Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

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ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2023, VOL. 36, NO. 1, 1688–1707
https://doi.org/10.1080/1331677X.2022.2092524

How network structure and exchange rate volatility drive the industrial ecosystem towards collapse: a global perspective

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ABSTRACT

This study investigates the impact of topological structure and exchange rate volatility on the collapse of industrial ecosystems. To answer this question, we developed a multidimensional nonlinear dynamic model that captures the dynamics of industrial ecosystem structures. Furthermore, the formulated complex model is reduced to a 1 D model system without lowering its ability to predict the tipping point (total collapse point). Using 1995–2015 input-output OECD data, the study was divided into three phases (before, during, and after the global crisis) for empirical testing. The results reveal that a more robust topological structure is more resilient to economic shocks. Countries with higher exchange rate volatilities are more vulnerable to global crises, even though they have a strong topological structure to resist risk. Furthermore, the upsurge in foreign direct investment (FDI) enhances the robustness of the industrial structure and reduces the exchange rate volatility risk. The results of this study will help strengthen the robustness of the industrial structure of the system to withstand both local and global perturbations better.

ARTICLE HISTORY
Received 6 January 2022
Accepted 13 June 2022

KEYWORDS
Exchange rate volatility; industrial collapse; economic resilience; tipping point; topology structure; hedging

JEL CODES
F31; C50; C60; C67

1. Introduction

Industrial ecosystem collapse has always been an intriguing research issue and a great challenge because of the complex and volatile nature of the problem. Because industrial topology structures play a significant role in their overall dynamics, innovation, stability, and collapse, industrial ecosystem designs in this field have been prioritized (Mao et al., 2020; Morris et al., 2021). The technique for industrial interactions can be achieved through interactions among the industrial sectors comprising the network that involve different network densities and heterogeneity (Mao et al., 2020).

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Supplemental data for this article is available online at https://doi.org/10.1080/1331677X.2022.2092524.

Structuring industrial ecosystems is the most common method used to solve this problem (Chen & Ma, 2022; Innocenti et al., 2020; Mysachenko et al., 2020). However, most of these methods focus on the innovation and advancement of industrial goods and services, disregarding the large amount of useful information that exists among industrial topology structures. In an attempt to overcome this problem, a new complex model adopted from the Lotka-Volterra complexity theory was developed to represent the relationships among attributes from different transactions, which has proven to be quite useful in industrial ecosystems.

1.1. The role of industrial ecosystem structure and exchange rate volatility on collapse

The industrial topology (network structure) plays a vital role in promoting the resilience of industrial ecosystems. This study investigates the role of industrial structure and exchange rate volatility in industry failure to mitigate economic risks. It was revealed that industrial structure and exchange rate volatility could either enhance the system's resilience or divert toward its collapse (Bahmani-Oskooee & Karamelikli, 2022; Neumann & Tabrizy, 2021; Tan et al., 2020). An industrial ecosystem with a strong (robust) topological structure helps absorb external shocks and maintains the ecosystem to produce the maximum output. However, industrial ecosystem collapse affects the production capacity and damages the linked industries and the overall growth of the country (Telford & Lloyd, 2020). In the era of an open economy, exchange rate volatilities can influence the industrial ecosystem, affect international trade, and eventually affect industrialised countries' economies (Bahmani-Oskooee & Nouira, 2020). Therefore, any improper policy measure might drive them towards financial crises, as witnessed in East Asia in 1997. The shock resulted from the fixed exchange arrangements set by Eastern Asian countries (Rethel & Thurbon, 2020).

Moreover, understanding the role of FDI is of utmost importance to the world economy, given the increasing complexity of industrial ecosystems. First, FDI has a significant effect on the industrial structure of emerging economies (Han et al., 2022; Papaioannou & Dimelis, 2019). To what extent do they depend on the home country's industrial ecosystem? (Jiang et al., 2020). FDI brings new technology skills (Vujanović et al., 2021) and causes market expansion, as investigated by (Pasquinelli & Vuignier, 2020). As a result, it facilitates technological spillover benefits that help improve the industry structure and, thus, the system's resilience in withstanding economic shocks (Mahbub & Jongwanich, 2019). Secondly, the domestic policy difference that promotes the attractiveness of FDI inflows shifts the location of tipping points to larger exchange rate volatility (Gautam et al., 2020; Murali et al., 2021).

Because of the complexity of industrial ecosystems, the most persistent problem in the current global economy is understanding how economic systems are influenced by the topological structure that arises from business interactions in the global market (Jack, 2021). This study contributes to industrial ecosystem literature in several ways. First, a new complex model based on the Lotka-Volterra complexity theory is designed to determine the influence of the industrial topology structure and exchange rate volatility on industrial collapse, which is regarded as an approximate solution.

Second, industrial network density and heterogeneity are used to identify the topology structure, which is more important and reliable in policymaking. Third, this study offers a concretely visible prediction of how many industries will default after the coronavirus (COVID-19) and thus avoid systemic collapse. A novel contribution of the new model formulation is that it is a dynamic structure of industrial ecosystems. This is of special importance because, in time-series data, the revenue of each industry cannot be fixed. It should be emphasised that the proposed model system can be used in industrial ecosystems and many other fields, such as financial systems.

The remainder of this paper is organised as follows. The next section discusses the related literature review and knowledge gaps. Section three develops the model for the theoretical relationships and simulations of the empirical relationships. This section also explains the data and the country under study. Section four presents and discusses the results. The final section concludes the study and provides future recommendations.

2. Literature review and knowledge gap

The empirical literature discusses the said topics using different scenarios. For instance, Li et al. (2019) point out that regional industrial structure influences firm productivity. Using firm-level data from China, the researchers concluded that industrial structure plays a vital role in localisation and agglomeration, enhancing firm productivity. A good industrial system anchors stability during an economic crisis, thereby maintaining resilience (Zeng et al., 2021). Zhu, Guo, and He et al. (2021) studied the network properties of the industrial space. They investigated unrelated and related industries and argued that diversified industries with a small number of strong links tend to strengthen the resilience of the ecosystem. Countries with different industrial structures absorb external shocks differently. Previous studies have pointed out that the core differences between developed and emerging economies are good institutions and industrial systems (Tan et al., 2020). In this scenario, emerging countries need to undertake structural transformation to avoid economic collapse because the industrial structure has been at the centre of economic growth (Kucera & Jiang, 2019). Industry structural transformation towards a more advanced and sophisticated industrial base is essential for emerging economies to converge with developed economies (Mao et al., 2021). Furthermore, the results argue that a weak industrial structure and exchange rate volatility could be disastrous for economic growth (Combes et al., 2019; Qureshi & Aftab, 2020). Robust industrial networks can help combat market imperfections. When the system fails to withstand the perturbation, it indicates a weak industrial structure, which can cause catastrophic shifts. In the model analysis, we consider a critical transition (bifurcation) as an important tool that describes the industrial structure of the phase space. Trading activity does not decrease with major industrial structure parameter changes, indicating economic resilience. The rationale is that the system can withstand disruptions (Choi et al., 2021). This study investigates the influence of topological structure on the industrial ecosystem and its collapse when subjected to exchange rate volatilities.

Similarly, the exchange rate is an essential factor influencing a country's economic resilience (Ribeiro et al., 2020). It enables global economic cooperation and competition (He et al., 2021). Scholars have suggested that countries should have more flexible exchange rate arrangements to avoid financial crises (Aizenman, 2019). In recent studies, exchange rate volatility has attracted growing interest from scholars. The studies conducted examined the impact of exchange rate volatility on economic growth (He et al., 2021; Kalemli-Ozcan et al., 2021). However, the depreciation of real exchange rates fosters tradable capacity expansion and promotes economic growth (Kalemli-Ozcan et al., 2021). In industrial ecosystems, it is essential to investigate the asymptotic behavioural features of the model. This can be achieved by exploring the concepts of resilience and exchange rate volatilities and, hence, the tipping points. Only a few studies touch on the issue of recent industrial ecosystem shocks caused by weaker topology industrial structures and exchange rate volatility impacted by industrial risks. Floetgen et al. (2021) and Shutters and Waters (2020) researched the concept of industrial resilience influenced by the industrial structure and has proven helpful in overcoming exogenous shocks. Furthermore, the latest study by Boyer et al. (2021) investigated the role of industry structure in the collapse of the industrial ecosystem. They investigated how industrial ecosystems (industrial structures) affected a firm's adaptive capacity and concluded that firms belonging to local innovation industrial structures centred on innovation parks are more technologically diversified and resilient than others.More importantly, innovation has an asymmetric (industrial structural) effect on firms in the industry.

FDI has attracted considerable attention from researchers, development agencies, and policymakers in the current global economy. Improving the welfare of the many people living in emerging countries is important, because they complement each other (Wu et al., 2020). Myriads of studies explored the importance of FDI in terms of monetary benefits. However, the results provide evidence of a relationship between FDI and economic prosperity via spillover efficiency and new technology transfer (Mahbub & Jongwanich, 2019; Pasquinelli & Vuignier, 2020; Vujanović et al., 2021). Many researchers have used simulation models to understand and predict the impacts of natural hazards on ecological systems (Morris et al., 2021; Pettersson et al., 2020; Rounsevell et al., 2021). These complex models with many parameters make the model analysis less feasible.

This study is the first to investigate industrial collapse by examining the critical economic resilience transition (economic bifurcation) of industrial ecosystems. First, our developed model incorporates the industrial system structure and exchange rate volatility. Second, it empirically examines the impact of industrial design and exchange rate volatility on the collapse of industrial ecosystems. Third, we introduce a unified chaotic industrial system in which disruptions occur because of a weaker industrial structure and an increase in exchange rate volatility. Finally, we incorporate FDI parameters. These concepts have been encompassed in a single developed model, which other scholars have not discussed.

3. Econometric methodology and data

This study adopts the general theory of the complex systems approach (Janzwood & Piereder, 2020). This approach highlights systems' nonlinear, networked, adaptive, and emergent behaviour (Bento et al., 2020). Therefore, we developed a new system model based on the Lotka-Volterra approach and reduced it from multiple dimensions to one dimension. The rationale behind model reduction is to enhance the efficiency and reliability of empirical outcomes (Laurence et al., 2019). The stepwise derivation of the model from formulation to analysis is provided in Appendix C (see *Supplementary Material*).

3.1. Model formulation

Let $x_i \in \mathbb{R}$ be the growth rate of the industrial sector at node i at time t with, assuming that one sector has business connections with the other sectors. The industrial sectors are nodes in the networks, and business transactions correspond to edges, as shown in Figure 1a. The highest possible industrial growth rate $K_i(K_i > 0)$ with an intrinsic revenue growth rate constant $\alpha_i(\alpha_i > 0),$ as per the logistic model system for this industry, is as follows:

$$\frac{dx_i}{dt} = \alpha_i x_i \left(1 - \frac{x_i}{K_i}\right) \tag{1}$$

In the model, we assume that the value of x_i for industry i, decreases linearly with network density and heterogeneity and, hence, the interaction strength. Thus, the model may become unrealistic when revenue growth rates diminish to very low densities. If industrial revenue is too low, it is difficult for the industrial sector to interact with other industries and fail to sell at an optimal amount. Thus, we make the model realistic by incorporating the Allee effect suggested by Martinez-Jeraldo and Aguirre (2019), and Equation (1) becomes

$$\frac{dx_i}{dt} = \alpha_i x_i \left(1 - \frac{x_i}{K_i}\right)\left(\frac{x_i}{C_i} - 1\right) \tag{2}$$

where C_i is the lowest possible revenue growth rate of industrial sector i, called the Allee-Saha model (Sau et al., 2020). The revenue growth rate x_i of sector i can also be affected by the exchange rate volatility and trade openness. Here, we apply population dynamics and organisational ecology concepts to adopt and investigate dynamic systems and economic variation. This computation can be achieved by adopting the price index as a harvesting effort parameter and introducing it into Equation (2) to obtain the harvesting effort model (Singh & Malik, 2021). The equation becomes:

$$\frac{dx_i}{dt} = \alpha_i x_i \left(1 - \frac{x_i}{K_i}\right)\left(\frac{x_i}{C_i} - 1\right) - P_i(p, x) \tag{3}$$

where P is determined by a price index, and $P(p, x) = px$ and p are much-expanded by relating the exchange rate parameter to obtain $p_i = \gamma_i T_i,$ where γ_i is the exchange rate volatility and T_i is the value of trade openness at $i,$ as suggested by Bahmani-Oskooee and Karamelikli (2021). Then, the above equation becomes

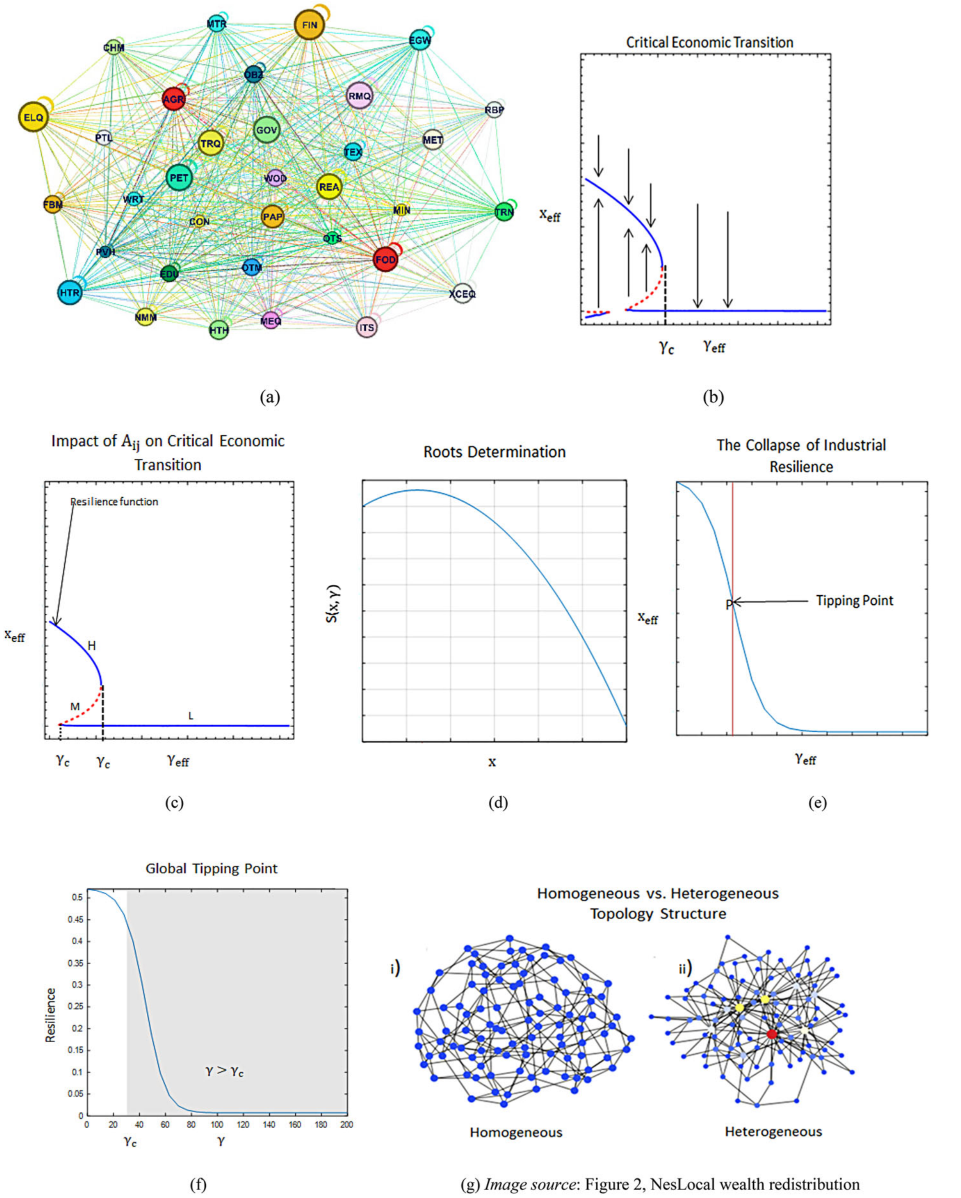

Figure 1. Economic transition and tipping point.
Source: (a) Authors' simulation using GEPHI software; (b-f) Authors' simulation using MATHEMATICA and MATLAB mathematical tools; (g) NesLocal wealth redistribution.

$$\frac{dx_i}{dt} = \alpha_i x_i \left(1 - \frac{x_i}{K_i}\right)\left(\frac{x_i}{C_i} - 1\right) - \gamma_i T_i x_i. \tag{4}$$

The functioning of the entire industrial system is determined by the topology structure in which the industrial sectors are connected. The topology structure of the system is a weighted connectivity matrix that captures mutualistic interactions between nodes (industries) (Agha Mohammad Ali Kermani et al., 2021). Figure 1a shows how industrial sectors (nodes) are connected to form a topology structure A_{ij} of the industrial ecosystem. Thus, Equation (4) can be further developed by incorporating the mutualistic interaction term to obtain:

$$\frac{dx_i}{dt} = \alpha_i x_i \left(1 - \frac{x_i}{K_i}\right)\left(\frac{x_i}{C_i} - 1\right) - \gamma_i T_i x_i + \sum\nolimits_{j=1}^{N} A_{ij} G(x_i x_j) \tag{5}$$

For simplicity, the topology structure can be expanded by introducing the interaction strength parameter together with applying the Holling type II functional response as suggested by Huang et al. (2021) to obtain

$$\frac{dx_i}{dt} = \alpha_i x_i \left(1 - \frac{x_i}{K_i}\right)\left(\frac{x_i}{C_i} - 1\right) - \gamma_i T_i x_i + \frac{\sum\nolimits_{j=1}^{N} \beta_{ij} x_i x_j}{(d_i + q_i x_i + r_j x_j)} \tag{6}$$

where d_i, q_i and r_i are parameters that characterise the saturation rate of the response function $g(x_i) = \frac{\beta_i x_i}{(d_i + q_i x_i + r_i x_j)}$

The expansion of FDI can also enhance x_i (Papaioannou & Dimelis, 2019; Sinha & Sengupta, 2019; Vujanović et al., 2021). We adopted the system by adding the FDI parameter to the resilience function $f(x, \gamma)$. This can be achieved by incorporating the term $W(x_i)$ into the governing parameter coefficient a_i of FDI in (6). This parameter influences the industry's effective revenue growth rate. Thus, the developed model becomes

$$\frac{dx_i}{dt} = W(x_i) \quad + \alpha_i x_i \left(1 - \frac{x_i}{K_i}\right)\left(\frac{x_i}{C_i} - 1\right) - \gamma_i T_i x_i + \frac{\sum\nolimits_{j=1}^{N} \beta_{ij} x_i x_j}{(d_i + q_i x_i + r_i x_j)} \tag{7}$$

If $W_i(x) = a_i$, Equation (7) can be expanded to obtain the following resilience function:

$$\frac{dx_i}{dt} = a_i + \alpha_i x_i \left(1 - \frac{x_i}{K_i}\right)\left(\frac{x_i}{C_i} - 1\right) - \gamma_i T_i x_i + \frac{\sum\nolimits_{j=1}^{N} \beta_{ij} x_i x_j}{(d_i + q_i x_i + r_i x_j)} \tag{8}$$

In Appendix C (see *Supplementary Material*), we detail the steps of our dimension-reduction procedure, which leads to the reduced model.

$$\frac{dx_{eff}}{dt} = a + \alpha x_{eff} \left(1 - \frac{x_{eff}}{K}\right)\left(\frac{x_{eff}}{C} - 1\right) - \gamma_{eff} T x_{eff} + \frac{\beta x_{eff}^2}{(d + (q + r) x_{eff})} \tag{9}$$

3.2. Data structure

The data structure investigates the impact of the topological structure of industrial ecosystems and exchange rate volatility on economic resilience. To calibrate the model, we selected 33 industries and relied on three data sources. First, we obtained input-output (IO table) data for 62 OECD countries from 1995–2015, sourced from the OECD database. The list of industries and countries is summarised in Tables A and B, respectively (see *Supplementary Material*). Second, we obtained exchange rate data sourced from (https://fxtop.com/). FDI data were gathered from OECD sources (https://data.oecd.org/). The selected data suit the study because of the 2008–2009 global crisis, making the study robust. Moreover, OECD member countries collectively comprised 62.20% (49.6 trillion) of global nominal GDP and purchasing power parity of 42.89% (54.2 trillion). This is larger than the threshold value of the sample size as '*Report for Selected Country Groups and Subjects (PPP valuation of country GDP)*' Retrieved 9 May 2018. These two values of GDP and purchasing power parity unveils the required information in the study of industrial ecosystems structure.

4. Simulation

This section presents the details of our study on the profitability and accuracy of this method to examine the influence of industry topology, exchange rate volatility, and FDI on industrial revenue (industrial ecosystem resilience). The simulation was conducted by selecting data from 33 industrial sectors for 1995–2015, including the 2008–2009 global crisis. This selection ensured that the target industrial sectors were more representative. The methodology outlined in this study can be applied to implement the simulation procedure in the following steps: Using Equation (C13) (see *Supplementary Material*), using MATLAB software, we begin by drawing a set of second derivatives of revenue growth (x_{eff}) against γ_{eff}. This approach determines the threshold value of x_{eff}(that is.,x_c) thereby obtaining the threshold values of γ_{eff}(i.e., γ_c). We then ran other algorithms using threshold values and drew the salient information required.

5. Simulation results

The results show that, regardless of the particular parameter values (i.e., K, C, D, E, and α), mutualistic industrial communities always exhibit two stable equilibrium states (i.e., $\frac{\partial f}{\partial x} < 0$, stable state H at $x_{eff} > 0$ and stable state L at $x_{eff} = 0$) and unstable $M\left(\text{i.e., } \frac{\partial f}{\partial x} > 0\right)$. The variation in the location of the critical points depends on the network structure A_{ij} of each ecosystem. This shows that network structure plays an essential role in improving resilience (Tan et al., 2020). Furthermore, industrial business transactions and FDI strengthen industrial resilience, as described by Ghosh et al. (2018), Han et al. (2022) and Tan et al. (2020), shifting the collapse location point to the immense value of exchange rate volatility.

(a) Industrial network (b) Economic transition (c) Economic transition based on empirical outcomes during the period 1995-2015 (d) features of the equilibrium points that are captured by the intersection with the x axis (i.e., $f(\gamma_{eff}, \gamma_{eff}) = 0$). (e) The collapse of industrial resilience (f) Global tipping point based on empirical outcomes. (g) Homogeneous and heterogeneous network structures.

5.1. Influence of topology structure on industrial system collapse

5.1.1. Effect of topology structure on the critical transition

Figure 1b presents the bifurcating resilience of 33 industrial sectors. The system exhibits a single stable state for $\gamma > \gamma_c$ that occurs at $x_{eff} = 0$ and two stable fixed points: a desired (thick line) and an undesired (dotted line) for $\gamma < \gamma_c$. The resilience function with a single stable state for $\gamma > \gamma_c$ at $x_{eff} = 0$ has no solution, resulting in a chaotic behaviour. The topology structure A_{ij} of the system influences the resilience bifurcations when exchange rate volatility increases with time. The industrial system structure and its critical points γ_c (dashed lines) are determined entirely by the network dynamics $F(x_i)$ and $G(x_i x_j)$ of the model in (8). The system topology A_{ij} (Figure 1b) determines the network-specific states along resilience function $f(x, \gamma)$. Figure 1c shows that a system for $0 < \gamma < \gamma_c$ always exhibits three equilibrium states, two stable states (L and H) and an unstable M. For $\gamma > \gamma_c$, the system exhibits chaotic behaviour.

5.1.1.1. Effect of topology structure on the global critical transition. Figure 1d shows the equilibrium points captured by the intersection with the x axis (i.e., $f(\gamma_{eff}, x_{eff}) = 0$). From the figure, we see that the function has roots x_c that satisfy Equations (C4) and (C5) (see *Supplementary Material*), and these roots give the two threshold values of exchange rate volatility γ_c. Furthermore, the results reveal that the economic system bifurcates annually when exchange rate volatility deviates from the lowest value of $\gamma_c = 0$.

From 1995–2015, the global economy bifurcated differently depending on the system structure A_{ij} in each year. To understand the underlying role of topology structure and exchange rate volatility, empirical outcomes were unveiled in three phases (before, during, and after the global crisis). The results show that from 2007 (before the global crisis) to 2008 (during the global crisis-shock 1), the global network density dropped from $\langle s \rangle = 32.73$ billion dollars to $\langle s \rangle = 32.65$ billion dollars. Heterogeneity dropped from $\Phi = 238.51$ billion dollars to $\Phi = 209.56$ billion dollars. The drop further continued in 2009 (during the global crisis-shock 2), experiencing the network density of $\langle s \rangle = 32.63$ billion dollars and heterogeneity $\Phi = 207.26$ billion dollars. From 2010–2015 (after the global crisis), network density and heterogeneity increased and particularly in 2010 (after the global crisis-recovery 1), we see that the network density increased to $\langle s \rangle = 32.81$ billion dollars while heterogeneity increased to $\Phi = 230.57$ billion dollars (see *Table B1 Supplementary Material*). The changes in $\langle s \rangle$ and Φ caused the interaction strength β to vary, leading to changes in the network structure $\mathrm{A_{ij}}$. Furthermore, from 2008–2009, the system experienced the weakest topology structure, with $\beta = 242.21$ billion in 2008 (shock 1) and $\beta = 239.89$ billion in 2009 (shock 2). The most robust topology structure was experienced in 2010 with $\beta = 263.38$ billion dollars, followed by the structure experienced from 2011–2015 (after global crisis recovery 2) with $\beta = 255.08$ billion dollars (see *Table B1 Supplementary Material).*

Moreover, this observation indicates that the stronger A_{ij}, the higher the system resilience (Cheng et al., 2022); hence, it withstands the perturbation at a larger value of the threshold exchange rate volatility γ. In 2008 (shock 1), a global industrial topology structure experienced threshold exchange rate volatility $\gamma_c = 32.64$ while $\gamma_c = 32.83$ for the year 2009 (shock 2). This outcome indicates that during the global crisis-shock 1, the volatility regime was $\gamma = 31.29 < \gamma_c$ which implies the system is resilient at $x \geq x_c = 42.55$ at a stable state H. The system was less resilient in the unstable state M when $x < x_c = 42.55$. In 2009, the ecosystem experienced chaotic behaviour because the exchange rate volatility exceeded the threshold (i.e., $\gamma = 33.52 > \gamma_c = 32.83$). In this phase, the ecosystem could not withstand the disruption of the financial crisis that led to the economic collapse.

5.1.1.2. Effect of topology structure on the country's critical transition. Table B3 (see *Supplementary Material*) reveals the different values of network density, heterogeneity, and interaction strength that determine the topology structure A_{ij} of each industrial ecosystem. The results were obtained for seven countries with the highest GDP (see *Supplementary Material*). The results show that the USA, with $\gamma_c = 7.82$ or $\gamma_c = 2,082.8,$ was the most resilient country with a single stable state H at an interval $0 \leq \gamma_c < 7.82$. For regime $7.82 \leq \gamma_c < 2,082.81,$ they experienced stable states H and L and were unstable at $M,$ as shown in Figure 1c. This indicates that within the volatility regime, country is resilient at $x_c \geq 49.50$. Since the country was very resilient at any value of economic growth rate when $\gamma_c < 7.82$ and beyond, the country must reach $x_c \geq 49.50$. Furthermore, the country experiences disrupted behaviour when the value of exchange rate volatility exceeds $\gamma_c = 2,082.81$. Brazil was the least resilient country with a single stable state H at an interval of $0 \leq \gamma_c < 0.02$. The results indicate that, at $\gamma_c \geq 0.02$ the country will struggle to reach the economic growth of $x_c \geq 50.01$ to avoid resilience loss. China and Japan were a single stable state H under the regimes of $0 \leq \gamma_c < 3.45$ and $0 \leq \gamma_c < 3.85$ respectively. The results imply that at any value of x_{eff} Japan was more economically strong with a stable state H at an immense value of the threshold exchange rate of $\gamma_c = 3.85$ compared to China with $\gamma_c = 3.45$. Spain, India, and South Africa were in a single stable state H for all x_{eff} in the regimes of $0 \leq \gamma_c < 0.56$, $0 \leq \gamma_c < 0.79$ and $0 \leq \gamma_c < 3.38$ respectively. Here, we see that South Africa was more resilient than the other two countries, with a more extensive regime of γ_{eff}. We observed equilibrium point shifts during global crisis shock 1 (in 2008). Some countries dropped economically, while others rose depending on structural changes. At a single stable state H, the regime of South Africa and Japan fell from $\gamma_c < 3.38$ (before the global crisis) to $\gamma_c < 0.97$ (during the global crisis-shock 1) and $\gamma_c < 3.85$ to $\gamma_c < 3.45$ respectively. The remaining five countries surged by different percentages depending on the system structure of each country. The global crisis that started in 2008 suppressed the growth of South Africa and Japan. At the same time, the rest of the countries were not affected by economic decline.

The results further indicated that for all values of x_{eff}, the USA and China volatility regimes dropped from $\gamma_c < 8.92$ (in 2008) to $\gamma_c < 6.09$ (in 2009) and $\gamma_c < 6.09$ to $\gamma_c < 5.20$ respectively. The outcome implies that the USA dropped by 31.73%, while China dropped by 12.97%; thus, the 2009-critical global crisis hit the USA harder than it did China. Spain was the most affected country as its volatility regime dropped by 57.80%. Despite the economic fall in 2008, South Africa improved its control by 54.64% in 2009. After global crisis recovery 1 (2010), we see an economic recovery for many countries, except Japan, South Africa, and India. The exchange rate volatility regime at a single stable state H surged in the USA, Spain, Brazil, and China. The results reveal the most significant drop of 58.67% in South Africa, making the country the least resilient. In Phase 5, all nations were resilient to exchange rate volatility, except Spain. Spain showed a drop in the exchange rate volatility regime from $\gamma_c < 2.47$ (in 2008) to $\gamma_c < 0.69$ (in 2009), which is equivalent to a 72.06% drop (see *Table B2 Supplementary Material*). This empirical result indicates that the structural change in Spain failed to withstand disruptions when exchange rate volatility increased.

5.1.2. Effect of topology structure on tipping point location

5.1.2.1. Effect of topology structure on the global tipping point. Structural changes in the system, such as an increase or decrease in the interaction strength β, can generate a tipping point and twist its location. These changes are expected in the real world, as shown in Figure 1e. Figure 1f shows that tipping points are likely to occur within the confidence interval (shaded area). Disorderly behaviour occurred in 2009 (shock 2) with the regime $\gamma_{eff} = 33.52 > \gamma_c = 32.83$. We further argue that economic resilience diminished at $\gamma_c > 0$ and experienced total collapse at the tipping point in all networks. From 1995–2007, the tipping point occurred at $x_c < 45.65$. These results imply that economic resilience should be larger than the threshold value x_c to avoid collapse of the system. Furthermore, the results reveal that in 2008, exchange rate volatility surged to $\gamma_{eff} = 31.29$. This was sufficiently large to weaken resilience at $x_c < 42.65$, within which the tipping point was predicted.

5.1.2.2. Effect of topology structure on a country tipping point location. Figure 2 shows that, for all seven countries, economic resilience was diminished at $\gamma_c > 0$ and experienced total collapse at the tipping point. Here, we also see that the USA with topology structures A_{61} to A_{65} has an enormous value of γ_{eff} to which the tipping point is likely to occur, followed by China, as shown in the shaded area. All the remaining nations were predicted to collapse at a small γ_{eff} value because they have weaker topological structures compared to the USA and China. Here, we further observe that the more fragile the topology structure, the smaller the threshold value γ_c for the collapse of the system. The results further reveal that during the global crisis-shock 1, at a single stable state H, the regime of South Africa and Japan dropped from $\gamma_c < 3.38$ (in 2008) to $\gamma_c < 0.97$ (in 2009) and $\gamma_c < 3.85$ to $\gamma_c < 3.45$ respectively. These results led to the tipping point for the two countries to experience a lower value of γ_{eff} as shown in A_{71} to A_{75} (South Africa) and A_{31} to A_{35} (Japan). In 2009, the results showed that at $x_{eff} \in \mathbb{R}$, the USA and China (with structure change from A_{21} to A_{25}), volatility regimes dropped from $\gamma_c < 8.92$ (in 2008) to $\gamma_c < 6.09$ (in 2009) and $\gamma_c < 6.09$ to $\gamma_c < 5.20$ respectively. The weaker topology structures in the 2009-critical global crisis led the location of a tipping point to drop to a lower value of γ_{eff} compared to that in 2008. In 2010, the location of the tipping point shifted to a higher value of γ_{eff} and these shifts continued from 2011–2015. This

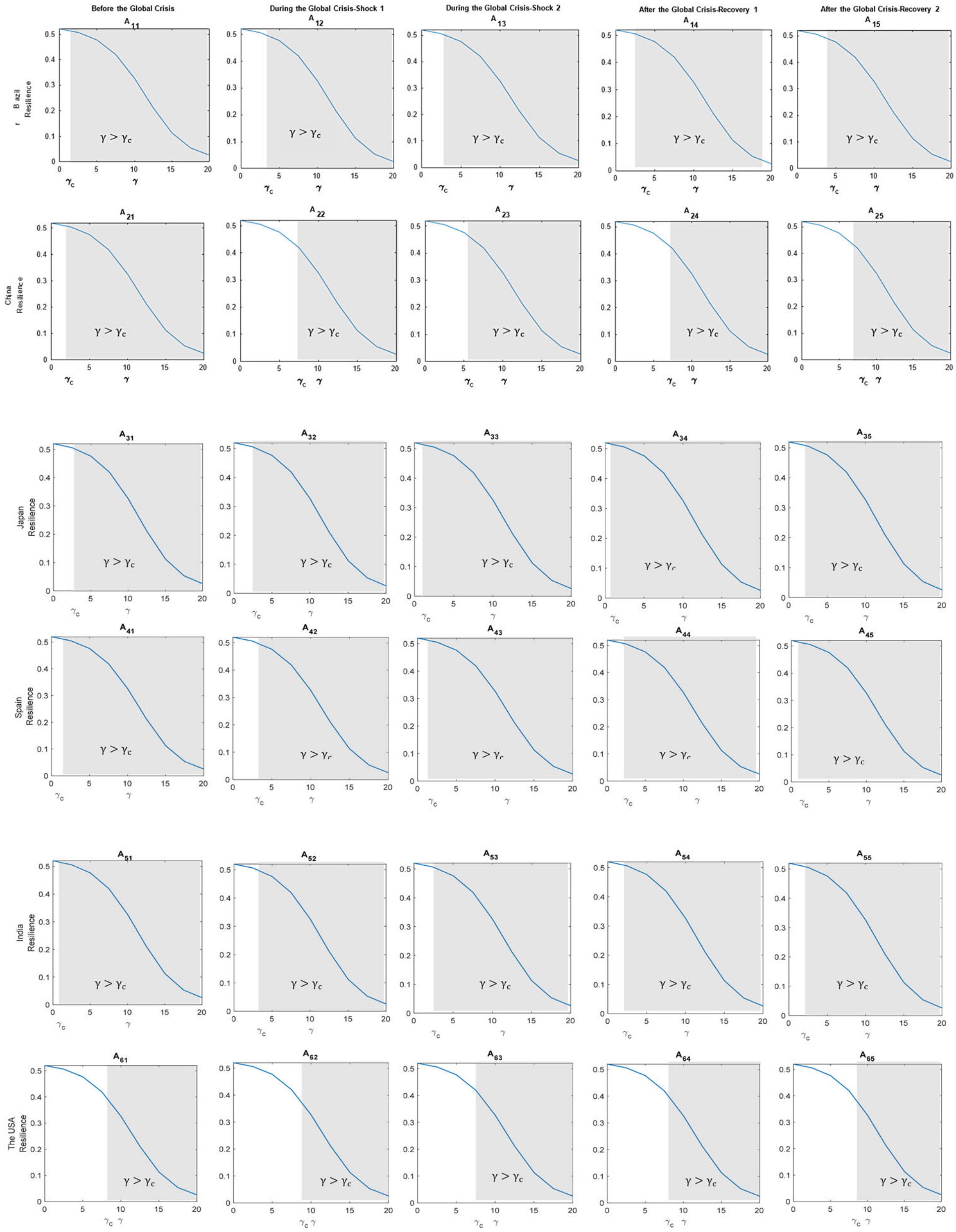

Figure 2. Tipping point's location for 35 topology structures.
Source: made by authors.

empirical outcome indicates that all the countries improved their resilience during this period.

Where $K = 100,\ C = 1,\ D = 25\ and\ \alpha = 1,\ E = 0.7,$ the figure shows how different countries with different industrial topological systems can vary in location tipping points when exchange rate volatility increases 1995–2015.

5.2. The impact of FDI on industrial system collapse when subjected to exchange rate volatility

FDI is an essential characteristic of ecosystem features that stimulates the economy (Lim & Teo, 2019). Investment can boost output in the market and thus increase interactions within industries (Wu et al., 2020). The results show that increasing FDI enhances system resilience.

5.2.1. The influence of *FDI* on the global tipping point location

Figure 3a shows the variation in the location of the tipping points for the three phases when the amount of FDI changes. In phase 1 (before the global crisis), the global average FDI amounted to 19.4 billion dollars, making the network system resilient when subjected to exchange rate volatility. In 2008, a surge in the global market size became a catalyst for expanding FDI receipts. With a worldwide average FDI of 36.31 billion dollars during this period, the system experienced the highest resilience. This implies that the industrial system collapses at higher values of γ_c. In 2009, we saw a drastic fall in FDI to 20.10 billion dollars; this led the system to chaotic behaviour and collapsed at a smaller value of exchange rate volatility. This implies that even a smaller value of γ_{eff} can disrupt a less resilient system. The system continued to improve from 2011–2015, with an FDI expansion of 23.60 billion dollars (see *Table B1 Supplementary Information*). These results lead to a shift in the location of the tipping point to a higher value of exchange rate volatility.

5.2.2. Influence of *FDI* on the country's tipping point location

The effect of FDI on the location of the tipping point of the USA, China, Brazil, Japan, India, Spain, and South Africa is shown in Figure 3b–f. The varying values of FDI and exchange rates are summarised in Table B4 (see *Supplementary Material*). Figure 3b shows the variation in resilience under the influence of FDI in Phase 1. The USA experienced the largest value of FDI, amounting to 197 billion dollars, followed by China, with an FDI of 66.10 billion dollars. A large FDI for the USA and China made the countries economically resilient, with a higher tipping point location. Spain and South Africa were the least resilient countries, both with an FDI of 2.53 billion dollars. In 2008, the FDI values expanded more than in 1995–2007 because of market expansion and infrastructure enhancement.

The USA led with a 73% rise in FDI, amounting to 341.10 billion dollars. China followed with an upsurge to 171.50 billion dollars, equivalent to 160% growth, which was significant for enhancing tipping point locations. South Africa reached only 9.9 billion dollars.

Figure 3c shows that the global crisis resulted decreased FDI in all the countries. Spain was the most affected country with an FDI decrease of 87%, from 74.10 billion dollars (in 2008) to 10 billion dollars (in 2009). FDI in South Africa dropped by only 23%, from 9.89 billion dollars during the global crisis shock of 1 to 7.62 billion dollars during shock 2. The inward FDI to China fell by 24%, from 171.50 billion dollars (in 2008) to 131.10 billion dollars (in 2009). Despite South Africa experiencing the smallest FDI drop, the topology structure still favours the USA and China to

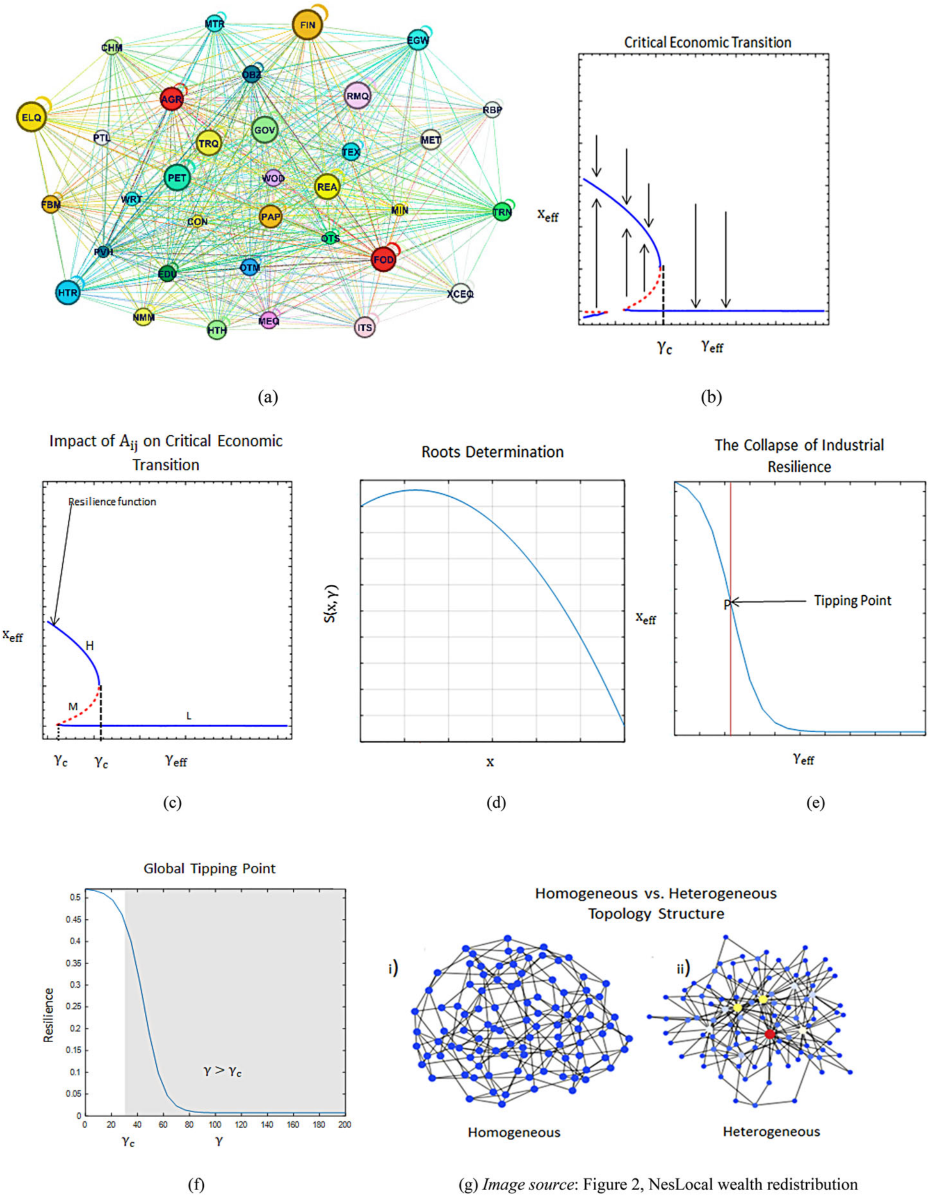

Figure 3. (a–f) Influence of FDI on the countries' tipping point location from 1995–2015 (g) Effect of optimal control on the economic system.
Source: made by authors.

withstand the global crisis. However, South Africa was the least resilient country during the global crisis-shock 2 (in 2009).

In 2010, countries began to experience recovery on different scales. This continued in2011–2015. Spain was the most improved country and expanded from 9.96 billion dollars to 36.60 billion dollars; equivalent to 288% FDI growth. They were followed by China, which increased by 86% to 243.70 billion dollars. Japan and South Africa continued to drop by 40% and 52%, respectively, making South Africa the country with the smallest tipping point location. From 2011–2015, countries' economies improved to a stable state, with improvements in FDI. The results show that the USA and China were still the leading resilient countries with FDIs amounting to 312.90 (18.5%) billion dollars and 264.60 (8.6%) billion dollars, respecrively. In this phase, the highest FDI drop was recorded in Spain, which fell from 36.60 billion dollars to 4.86 billion dollars, equivalent to 86.7%. Consequently, it lowered its location at the tipping points, as shown in Figure 3b–f.

5.3. Hedging strategy for controlling the industrial system collapse

The challenge of exchange rate volatility may lead to the collapse of the economic system, and risk can be mitigated by controlling the system. This strategy can be achieved by applying optimal control theory to the model equation (Browning et al., 2021). Here, we introduce a hedging strategy to manage the risks associated with exchange rate volatility. Hedging is a threat management strategy that can offset investment losses (Cho et al., 2020). Hedging optimised the objective function J by introducing an optimal control to Equation (8). Figure 3g, shows that if no control (i.e., $u = 0$) measures are taken, the resilience will not change, as indicated by the dashed red line. The results further reveal that when control is carried out (i.e., $u \neq 0$), the resilience of the system increases, as shown in Figure 3g (green circle line). The increase in system resilience shifts the location of the tipping point to a larger value of exchange rate volatility.

Additionally, the results confirm that improving the strength of economic resilience by applying hedging controls will enable the system to withstand the disruption of exchange rate volatilities. Our numerical results suggest that optimal control as a strategy for mitigating the effect of exchange rate volatilities has the greatest impact on system risk control.

6. Conclusion and future work

A weak network structure and exchange rate volatility movement jeopardise the resilience of the industrial ecosystem and can trigger massive industry failures and collapse. This study proposes a theoretical framework to reveal the mechanism of the industrial system collapse after an economic shock. Our model is based on a complex network theory. The model incorporates exchange rate volatility, FDI, and the network structure, which affect network density and heterogeneity. We demonstrate that weak industry interconnectedness boosts the transmission of a collapse within the system. The industrial ecosystem is more likely to crash when industries are not tightly interconnected (fragile topological structures). However, the industrial network structure is not the only dominant risk channel. Owing to an unusual upsurge in exchange rate volatility, the fire sale effect triggered by the exchange rate risk joins the network effect.

Finally, we confirm that an industrial system is susceptible to network structure and exchange rate volatility. A weak network structure and exchange rate volatility exert a tremendous negative impact on the resilience of the industrial ecosystem and trigger industrial system collapse. In this study, we further argue that our developed model applies the Lotka-Volterra complex system theory. This model approach bridges the bifurcation analysis of industrial ecosystems and their tipping points. Many previous scholars have discussed the Lotka-Volterra model on the structure of ecological ecosystems and their corresponding tipping point (Cressman et al., 2020; Remien et al., 2021; Zhang & Huang, 2021), and pointed out the effect of exchange rate volatility on economic collapse (Bahmani-Oskooee & Karamelikli, 2021; Bahmani-Oskooee & Nouira, 2020; Ribeiro et al., 2020). Applying the complexity theory approach to investigate industrial structure and exchange rate volatility provides the novelty of this study.

Our study sheds light on several concerns for economic regulators and policymakers. First, from an ex-ante perspective, economic regulators can improve the resilience of the industrial ecosystem by regulating the structure of the industrial network formed by the transaction interconnectedness between industries. This can be achieved by enhancing FDI and trade activities. This outcome will strengthen the industrial structure and focus on limiting economic collapse, the risk of a crisis in the industrial ecosystem, and its spillover to the economy. Second, stressed scenarios can be generated by cascading the increase in exchange rate volatility. This study contributes an intuitive and straightforward way to measure the threshold value of exchange rate volatility that can push the industrial ecosystem towards total collapse.

Future studies should consider extensions. First, this study investigated the topological structure of industrial networks in standard technological settings. Future research can examine the influence of technological advancement on industrial ecosystems, their growth, and its effect on improving system resilience. Second, the study considers a Lotka-Volterra model with the interaction coefficient of transaction links without considering trade-off parameters. Therefore, investigating the trade-off parameter in these settings may portray the key distributional aspects driving policy decisions.

Funding

This study received no external funding.

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Data availability statement

All data outcomes used in this work (see *data file*)

Disclosure statement

No potential conflict of interest was reported by the authors.

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