirming the use of the complex system perspective in international trade. Finally, we also examine the countries' level of self-organization and the window of vitality in terms of resilience.

Keywords: resilience, economic structure, input-output economies, globalization, deglobalization

1 Introduction

In recent years, debates related to international trade and global value chains have intensified in the economic literature. Seeking efficiency in production processes, economies have specialized and elements of the production process have been relocated over borders. As a result, the role of intermediate goods in trade (Johnson and Noguera, 2012; Baldwin and Lopez-Gonzalez, 2015) and the length of the global value chains (Wang et al., 2017) has increased. From a structural perspective, international economic relationships and global value chains have become a complex system, and economies have shifted towards globalization.

Although international trade increases the efficiency of production activities, the high level of interconnectedness between countries goes hand in hand with the rapid spread of shocks (Fang et al., 2020; Iloskics et al., 2021) in which the structural properties of international linkages have a huge impact (Barrot et al., 2020; Guan et al., 2020). In the case of a crisis, like the lockdowns triggered by COVID-19, the exposure to foreign trade relations carries a high risk (Barrot et al., 2020; Bonadio et al., 2021; Fang et al., 2020; Guan et al., 2020) and the need for self-sufficiency increases (Barbieri et al., 2020; Braun et al., 2021). In addition to the cross-border spread of shocks, the intention to reduce international trade has recently been seen for political reasons, such as Brexit or the US-China trade war.

However, these studies show that Brexit has a negative impact not only on the welfare of Great Britain but also on the member states of the European Union (Dhingra et al., 2017; Giammetti, 2020; Giammetti et al., 2020). Moreover, a similar pattern emerges in the case of the US-China trade war. The two countries raised tariffs on certain products, which increased prices and reduced their welfare (Balistreri et al., 2018; Li et al., 2018; Redding et al., 2019; Itakura, 2020), and cause losses to third countries indirectly through global supply chains (Mao and Görg, 2020; Wu et al., 2021). More generally, modelling the effect of rising tariffs show that the cost of protectionism is considerable (Ossa, 2014). On the other hand, backshoring, nearshoring (Piatanesi and Arauzo-Carod, 2019; Barbieri et al., 2020) or 'renationalization' (Barrot et al., 2020) do not necessarily make economies less vulnerable because this restructuring of production networks can lead to more fluctuations arising from domestic shocks or lockdowns (Barrot et al., 2020).

It can be seen from the agenda above that there is a trade-off between self-sufficiency and highly globalized international trade. Self-sufficiency seems to be a less efficient economic structure, where the benefits of international division of labor cannot be realized, but exposure to global value chains, hence the risk of shock contagion is lower. The other side of the coin is that highly globalized international trade provides a more efficient way of organizing production processes and generates higher welfare, but due to the high level of global interconnectedness, economic shocks spread between countries more easily resulting in stronger fluctuations in economic activity. The question may arise: is there an optimal level of international trade for the countries.

To find the answers, it is worth starting from the assumption that the responsiveness of countries to shocks is linked to the economic resilience of the countries. Resilience, in other words, could mean the ability to react to shocks (Reggiani et al., 2002), and it can be defined more precisely as 'The ability to resist and respond to a shock (internal or external) and recover once it has occurred ...' (Annarelli and Nonino (2016) p. 2.). The reaction, therefore, means adaptation to the new environment, in this case, adaptation to an economic shock or crisis. One of the most significant contributions to resilience research is Ecological Network Analysis (ENA). Applying the methods of ENA to examine the structure of global value chains/production networks (Alves et al., 2019; Braun et al., 2021) or resilience (Kharrazi et al., 2013; Chatterjee and Layton, 2020) is not without precedent in the literature.

In our study, we measure the resilience of an economic system (described with its input-output or production network) with the method developed by Ulanowicz et al. (2009). In this method, a system's (economy's) resilience level derives from two structural properties: efficiency and redundancy. Neither complete efficiency nor complete redundancy is an optimal arrangement, but the latter can be found somewhere in between, in a system structure which shows some redundancy and efficency at the same time. If there is a lack of strong relationships between the system elements, or in other words the links are similarly weak, the system is very redundant showing a low level of resilience. On the contrary, if the system is firmly bound by mutual strong relationships, i.e. some connections are extremely strong while others are extremely weak, the system is said to be efficient, but at the same time it provides less place for change, adaptation, so it is also not too resilient.

In case of an economic system, an effective structure emerges when countries specialize and participate intensively in the international division of labor. In this case only few steps of production processes are carried out within the country, focusing on the production of a small set of input and output products. This will lead to a production or input-output network structure which is dominated by a few strong mutual connections within the domestic sectors together with large external trade flows of the specialized products. This is the description of a highly globalized economy. On the other hand, if the country steps back in the degree to which it is involved in the international division of labor (these situations are exemplified, with different reasons or sources, by the case of COVID, the US-China trade war, or the Brexit), then it produces much more products within its borders, within its domestic production network and the connections between the production system become less asymmetric and more redundant. This type of structure is expected to be more self-sufficient, with the capability of producing more goods and services within borders.

This paper has threefold objectives. First, using empirical data on the structure of production networks, we can determine the observational optimum within the trade-off between efficiency and redundancy assuming that countries ar resilient *on average*, given the current global economic environment. This observational optimum is calculated from the WIOD database, using the ENA methodology. The second objective is to show the connection between a country's position on the redundancy/efficiency scale and the self-sufficiency/globalized scale. The third is to determine the optimal level of self-organization in terms of resilience. In our previous paper (Braun et al., 2021), we have already calculated and analyzed the self-organization level of countries according to the ENA methodology, but this was not connected to the countries' resilience level in that paper.

The study is structured as follows. After the Introduction, we present how the sectoral input-output network of countries is built and how the resilience of countries can be determined according to ENA in section Methods. In this section, we also introduce the formula of self-organization and two other structural properties, related to resilience: the number of roles and the level of connectivity. Then we provide a brief overview of the applied data. In section Results, we first show the resilience of countries and its dynamics over time. Second, we analyze the number of roles and the connectivity of the countries, and third, we reveal the connection between structural properties (redundancy and efficiency) and the level of international trade. Fourth, we analyze the effect of self-organization on resilience. Then, based on the empirical results, in the discussion part we draw some policy implications from the results. Finally, a conclusion closes the paper.

2 Methods

In this section, we briefly describe the method applied in the measurement of structural economic resilience, self-organization as well as the roles and connectivity in production networks. These methods are borrowed from ecological network analysis (ENA) and builds on the input-output network (production network) of economies to describe the structure of relationships within the economic system.

2.1 The IO network

While in ecological systems the flow of energy among different species can be placed in the focus of analysis, in economic systems it is the flow of goods and services or similarly, the flow of value among economic agents constitute the key connections to be analyzed. Also, data on these input-output relationships are

	t_1	t_2	...	t_i	E_i	O_i
t_1	$t_{1,1}$	$t_{2,2}$	...	$t_{i,1}$	e_1	o_1
t_2	$t_{1,2}$	$t_{2,2}$	...	$t_{i,2}$	e_2	o_2
...	...	...	...	...	...	...
t_j	$t_{1,j}$	$t_{2,j}$	...	$t_{i,j}$	e_j	o_j
M_j	m_1	m_2	...	m_j	0	0
I_j	I_1	I_2	...	I_j	0	0

Figure 1: The representation of the IO system

Notation: In the IO system, t_i represent the sector t where $i, j = 1, 2, ...t$. The export flow of sector t_i is E_i, the other output is O_i, the import is M_i, and the other input is I_i.

relatively widely available providing a promising area to adapt tools from ecology into economic systems.

The starting point in this respect is the flow of goods and services or the value of transactions between any two economic sectors i and j, measured by T_{ij}. These values are rendered in an input-output table whose rows and columns are the economic sectors and an entry reflects the flow of goods and services from sector i (rows) to sector j (columns). Similar to ecological systems, the elements of economic systems also have other types of relationships. On the one hand, the sectors use imported inputs and other inputs to production. On the other hand, they can export abroad and sell their products to final users. For this reason, the number of elements in this system is $n + 2$ where n denotes the number of sectors $(i, j = 1, 2, ...n)$. From the input side, the two other elements are the imported inputs (M_j) and the other inputs I_j while these are the exported goods (E_i) and other output (O_i) from the output side. The structure of this system is shown in Figure 1.

Row sums $T_{i.} = \sum_j^{n+2} T_{ij}$ of this table represent the total output of every sector that leaves the system (the national economy), or in other terms the total demand for this output. Column sums $T_{.j} = \sum_i^{n+2} T_{ij}$ represent the total input which is used by sector j from outside the system. We define total system throughput as the sum of all entries in the table: $TST = \sum_{ij}^{n+2} T_{ij}$.

Dividing the value of every entry by the total throughput, we obtain the relative importance or probability of the connections in the IO network: $p_{ij} = T_{ij}/T$. In economic terms, this can be interpreted as a probability of one dollar transaction being observed between any pairs of sectors i and j.

To measure the countries' level of international trade, we use the method described by Braun et al. (2021):

$$Z = \sum_{i}^{n} \frac{T_{.i}}{\sum_{i}^{n} T_{.i}} \frac{M_i}{T_{.i}} \tag{1}$$

where Z reflects economic openness, calculated as the weighted average of sector-level input shares. Weights are the relative importance of sectors in total output, while import shares reflect the share of imported goods and services within total sectoral inputs.

2.2 Measuring structural resilience

In this subsection, we derive a system's resilience as described in Ulanowicz et al. (2009). Using the connection-level probabilities, we can determine the entropy of the system as

$$H = -k \sum_{ij} p_{ij} \log(p_{ij}). \tag{2}$$

According to information theory, this reflects the overall surprise associated with the flows occurring within the system. In a very structured system where a few strong links serve as the key backbones to the system, surprise is not present, as all transactions are easily predictable. On the contrary, if the system is based on a diverse set of possibly redundant relationships, surprise is large. The term $s_{ij} = -k \log(p_{ij})$ account for the surprise inherent in the connection between i and j: the stronger the connection (the larger p_{ij}), the smaller the surprise associated with it. Then, these connection-specific surprise values are weighted by their 'presence' (p_{ij}) in the system to get H. According to ENA (Shannon, 1948; Ulanowicz et al., 2009), the value H refers to the (flow) capacity of the system, given by its actual structure.

While the term H is useful in describing the capacity of a system, we also have to take into account that the relative size of the system elements determine this capacity at least partly, or in other terms, it pins down part of the probabilities at which transactions are observed in specific relationships. In concrete, we can define the expected probability of a transaction from sector i to sector j as the product of the unconditional probabilities that a transaction starts from sector i and ends in sector j. These unconditional probabilities are the row- and column sums of the probability matrix: $p_{i.} = \sum_j p_{ij}$ and $p_{.j} = \sum_i p_{ij}$. The expected probability of the transaction on (i, j) is thus $p_{ij}^{exp} = p_{i.} p_{.j}$. This works as an expected value for the transaction, determined by the size of the nodes i and j in the system. One expects more transaction between large nodes than between small ones, where the row- and column sums of the input output table T_{ij} and the probability matrix p_{ij} are high and low respectively.

Defining the surprise associated with a given transaction as before, we label the difference between actual and expected surprise as

$$u_{ij}^s = s_{ij} - s_{ij}^{exp} = -k \log \left(\frac{p_{ij}}{p_{i.}p_{.j}} \right). \tag{3}$$

In other terms, u_{ij}^s provides a quantification of the surprise that comes from observing a transaction between i and j, *relative to* the surprise which is natural or logical from the pure size of the nodes i and j. In economic terms, observing a few transactions between two large sectors is not that surprising as finding the same amount of transactions between two small sectors of the economy. Putting it more simply, a high u_{ij}^s reflects a stronger relationship than expected (the term in the denominator), weighted by the strength of the connection itself (nominator).

As with total system capacity H, the relationship-specific measures of structure above can be aggregated over the whole system as

$$U = \sum_{ij} p_{ij} u_{ij}^s. \tag{4}$$

This value reflects the overall control over the system: the larger U, the more transactions/connections are concentrated to a few strong links which are larger than expected according to the size of the sectors.

The values H and U refer to the total capacity and the cohesion level (already bounded part) of the system respectively. These values are then used to capture resilience at the system level, as determined by the structure of connections between system elements.

Dividing U with H, we get a measure, which describes the extent to which the system is structurally bounded:

$$\alpha = \frac{U}{H}. \tag{5}$$

This α is going to be a key element in measuring structural resilience. The higher is α, the more structurally bounded and hence, more efficient the system is: it is characterized by a few specialized sectors and a few strong connections among them. As α gets smaller, redundancy or diversity increases in the system. The theoretical and empirical challenge is to determine the α value associated with the most resilient system structure. Clearly, it lies somewhere between the most efficient and structurally bounded ($\alpha = 1$) and most redundant and structurally diverse ($\alpha = 0$) systems. To get the optimal value of α, Ulanowicz et al. (2009) defines the Fitness for Evolution (F) as

$$F = -k\alpha \ln \alpha. \tag{6}$$

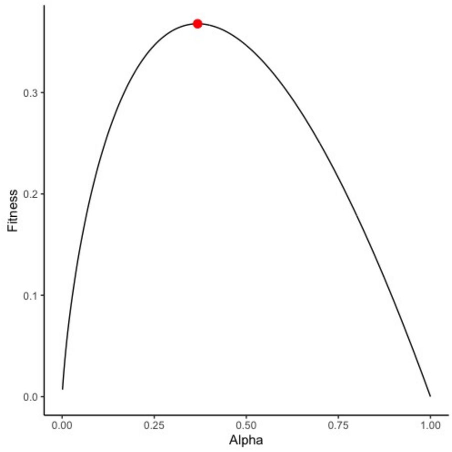

Figure 2: The possible Fitness for Evaluation values of a system, as a function of α

Notation: The black curve represent α values on the horizontal axis and the corresponding fitness values according to Eq 6. The green dot denotes the ecological optimum where $\alpha = 1/e$ and $F = 1/e$.

This formulation comes from the observation that in mature ecosystems, which can be assumed around optimally resilient, α values are found to be around $1/e$. The formula for F takes its maximum value at $\alpha = 1/e$, as shown in Figure 2. In this paper, the α value is called the resilience indicator while the level of a system's resilience is measured by F, called fitness indicator. As this optimum is based on observations about ecological systems, we define the ecological optimum as $\alpha^*_{eco} = 1/e$, and the corresponding ecological optimum fitness as $F^*_{eco} = 1/e$, given that $k = 1$. If we use the transformation of F as

$$\hat{F} = -e\alpha^{\beta} \ln \alpha\beta \tag{7}$$

with $\beta = 1/ln(\alpha)$, $\hat{F}$ will be bounded between 0 and 1, with $\hat{F} = 1$ at $\alpha^*_{eco} = 1/e$. Using this form and the empirical value of a system's α, we can calculate the normalized level of the system's fitness.

2.3 The window of vitality

A system's structure can be described by two other system metrics: roles and connectivity (Zorach and Ulanowicz, 2003). The number of roles (R) shows how many different functions the sectors have (also referred to as the 'depth' of the system), while the connectivity (C) shows the average value of flows into or out of a sector (the 'breadth' of the system). The weighted form of these metrics can be determined as (Ulanowicz et al., 2014)

$$C = \prod_{i,j} \left(\frac{\sqrt{p_{i.}p_{.j}}}{p_{ij}} \right)^{p_{ij}} \tag{8}$$

$$R = \prod_{i,j} \left(\frac{p_{ij}}{p_{i.}p_{.j}} \right)^{p_{ij}}. \tag{9}$$

The Window of Vitality refers to the neighborhood of the optimal point in Figure 2. Just as the resilience indicator (α) and the corresponding fitness values (F, $\hat{F}$), C and R are functions of the structure of the system, described by the p_{ij} values. It follows that roles and connectivity can also be used to describe a system's closeness to the optimal structure (Ulanowicz et al., 2014). Randomly 'wired' systems show an even distribution of the latter two indicators, while well-operating ecological systems confine themselves to the range between 1 to 3.25 in terms of connections (C) and between 2 to 5 in terms of roles (R).

2.4 Self-organization

A further important structural characteristic of an input-output system is the extent to which it can organize itself, rely on inner connections or how strong the feedbacks are within the system. We capture the level of self-organization with the method developed by Finn (1976). The Finn cycling index computes the power of internal circulation in an input-output system. It quantifies how many times an average unit flows through the system before it leaves it. Using the Leontief-inverse, the sectoral level of self-organization (FCI_i) can be defined as

$$\mathbf{L} = (\mathbf{I} - \mathbf{T})^{-1} \tag{10}$$

$$\hat{l}_i = \frac{l_{ii} - 1}{l_{ii}} \tag{11}$$

$$FCI_i = \hat{l}_i \frac{T_{.i}}{\sum_i^n T_{.i}} \tag{12}$$

where $\mathbf{I}$ is the identity matrix and l_{ii} is the ith diagonal element of $\mathbf{L}$. Similar to openness, the country level of self-organization is the sum of sectoral values

$$FCI = \sum_i^n FCI_i. \tag{13}$$

3 Data

All the measures and indicators introduced so far are going to be used in the context of input-output systems, as described in Figure 1. The empirical basis for this is data from the World Input-Output Database (2016 release) (Dietzenbacher et al., 2013; Timmer et al., 2015), that provides sector-level information on within-country and between-country flows of economic transactions. The WIOD database contains data between 2000-2014 for 43 countries, with 56 sectors in each country. The structural indicators can be calculated from the 56x56 input-output tables given for every national economy. As a result, we work with separate networks for every economy in every year, with these networks describing the input-output connections of the given economy. First pairwise connections are taken into account between every economic sector, and exports, imports as well as other outputs and inputs are considered in the network to have a complete representation of the economic structure of the countries.

Other macroeconomic variables (GDP, employment and capital) are also used in order to refine the results. The source of this data series is the Penn World Table (9.1 release) (Feenstra et al., 2015).

4 Results

In this section, we first describe the structural resilience of the countries and its dynamics, based on the resilience indicator and the fitness values. Then, we examine the roles and connectivities of these economic systems. In the third step, we test the connection between the resilience indicator and the level of international trade, and finally, we reveal the effect of self-organization on resilience.

4.1 The structural resilience of the IO economies

In the first step, the α values were calculated according to Eq 5 for every country and for every year in the dataset, together with the corresponding fitness indicators (F), as in Eq 6. Figure 3 visualizes the main observations arising from these calculations, with respect to how countries are located along the redundancy/efficiency scale (α), how this relates to their fitness (according to α^*_{eco}), and how the dynamics of these characteristics look like.

Panel a) of Figure 3 represents the final year of the dataset, 2014. The blue dots correspond to countries in the sample and their 2014 resilience indicator values are measured on the horizontal axis, while the vertical axis show the respective fitness values. The red point denotes the optimal α and F values observed for ecological systems (α^*_{eco} and F^*_{eco} respectively). The purple point shows the most frequent α and F values observed in the sample countries for 2014 (see panel b) for details). The most important observation is that the economies in our sample are found within a relatively small range of the alpha values, showing a relatively similar level of the resilience indicator α and fitness F. These values group to the left of the ecological optimum, indicating that these economic systems are more redundant than ecological systems. This finding is consistent with previous literature in this field (Kharrazi et al., 2013). Fath (2015) has identified two reasons for this observation: one is that economic data collection is not that accurate and this type of input-output data is not available for a wide range of economies and the other is that economic networks are larger networks, with more nodes (depending on the level of analysis) than the typical ecological system.

We emphasize additional possible reasons for this relatively high redundancy of economic systems. First of all, the cost and time of transportation are still considerable in the 21st century. There are many products and services which is produced spatially close to its consumption. Second, due to national security reasons, for example, in the case of food and energy supply, countries support some economic activities even though comparative advantage lies elsewhere. Third, international trade is hindered by tariffs and other political reasons, such as in the case of Brexit or the US-China trade war. Although this list is far from being exhaustive, but it provides some examples why the redundancy of sectors in the sector-level IO structure is high.

Especially on the basis of the arguments above, one may infer that the optimal α values observed for ecological systems may not be adequate for economic systems. Along this line, we determine the 'optimal' α value in another way: we assume that most countries have a close to optimal economic structure, given the actual technological framework of the global economy. This calls for a definition of optimal structure which coincides the most frequent setup observed within our sample. Although this solution seems tautological at the first sight, we must note that the same principle lies behind the definition of the ecological optimum, α^*_{eco} and F^*_{eco}.

Technically, we fit an empirical density function to the histogram of the observed α values and then calculate the maximum point of this density function and label it as the 'empirical optimum'. The location of this maximum point is denoted with α^*_{emp} while the maximum fitness value is F^*_{emp}. This histogram and density function, together with the maximum point are shown on panel b) of Figure 3 (the purple point representing the optimal point). This point is also marked in panel a) with purple. While panel b) shows the empirical α values and the corresponding density function for 2014, panels c) and d) show the dynamics of these indicators over the whole sample period between 2000 and 2014. These visualizations show that the countries have gradually but steadily become more efficient over time

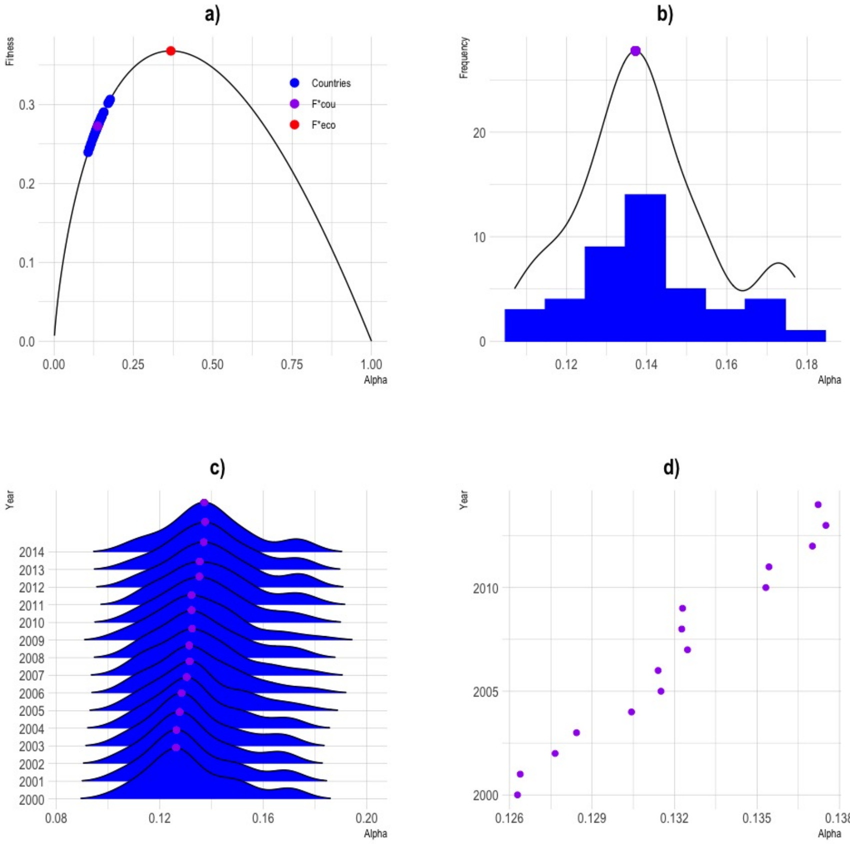

Figure 3: Structural resilience of the countries

Notation: Figure a) shows the empirical fitness values (F) values of the countries by blue points in 2014. The purple point is the empirical, the red is the ecological optimum. Figure b) represent a histogram and density function by the empirical α values in 2014 where the maximum point of the density function is the empirical optimum, denoted by purple point. In Figure c the annual density functions and their maximum values are shown together with the empirical α values. Figure d) also depicts the empirical optimum of α values separately.

along the α scale. This development moved economies closer towards the ecological optimum on average. The background of this may be that trade barriers, for example, the cost of transportation, have decreased between 2000 and 2014, while the global economy went through a relatively steady globalization period over this period of time which rendered production networks more efficient and less reliant on within-country feedbacks and supply chains. Also, panel d) reflects a temporary stagnation in this process around the financial crisis in 2008 and 2009. In the following analysis, we use the latter empirical optimum values to derive the level of resilience for the countries in our sample. In the discussion section we will present the resilience of the countries.

4.2 Roles and connectivities - window of vitality

Based on the ecological optimum value of alpha (α^*_{eco}), Ulanowicz et al. (2014) define roles and connectivites as mentioned in section 2.3, together with the connection between them as $C = R^{(1-\alpha^*_{eco})/(2\alpha^*_{eco})}$. Using this relationship and α^*_{eco}, we can determine the values of role (R) corresponding to different values of connectivity (C) in order to reach the maximum level of resilience. These combinations of C and R values are described in panel a) of Figure 4 by the black line. As we described earlier, well-operating ecological systems have a connectivity score between 1 and 3.25, while roles tend to be found between 2 and 5. These values provide the limits for the Window of Vitality (see the square on Figure 4). The blue points represent the empirical values of the two indicators for the sectoral IO economies, based on data for 2014. The results show that countries are reaching the lower limit for the role range (horizontal axis), but lay far above the upper limit for connectivity. This means that domestic trade flows of the countries are larger than necessary for this ecology-based measure of resilience. This result is in line with the previous observation in Figure 3, where it was shown that observed economic systems are more redundant than ecological systems.

The dynamics of the role and connectivity indicators are represented in panel b) and c) of Figure 4 respectively. These images indicate that the number of roles has increased while the level of connectivity has decreased in general, apart from the last two years of the sample. Also, the financial crisis in 2008 and 2009 is visible in the case of roles: there is a sudden drop in that year. These observations mark a gradual approach towards the ecological optimum of system resilience for the observed economies.

4.3 Globalization and deglobalization

One of the key motivations behind this study is to reveal the connection between the level of integration into the global production networks and the extent to

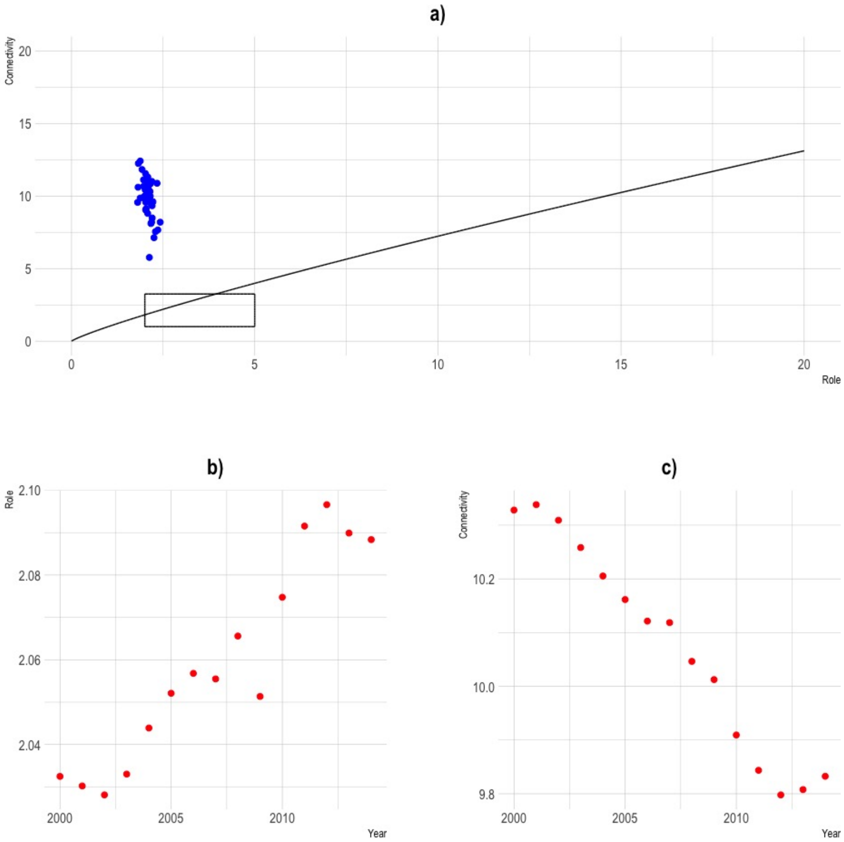

Figure 4: Window of Vitality, the optimal combination of role and connectivity and the empirical values of the countries (2014)

Notation: The figure a) plots the countries by their role R and connectivity C together with the Window of Vitality in 2014. The figure b) shows the change of the roles in time while figure c) the change of connectivities for the whole period.

which countries show resilient properties. So far, we discussed a method and some descriptive results for the latter, i.e. the resilience of national economies based on empirical solutions borrowed from ecological network analysis – this is the resilience indicator α. Also, we have defined the openness measure (Z) based on the input-output data in section 2.1. Practically, we search for the connection between α, a primary measure of resilience and Z, the economic openness of a country.

As a first step in this search, we calculate the correlation coefficient which is found to be 0.58 for the whole examined period (pooled sample). In order to obtain more detailed and robust results, we employ the panel nature of the data at hand and estimate different setups of fixed effects panel models with country and time fixed effects, while also controlling for macroeconomic factors such as GDP per capita, the level of employment, and the size of the capital stock. The results of these estimations with different model versions are found in Table 1, placed in the Appendix. The results from these estimations show that the positive connection between the resilience indicator (α) and economic openness (Z) is robust. This result suggests that by pointing to resilient systems along the α axis, we can also capture an optimal level of international trade.

4.4 The optimal level of self-organization

In a previous study (Braun et al., 2021), we have thoroughly examined the countries' Finn cycling index (as defined in section 2.4), but haven't determined any desirable level of this index in terms of economic resilience. In the first step, we calculated the FCI as in Equation 13 for every country and year. Then, these values were put into a panel regression model with country and year fixed effects, with the dependent variable being the economies' normalized fitness value, $\hat{F}$.

The results of these panel estimations are summarized in Table 2, placed in the Appendix. The findings suggest that there is a significant inverted U-shaped relationship between resilience ($\hat{F}$) and the cycling index (FCI) as shown in Table 2. It indicates that neither a high nor a low level of self-organization is optimal in terms of resilience. In the case of high self-organization, the sectors rely on high amounts for domestic inputs directly and indirectly, and the shocks can more easily spread within the system. The level of self-organization is low, the spread of shock will be smaller, and the exposure to foreign relationships will be higher. It is important to note that the Finn cycling index takes into account indirect and mutual links between the elements (feedbacks). Using the coefficients of model Panel B5, we can calculate the optimal level of self-organization in terms of resilience. The inverted U relationships, the countries' values and the optimum (0.107, green point) can be seen in Figure 5. In the next section, we describe some ways how countries can increase their resilience by the change of openness and cycling index.

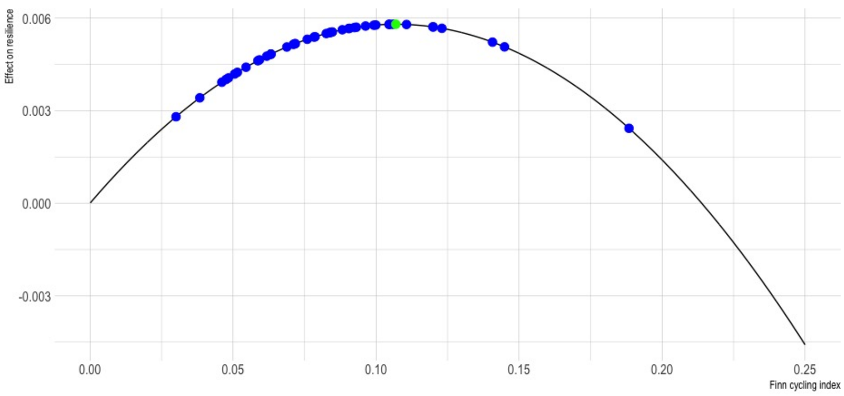

Figure 5: The effect of the Finn cycling index on resilience (2014)

Notation: Using the coefficients of the panel model B5, Figure 5 shows the estimated values of the resilience indicator (α) by the black curve. The blue points are the empirical cycling indexes while the green point shows the maximum impact of the cycling index on resilience.

5 Discussion, policy implications

The main goal of this study is to find an optimum between self-sufficiency and highly globalized international trade in terms of resilience. Based on data from the latest available year (2014), this section shows which countries are far away from this optimum and in which direction, and finally, what these countries might do to get closer to a more resilient structure.

We start this analysis by the resilience indicator and the level of resilience in Figure 6. Panel a) of this figure ranks the countries by the difference between the empirical optimum α^*_{emp} and the individual, observed α values. The largest negative values mean that the countries, such as Romania, Poland, or the USA, have a more redundant structure compared to the optimum. The largest positive values show that the countries, such as Luxembourg, Cyprus, Taiwan, Malta and Ireland, have a very effective structure. Belgium is really close to the optimum which means that Belgium is the most resilient country in this sample. Panel b) of Figure 6 ranks the countries by normalized fitness ($\hat{F}$). This ranking shows that in addition to Belgium, Switzerland, India, Norway and the Czech Republic are also among the most resilient countries. However, countries with very redundant or effective structures are found at the end of the ranking.

We can also rank the countries in terms of self-organization. Figure 5 shows the countries' positions relative to the empirical optimum. Figure 7 also ranks countries in two other ways. Panel a) depicts the deviations from the estimated optimum of 0.107 (see Figure 5). The largest negative values suggest that the

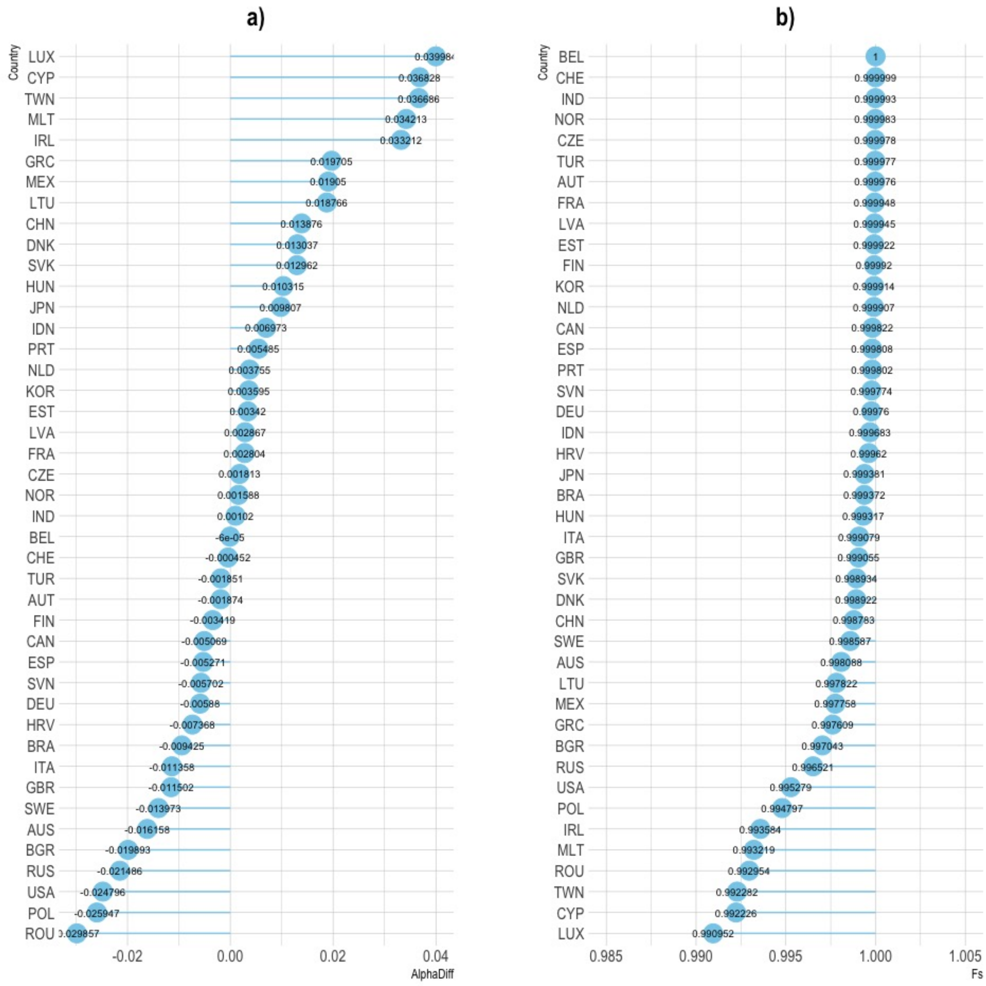

Figure 6: Countries' redundancy and efficiency (2014)

Notation: The figure a) ranks the countries by the difference of the empirical optimum of α and the empirical α of a country. The figure b) ranks the countries by a the fitness of evaluation $\hat{F}$.

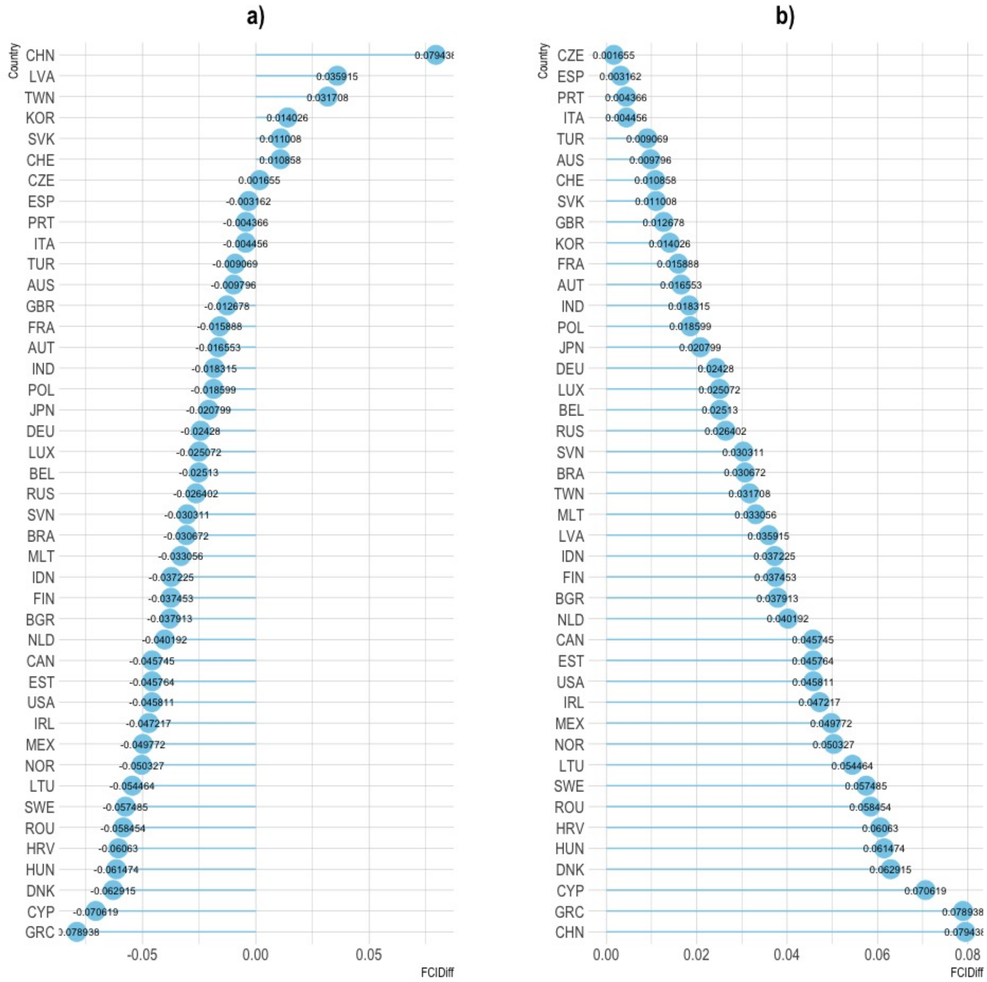

Figure 7: The level of countries' self-organization (2014)

Notation: The figure a) ranks the countries by the deviation from optimal Finn cycling index which is optimal Finn cycling index in terms of resilience minus empirical FCI of a country. The figure b) ranks the countries by these deviations in absolute values.

level of self-organization is higher than necessary from a resilience point of view, for example, in the case of Greece, Cyprus, Denmark, or Hungary. The largest positive values show that these countries have low self-organization levels, such as China, Latvia, or Taiwan. Panel b) of Figure 7 ranks the countries according to the deviation from the optimum, independently of the direction of this deviation. In terms of resilience, Czech Republic, Spain, Italy, and France are close to the optimal of self-organization.

The resilience can be increased in two ways. On the one hand, through the level of international trade, and on the other hand, through the level of self-organization. We plot the countries by their α value (vertical axis) and Finn cycling index (horizontal axis) in Figure 8. The purple line shows the empirical optimum of redundancy/efficiency, while the green line indicates the optimal level of self-organization. These lines separate 4 different areas, while the optimal structure is found at the intersection of the two colored lines. Countries in the upper left area (e.g. Cyprus, Ireland, or Greece), should decrease their openness and increase self-organization. It is important to note that, there is a negative connection between self-organization and openness, therefore, when a country decreases its openness, in parallel, it also raises the level of self-organization. Overall, for these countries, it seems to be a straightforward strategy to move the best - and easy - strategy.

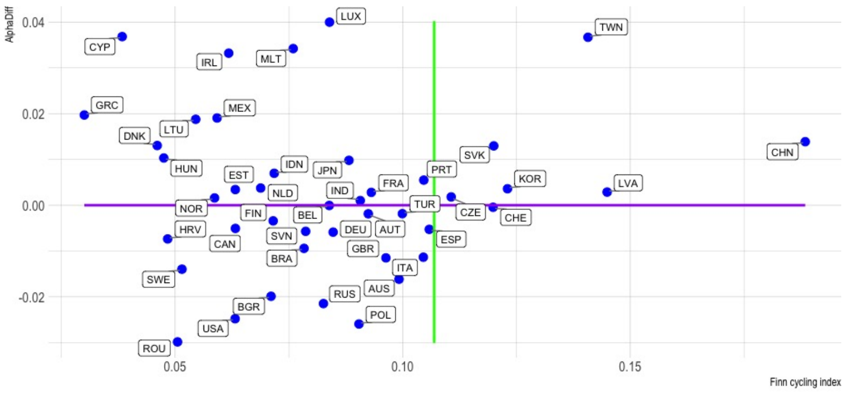

Figure 8: The optimum level of self-organization and international trade (2014)

Notation: The figure plots the countries by their AlphaDiff and Finn cycling index, based on data 2014. The green line indicates the optimal level of Finn cycling index in terms of resilience while the purple line represents the optimal α.

For the countries in the upper right area (China and Taiwan,) the strategy is more complex, because a decrease in openness increases self-organization, instead of decreasing it, therefore, they would move away from the centre along this dimension. Similarly, the countries such as Romania, the USA, or Sweden, can become more resilient when they increase their openness, however, they would decrease the self-organization, instead of increasing it. The regression results in Table 2 and the coefficients of the cycling index in these models show that the cycling index has a moderate impact on resilience, therefore, changing the level of openness seems to be more powerful in this respect. Therefore, adjusting the openness level of these countries has more impact, but these countries should make structural changes to increase their self-organization in parallel. It is interesting to see that there are no countries in the lower right area, where a low level of openness coincides with a high level of self-organization. Finally, referring back to the introduction of this study, it is worth analyzing the resilience and openness in terms of Brexit and the US-China trade war. The results in Figure 7 show that Great Britain and the USA have a very redundant structure, while China is very effective. Brexit and the trade war can only increase this redundancy in the future, less desirable in terms of resilience for Great Britain and the USA.

6 Conclusion, future developments

Kharrazi et al. (2020) draw attention to making deeper analyses of economic systems, such as their dynamics and a wider range of structural properties. Using the methods of ENA, we examined the structure of national economies in several ways. This analysis contributes to a better understanding of how economic systems are functioning and how their structural properties evolve over time.

In this study, we analyzed the structural resilience of the countries through sector level input-output data. Compared to the ecological systems, these sectoral economies are found to be more redundant. The reason behind this may be the interest of societies to build redundant production systems for national security interests or the cost of transportation. However, there can be another important reason for this higher redundancy which is related to applied data. Fath (2015) mentioned that the economic data are not available for a large set of systems and the economic systems are larger compared to ecological ones. We also note that the sector level data that we use in this study in order to make country-level comparisons are relatively aggregated: transaction volumes in the IO tables hide very different interactions among very different individual economic actors, resulting in a relatively dense, hence redundant picture of the system under question. Putting it more simply, we expect individual firm-level economic IO systems to be more close to the ecological optimum, showing less redundancy (Fiscus, 2009; Kiss et al., 2019).

Measuring resilience with the ENA method developed by Ulanowicz, we have focused on resilience from a structural perspective. However, when searching for an optimal structure, we may also take into account the trade-off between efficiency arising from more specialized positions in global production networks on the one hand and exposure to rapid shock contagion and loss of diverse production capacities on the other. The risk embedded in this exposure manifests itself in crisis situations like lockdowns triggered by a pandemic, wars, or natural disasters. Evaluation of the costs of these events against the gains from efficiency requires a theoretical approach with some estimation of social welfare in the background.

Apart from its roots in system structure, resilience can be also identified by the speed at which a system is able to return to its steady state after being hit by a shock. Using this approach, it is possible to examine standard economic variables, like GDP or unemployment, where – by assumption – more resilient countries arrive back to their steady state more rapidly after the event of a shock. Testing this assumption is part of future work. On the other hand, we have only given a superficial analysis of possible strategies for countries to increase their resilience. It would also be desirable to examine more profoundly the role of the weights of the estimated relationships at sectoral level in building higher levels of resilience.

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Appendix

Table 1: Regression tables for the connection between the level of international trade and resilience indicator

	Pooled A	Panel A1	Panel A2	Panel A3	Panel A4
Intercept	1.080E-01***				
	(1.662E-03)				
Z	9.414E-02***	7.383E-02***	7.612E-02***	7.965E-02***	9.169E-02***
	(5.844E-03)	(2.600E-02)	(2.627E-02)	(2.524E-02)	(2.605E-02)
GDPPC	1.670E-07***		-4.227E-07***	-3.930E-07***	-3.651E-07***
	(4.108E-08)		(1.349E-07)	(1.314E-07)	(1.284E-07)
EMP	3.842E-05***			7.277E-05	-1.544E-04**
	(5.538E-06)			(1.620E-04)	(7.421E-05)
CAPITAL	-1.015E-04				4.703E-04***
	(7.749E-05)				(6.554E-05)
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Adj. R^2	0.3964	0.0405	0.0927	0.0984	0.1722
F-stat	106.7514	84.1537	61.9026	43.0833	48.4821

Dependent variable: α. Robust standard errors are parantheses. *** < 0.01, ** < 0.05, * < 0.1.

Table 2: Regression tables for the connection between self-organization and resilience

	Pooled B	Panel B1	Panel B2	Panel B3	Panel B4	Panel B5
Itercept	1.001E+00***					
	(7.752E-04)					
FCI	-7.424E-03	7.742E-02*	8.783E-02**	8.625E-02**	1.141E-01**	1.085E-01**
	(1.526E-02)	(4.002E-02)	(3.688E-02)	(3.831E-02)	(4.520E-02)	(4.696E-02)
FCI^2	6.966E-02	-3.174E-01**	-3.575E-01**	-3.475E-01**	-5.236E-01**	-5.073E-01**
	(8.106E-02)	(1.558E-01)	(1.445E-01)	(1.559E-01)	(2.052E-01)	(2.033E-01)
GDPPC	-6.225E-09		-5.744E-08	-5.901E-08	-5.316E-08	-5.144E-08
	(6.950E-09)		(4.708E-08)	(4.925E-08)	(4.804E-08)	(4.921E-08)
EMP	1.680E-06			-3.982E-06	-3.480E-05*	-3.496E-05*
	(1.022E-06)			(1.372E-05)	(1.978E-05)	(2.003E-05)
CAPITAL	-6.260E-05***				7.816E-05*	7.562E-0*5
	(1.316E-05)				(4.671E-05)	(4.450E-05)
Z	-8.469E-03***					-2.084E-03
	(1.004E-03)					(8.091E-03)
Country FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.1459	-0.0643	-0.0499	-0.0513	-0.0289	-0.0293
F-stat	19.3393	9.5564	9.4705	7.1393	8.5810	7.2738

Dependent variable: $\hat{F}$. Robust standard errors are parantheses. *** < 0.01, ** < 0.05, * < 0.1.