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Dynamic patterns towards industrial ecosystem resilience and collapse: Dynamic Mode Decomposition Approach

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Abstract: **Recently, the world faces the economic challenges triggered by the shocks in the industrial sectors. The resilience of the industrial system after shocks, is a complex process. This work examine the role of dynamic patterns on industrial ecosystem resilience and collapse. Using the dynamic mode decomposition approach and the data of input-output for industrial transaction of OECD countries from 1995-2015 were simulated and the results unveiled. The empirical outcomes show that the amount of transaction between industrial sectors, dominant industries and transaction growth rate are the potential parameters that drive the system economy towards growth (resilience) or collapse, furthermore, the US followed by China is the most resilient country while South Africa, Brazil and Spain experience the least industrial ecosystem resilience. The study provides a good direction for policy making in industrial growth and economy as well.**

Keywords: **Industrial ecosystem resilience, economic collapse, Dynamic patterns, Dynamic Mode Decomposition.**

I. INTRODUCTION

The industrial sectors distributed over the world are networked by complicated and dynamical relationships into a global system. Thus, the resilience of the industrial system after economic shocks, is a complex process. For instance the economic shock caused by the US financial crisis in 2007-2009 [1] and the recent economic shock due to COVID-19 and Russia-Ukraine war made unstable global economy.

Recently, the world faces the economic challenges triggered by the collapse in the industrial sectors [2, 3]. Weak topological industrial sector(small scaled transaction between industries) play an important role on pushing the economy towards collapse [4]. Scholars have been investigated on how to overcome the crisis [5–10]. Elekes and Halmai [11] suggested that more attention should be focused on total factor productivity(TFP) to overcome the European economic crisis. Ashraf [8] shows that Islamic finance has faith in social development and help people restore business and develop fair trade practices. Despite the success, the problem still persist as witnessed in 2019-2022 during COVID-19 crisis. Here we see the decline of industrial sectors [12]. The purpose of this study is to bridge the gap by investigating the dynamic patterns which appeals the ecosystem resilience.

Dynamic pattern is one of the measure which determine the behaviors of the complex dynamic systems [13–19]. Basole et al [20] investigated the dynamic patterns for understanding the business ecosystem dynamics. Schöner and Kelso [21] investigated the dynamic patterns and used to provide the prediction on the relation between dynamic of behavioral patterns and the nature of the process of behavioral change. Harush and Barzel [22] used the pertubative formalism to investigate the dynamic patterns of information flow in complex networks. Proctor and Eckhoff [23] used dynamic mode decomposition to discover the dynamic patterns from infectious disease data.

Dynamic Mode Decomposition (DMD) is built on the idea of Koopman operator approximation [24-26]. Although the dynamic process of a system is nonlinear, it can be mimicked in each time step by linear, and in a short time the system obeys the same law [27]. Researchers have shown the powerful of DMD in discovering the underlying mechanism from experimental records [28,29]. Widely is used in identifying and controlling the mobile objects, displaying the complicated dynamical patterns in turbulent fluids [30], diagnostics and predictions [31,32].

Herein, we adopt the dynamic mode decomposition to investigate the dynamic pattern which appeals the ecosystem resilience from input-output industrial transaction data. First, we collect the input-output transaction of 33 industries for 62 OECD countries from 1995 to 2015. The DMD is applied to 7 most volatility economy countries and the local dynamic patterns extracted to each country. The universal dynamic patterns revealed when the DMD applied to all 62 OECD countries. The results show that each industrial ecosystem is having the most important(highly connected) industrial sectors that governs the ecosystem resilience, i.e., the system with many strong sectors(dominant modes) is also resiliently strong. From the empirical outcomes, we confirms that the US is the most robust economically resilient followed by China. India and Brazil were the least resilience countries. Furthermore, the results reveal that, the larger amount of transaction in the dominant industry, the more the economic resilience system experiences. This further confirms the US and China to be the most resilience countries because of having the largest amount of transaction in their dominant sectors.

This study contributes to the literature regarding industrial ecosystem dynamic patterns in multi-fold. Theoretically, dynamic mode decomposition applied for the first time to unveil the dynamic patterns from the industrial ecosystem. Practically, used for policy unit to improve the industrial ecosystem and to forecast the number of sectors that may collapse in future and thus take the precaution to mitigate the risk. Improves the growth of industrial sectors. Identify the most important industries (highly connected sectors) and provide the optimal strategies for protection. Predict economic crisis triggered by industrial collapse, if the Ukraine-Russia war will doggedly persist. Currently, globally there is a challenge in food production. This work will answer the problem on how to design on an optimal industrial ecosystem that improves the agriculture sectors.

This work is organized as follows.The materials and methodologies are introduced in detail in Section 2. In Section 3 we present the results and discussion. Summaries and conclusions are provided in Section 4, followed by Acknowledgments and References.

II. MATERIALS AND METHODS

A. Data and data preprocessing

The input-output transaction of 33 industries/sectors for 62 OECD countries from 1995 to 2015 for this study are freely downloaded on https://www.oecd.org/sti/ind/input-outputtables.htm. The list of industries/sectors and the economic countries understudy is summarized in Table I and Table II, respectively. The selected years suit the study because of the 2008–2009 global crisis, making the study robust. Moreover, the selected countries contributes 62.20% (49.6 trillion) of global nominal GDP and purchasing power parity of 42.89% (54.2 trillion). This is quite large compared to the threshold value of the sample size as "Report for Selected Country Groups and Subjects (PPP valuation of country GDP)" retrieved on 9th May, 2018. These GDP and purchasing power parity values unveils the required information in the study of dynamic industrial structure.

TABLE I: THE LIST OF INDUSTRIAL SECTORS

ID	Code	Sector name	ID	Code	Sector name
1	C01T05	Agriculture, hunting, forestry and fishing	2	C10T14	Mining and quarrying
3	C15T16	Food products, beverages and tobacco	4	C17T19	Textiles, textile products, leather and footwear
5	C20	Wood and products of wood and cork	6	C21T22	Pulp, paper, paper products, printing and publishing
7	C23	Coke, refined petroleum products and nuclear fuel	8	C24	Chemicals and chemical products

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9	C25	Rubber and plastics products	10	C26	Other non-metallic mineral products
11	C27	Basic metals	12	C28	Fabricated metal products
13	C29	Machinery and equipment, nec	14	C30T33X	Computer, Electronic and optical equipment
15	C31	Electrical machinery and apparatus, nec	16	C34	Motor vehicles, trailers and semi-trailers
17	C35	Other transport equipment	18	C36T37	Manufacturing nec; recycling
19	C40T41	Electricity, gas and water supply	20	C45	Construction
21	C50T52	Wholesale and retail trade; repairs	22	C55	Hotels and restaurants
23	C60T63	Transport and storage	24	C64	Post and telecommunications
25	C65T67	Financial intermediation	26	C70	Real estate activities
27	C71	Renting of machinery and equipment	28	C72	Computer and related activities
29	C73T74	R&D and other business activities	30	C75	Public administration and defence; compulsory social security
31	C80	Education	32	C85	Health and social work
33	C90T93	Other community, social and personal services			

TABLE II: THE LIST OF ECONOMIC REGIONS UNDERSTUDY

AUS: Australia ITA: Italy TUR: Turkey MLT: Malta AUT: Austria JAP: Japan UK: Great Britain MYS: Malaysia BEL: Belgium KOR: South Korea USA: The US MAR: Morocco	CAN: Canada LVA: Latvia ARG: Argentina PER: Peru CHL: Chile LUX: Luxembourg BGR: Bulgaria PHL: Philippines CZE: Czech Republic MEX: Mexico BRA: Brazil ROU: Romania	DNK: Denmark NLD: Netherlands CHN: China SGD: Singapore EST: Estonia NZL: New Zealand COL: Colombia THA: Thailand FIN: Finland NOR: Norway CRI: Costa Rica TUN: Tunisia	FRA: France POL: Poland CYP: Cyprus ZAF: South Africa DEU: Germany PRT: Portugal HKG: Hong Kong ISR: Israel GRC: Greece SVK: Slovakia Republic HRV: Croatia	CHE: Switzerland HUN: Hungary SVN: Slovenia IDN: Indonesia LTU: Lithuania ISL: Iceland ESP: Spain IND: India IRL: Ireland SWE: Sweden KHM: Cambodia

Let us denote the input-output transaction matrix for the $k-th$ year with

$T^{t(k)}$; $t(k) = 1995, 1996, 1997, \ldots, 2015$; $k = 1, 2, 3, \ldots, 21$, (see Fig. 1), whose specific entity $T^{t(k)}(i,j); i = 1, 2, 3, \ldots, 33$; $j = 1, 2, 3, \ldots, 33$ is the total transaction from $i-th$ industry to $j-th$ industry. Each matrix at $k-th$ year vectorized by stacking the columns one underneath of other to form a 1089×1 single vector, i.e.,vector of the matrix $T^{t(k)}$, denoted as $\mathrm{vec}\left(T^{t(k)}\right)$ is $\left[T^{t(k)}(1,1), T^{t(k)}(2,1), \ldots, T^{t(k)}(33,1), \ldots, T^{t(k)}(1,33), T^{t(k)}(2,33), \ldots, T^{t(k)}(33,33)\right]^{\tau}$, the superscript τ denotes the transpose. Subsequently, $\mathrm{vec}\left(T^{t(k)}\right)$ for a single country of all 21-years united into a single 1089×21 tall and skinny data matrix: $T = \begin{bmatrix} | & | & | & & | \\ T^{1995}(i,j) & T^{1996}(i,j) & T^{1997}(i,j) & \ldots\ldots\ldots\ldots & T^{2015}(i,j) \\ | & | & | & & | \end{bmatrix}$.

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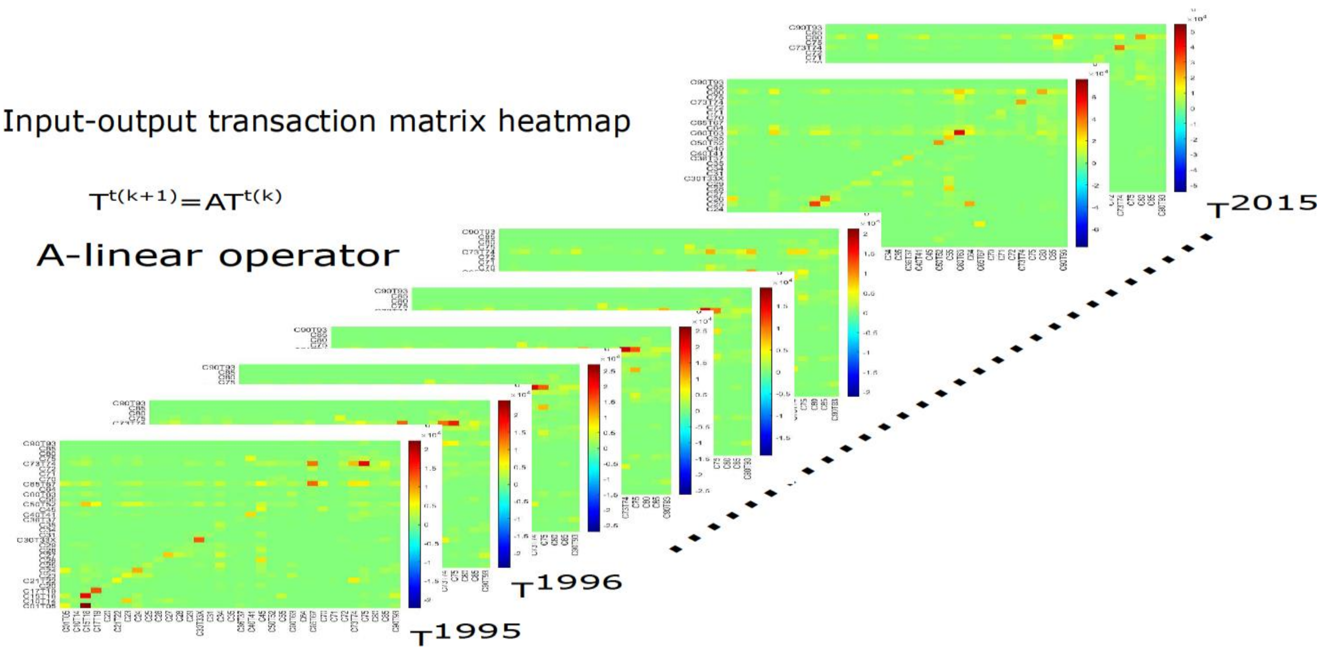

Fig. 1: Illustration of the DMD method where input-output transaction matrix $T^{t(k)}$ are vectorized and a linear transformation A is constructed. The DMD method constructs the best matrix A that minimizes the least-square error for all transformations $T^{t(k+1)} = AT^{t(k)}$; $k = 1995, 1996, 1997, \ldots, 2014$.

B. Dynamic mode decomposition methodology of the input-output transaction

The tall and skinny vectorized input-output transaction matrix T arranged into two matrix T_1 and T_2:

$$T_1 = \begin{bmatrix} | & | & | & | \\ T^{1995}(i,j) & T^{1996}(i,j) & T^{1997}(i,j) \ldots\ldots\ldots & T^{2014}(i,j) \\ | & | & | & | \end{bmatrix},$$

$$T_2 = \begin{bmatrix} | & | & | & | \\ T^{1996}(i,j) & T^{1996}(i,j) & T^{1997}(i,j) \ldots\ldots\ldots & T^{2015}(i,j) \\ | & | & | & | \end{bmatrix}.$$

The dynamic mode decomposition technique seeks the dominant eigenvalues and eigenvectors of the best-fit linear operator A that relates the two input-output matrices in time: $T_2 \approx AT_1$. The best fit operator A then establishes a linear dynamical system that best advances input-output transactions matrix forward in time. If the sampling is uniform in time, this becomes: $T^{t(k+1)} = AT^{t(k)}$. A simple computation reads to $A \approx T_2 {T_1}^{\dagger}$, where † denotes the Moore-Pen-rose pseudoinverse. It can be estimated by minimizing the Frobenius norm of the difference: $T_2 - AT_1 \equiv T^{error}$.

The operator A is a matrix with a size of 1089×1089, implying that it has a total of 1089 eigenvalues and corresponding eigenvectors. To preserve (discard) the eigenvectors reflecting the macroscopic transaction (microscopic details from noises and occasional transactions) of T_1, the singular value decomposition (SVD) is adopted (the detailed of SVD refer [33, 34]), i.e., $T_1 \approx U_r \Sigma_r V_r^*$, where * denotes the complex conjugate transpose, r refers to the number of the preserved rank of the data matrix and it is less than or equal to $\min(1089{,}20) = 20$. U_r and V_r is the eigen-time points and eigen-transaction, respectively, which span the space of time points of transaction and industry-industry transactions.

The dominant dynamic underlying input-output transaction can be captured by truncating to a small value of r. Herein, we find the truncation value r by ignoring components with relative variance is less than 0.005 threshold, because the cumulative relative variance of components with the relative variance greater than 0.005 is greater than 0.98 for all input-output transaction. Using the component of the SVD, the operator A approximated as $\tilde{A} = T_1 V_r \Sigma_r^{-1} U_r^*$, but the size of matrix $\tilde{A}$ is still 1089×1089. A low-dimensional is efficiently performed by projecting using the first r left singular vectors (U_r). The reduced operator defined to be $\bar{A} = U_r T_1 V_r \Sigma_r^{-1} U_r^* U_r = U_r T_1 V_r \Sigma_r^{-1}$, whose eigen-decomposition read, $\bar{A}W = W\Lambda$, where the columns of $W \in \mathbb{C}^{r \times r}$ and the diagonal entries $\mathrm{diag}(\omega_1, \omega_2, \omega_3, \ldots, \omega_r)$ of $\Lambda \in \mathbb{C}^{r \times r}$ are the eigen-vectors and the

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eigenvalues of $\bar{A}$, respectively. Then, W is used to approximate the eigen-vector (dynamic mode) of A. The approximated dynamic mode corresponding to the ω_k is $\varphi_k = T_1 V_r \Sigma_r^{-1} W_k$, where W_k is the $k - th$ column of W.

The dynamic modes describe how transaction are related (each industry/sector in industries structure). Within a single dynamic mode each element in a column (φ_k) has two important pieces of information; the magnitude of element (absolute value) provide a measure of industry transaction participate in the mode. The angle between the real and the imaginary component of the element provides a measure of the industry transaction phase of oscillation relative to others for that mode's frequency. By using the approximate eigen-decomposition, we reach a coupled transaction-temporal model, $T_{\text{dmd}}^{t(k)} = \Phi \Lambda^{t(k)} b$, where b is a set of weights satisfying $T^{1995} = \Phi b$, generally Φ is not a square matrix so that $b = \Phi^{\dagger} T^{1995}$. Note that entries of b are coefficients of the linear combination of T^{1995}in the eigen-modes basis, we call them DMD amplitudes.

III. RESULTS AND DISCUSSIONS

Using the DMD approach, the industrial ecosystem resilience that depends on the industrial transaction unveiled.

TABLE III: DOMINATED TRANSACTIONS INDUSTRIAL SECTORS

Country	Sector with highest transactions	Amount in USD million(year of transaction)
Brazil	C01T05 to C15T16	40424.4(2006),48533.5(2007), 64063.3(2008), 55332(2009), 66643(2010), 84536.5(2011)
China	C30T33X to C30T33X	197212.3(2006), 261129.9(2007), 288829.1(2008), 271325.2(2009), 315879.4(2010), 382364.5(2011)
India	C10T14 to C23	58775.7(2006), 80955.6(2007), 85723(2008), 83054.7(2009), 106764.8(2010), 170038.2(2011)
Japan	C34 to C34	183042.2(2006), 185142.3(2007), 218712.9(2008), 165093.9(2009), 214483.4(2010), 227445.1(2011)
Spain	C45 to C45	148871.4(2006), 148446.8(2007), 133165.9(2008), 117785.9(2009), 63284.3(2010), 44363.5(2011)
United States of America	C65T67 to C65T67	632554.6(2006), 700663.5(2007), 671190.7(2008), 732140.7(2009), 694919.2(2010), 567451.4(2011)

Fig. 2 exhibits the degree of transaction between the two connected industrial sectors. The results show that each industrial ecosystem is having the most important(highly connected) industrial sectors that governs the ecosystem resilience. This implies that the system with many strong sectors(dominant modes) is also resiliently strong. From the empirical outcomes, we confirms that the US is the most robust economically resilient with the most transaction connected from C65T67 to itself(C65T67) sector followed by China with highest connected transaction from C30T33X to itself(C30T33X) and Japan from C34 to C34 sector (the summary of the dominant transaction in each country see table III). India and Brazil were the resilience countries with the strongest transaction from C10T14 to C23 and C01T05 to C15T16, respectively. Additionally, despite the deep red color to show the most dominant industrial sectors in each system(country), the amount of transaction in USD million were differing from each country. The difference was led by how the industrial network is structured in each country. Furthermore, the results reveal that, the larger amount of transaction in the dominant industry, the more the economic resilience system experiences. This further confirms the US and China to be the most resilience countries because of having the largest amount of transaction in their dominant sectors.

Fig. 3 unveil the dynamic patterns that indicated with the cumulative probability of the singular values. The rationally behind cumulative probability is to approximate the dominant eigenvalues shown in solid circles in Fig. 3(b) and DMD modes. The positive modes (see Fig. 3(d), (e) and (f)) are those dominant modes that indicate the growth since then contain at-least one positive mode. This implies that the system with positive modes means it grows and negative modes means collapse. Furthermore, despite the positive modes to indicate economic growth (resilience), the higher the magnitude of eigenvalue of a mode implies the stronger the resilience than the resilience with lower magnitude of eigenvalue.

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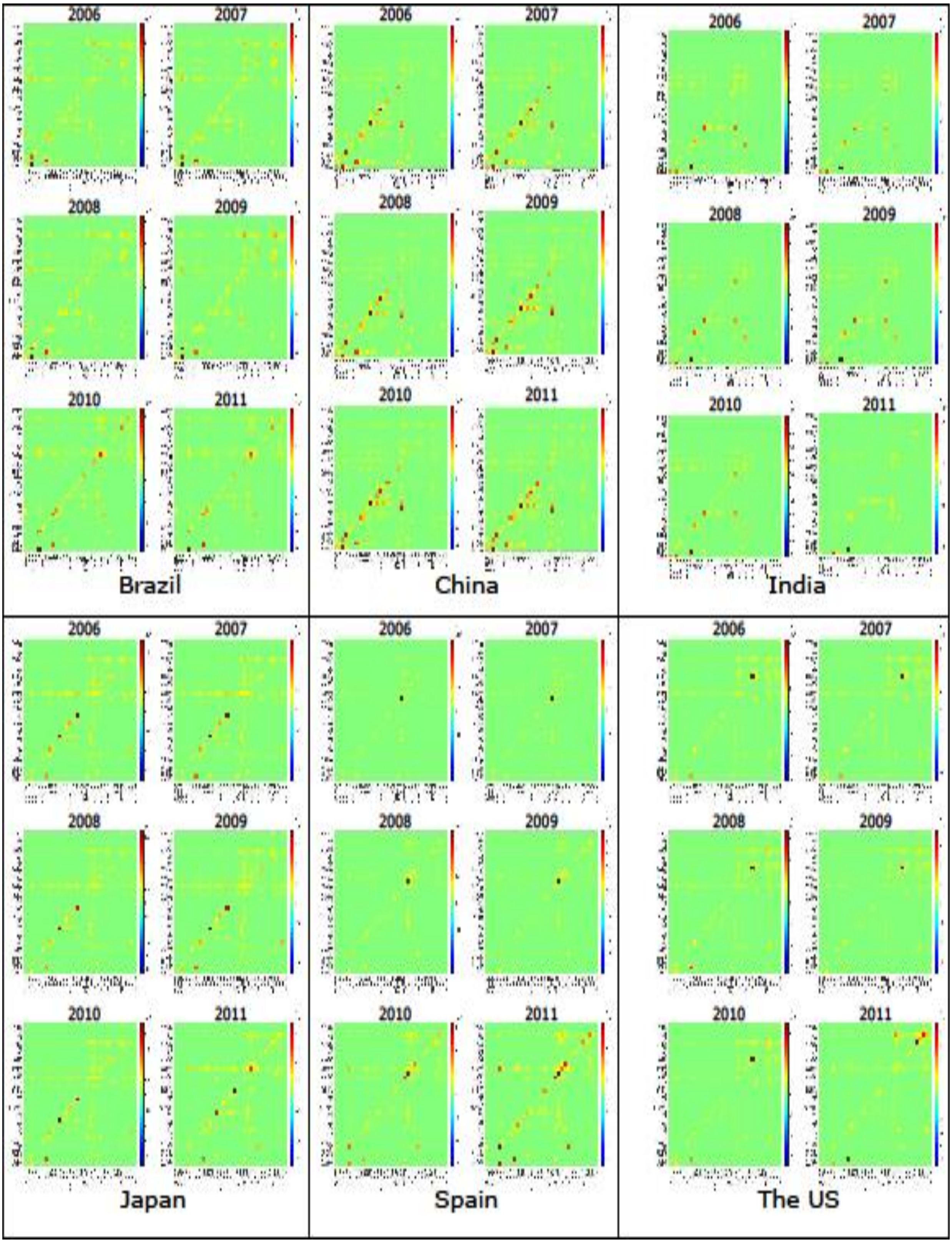

Fig. 2: (Color online) Heat-Map of the input-output transactions matrix for two years (2006-2007), during(2008-2009) and after(2010-2011) economic crisis.

This confirm that before discarding the data to retain largest modes, Brazil and the US contained the positive eigenvalues but the US grows more than Brazil because of experiencing the larger magnitude of eigenvalue than that of the Brazil. Having many dominant mode in the system is among the reason for a country to be resilience.

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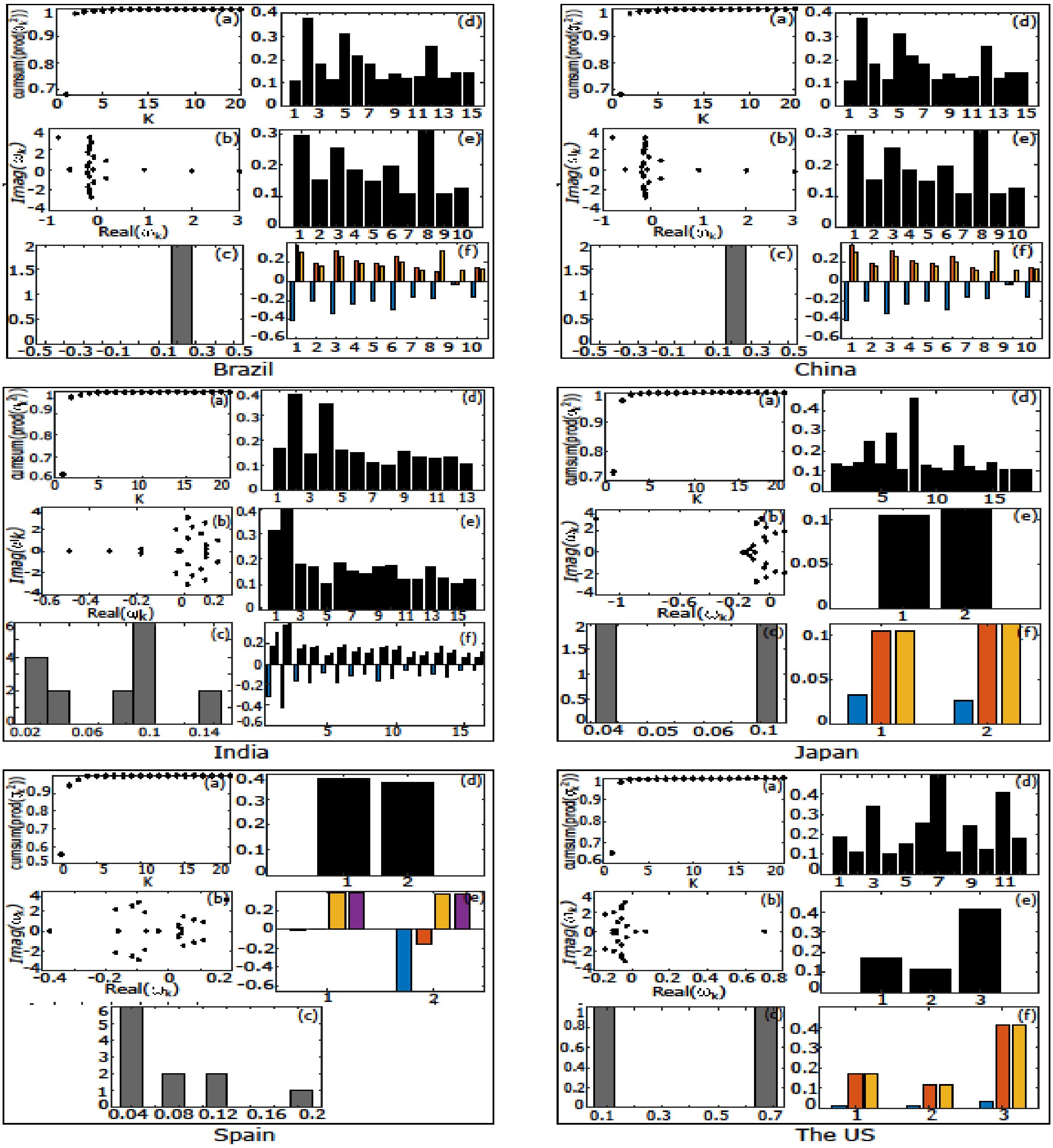

Fig. 3: (Color online) DMD decomposition of 21-years sampling of Input-output transaction data in 33 industries sectors. The top left(a's) panel of each country is the cumulative probability of the square information captured in each mode from the SVD decomposition ($\sigma_k^2/\sum_{k=1}^{K}\sigma_k^2$, where σ_k^2 are the diagonal elements of Σ). The solid circle is the cumulative probability of the dominant square singular values (each has at-least $\sigma_k^2/\sum_{k=1}^{K}\sigma_k^2$>0.005). The second (b's) left is the 20 eigenvalues (ω_k) of each mode in which the dominant represented by the solid circle used in the solution $X_{DMD}(t) = \sum_{k=1}^{K}\varphi_k(x)\omega_k^t b_k$. Eigenvalues with $\omega_k > 0$ represent the growth modes. The left third(c's) panel is the DMD distribution of eigenvalues ($\omega_k > 0$). The right panels is the leading DMD modes ($\varphi_k(x)$) and their composition.

This confirm China and India to grow faster than the rest because they contain 16 positive eigenvalues equivalent to 80% of an eigenvalues. Moreover, further discarding and retaining the dominant mode with highest magnitude, China and US remained with one positive eigenvalue but the US is more resilience than China because of the high magnitude of eigenvalue. The outcomes generally confirm that, the resilience of the system was governed by the number of dominant modes (the larger the number the stronger the resilience) and the magnitude in which the eigenvalues has (i.e., the larger the magnitude the stronger the resilience of the system).

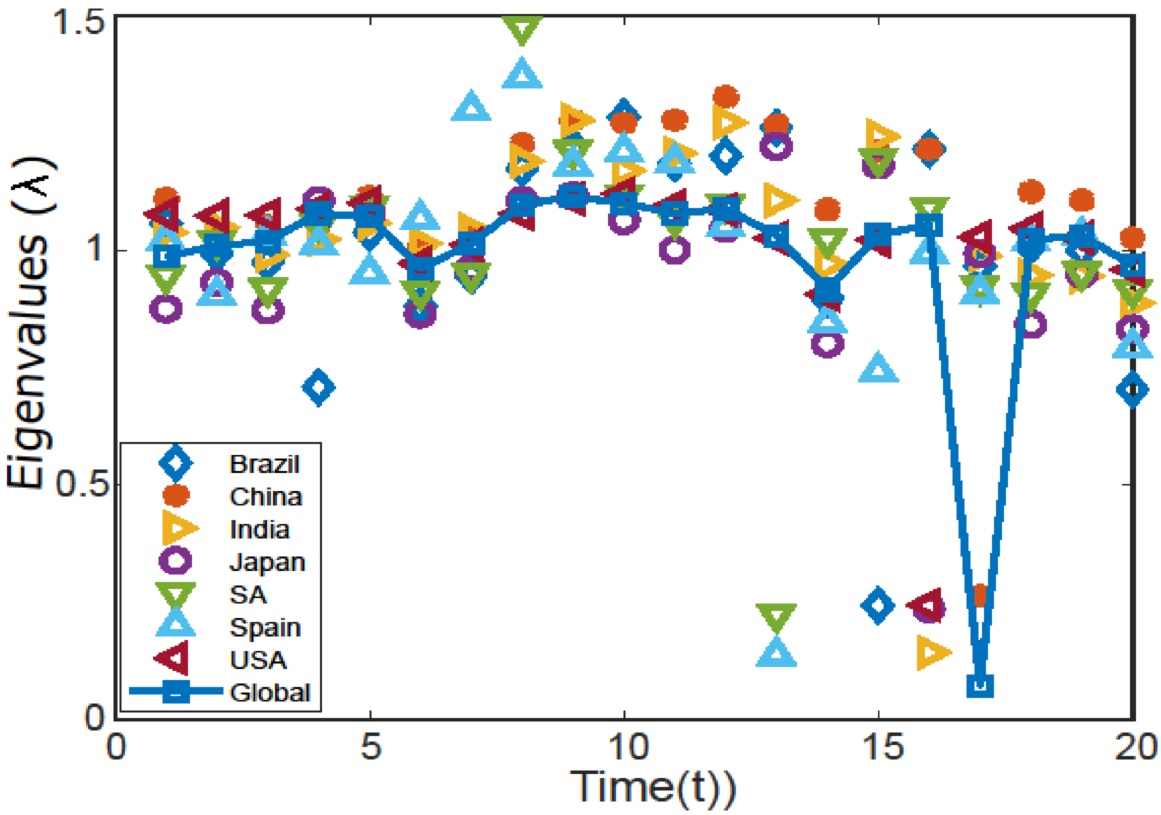

Fig. 4: (Color online) Transaction Index for seven(7)representative countries and global(Brazil, China, India, Japan, South Africa(SA), Spain, United States of America(USA) and Global).

Transaction index is another factor that control the resilience of the industries system. Fig. 4 shows the variation of eigenvalues (transaction index) with time. The results show that each industrial system experiences different value of index due to the system industrial structure and the other reason like economic perturbation. The US and China observed to experience the high value of transaction index. This indicate that, the two industrial system are the most resilient economically. All the systems experienced the least transaction index from 2008-2010 except China that faced small recession. The reason behind is that Chinese government introduces the economic stimulus policies following the 2008 economic crisis, but higher recession occurring in 2012-2013 because of the US economic recovery. Moreover, the global transaction index was moving proportionally with the US and China. This indicates that the US and China are predominant systems that control the global resilience, this is to say that, countries with the highest connection of industries should be protected to avoid the global crisis. As shown in the Fig. 4, the extreme recession of China and the US led to the global system to extremely drop as well.

IV. CONCLUSION

The aim of the study is to investigate the dynamic patterns that governs the industrial ecosystem resilience and the corresponding collapse. Dynamic mode decomposition approach applied and the empirical outcomes unveiled. The results confirmed that the amount of industrial transaction, the most important (highly connected) industrial sectors and transaction index (transaction growth rate) were the predominant factors for the industrial ecosystem resilience and collapse. The results revealed that the US followed by China is the most resilience country while South Africa, Brazil and Spain are among the countries with the lowest industrial ecosystem resilience and global economy was influenced and driven by the strongest resilience countries like the US and China. Duan et al [35] attempted the study on industrial structure conditions economic resilience that was appealing to industrial network characteristics which enhance resilience and circumvent economic collapse but didn't take into account the temporal dynamic of the network. Another similar study on economic resilience and collapse examined how network structure and exchange rate volatility drive the industrial ecosystem towards collapse [36] using Lotka–Volterra model but also did not explain temporal dynamic of the industrial connectives. This study bridges the gap by exploring more about temporal dynamic patterns of the input-output transaction data in the investigation of industrial ecosystem resilience and collapse.

This work stands as a pivotal point in the policy making unit that control the industrial network architecture across the global. The study did not consider the industrial spatial evolution and the industrial tipping point, thus, it is recommended for future researches to cover the gap by investigating the spatial-temporal dynamic pattern which can detect the early warning signal for industrial tipping point to make industrial investigations more relevant and robust.

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