Industrial Diversification as an Adaptive Capability: Examining the Resilience Quantification of Industrial Ecosystems

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***Abstract*—Industrial diversification is necessary for the industrial sectors and organizations to withstand and remain operational during the economic shocks. This study investigates the role of industrial diversification on industrial ecosystem resilience, particularly on the revenue growth of the industrial network. To discover the remedy, we adopted a stochastic system model that captures the dynamics of the industrial ecosystem. The stochastic model was adopted with the resilience triangle approach, the industrial revenue residues exhibited, and the resilience quantified. Data collected from the year 1995 to 2015 and was divided into five phases. The countries of the sixty-two (62) Organization for Economic Co-operation Development (OECD) were selected for empirical testing. This study also selected seven developed and emerging economies with the highest gross domestic product (GDP) to test the consistency and validity of the outcomes. The results reveal a significant positive relationship between industrial diversification and industrial ecosystem resilience. This indicates that the more industrial diversification, the more it is resilient against economic shocks. Moreover, an industrial diversification strategy can be applied as an optimal control approach to reduce the economic risks, increase industrial ecosystem resilience, and avoid economic collapse.**

***Index Terms*—industrial resilience, industrial diversification, industrial ecosystem, stochastic system, resilience triangle, resilience index**

I. Introduction

Risk and unpredictable disruptions are inevitable facts of life for ecological and industrial ecosystems [1, 2]. These disruptive economic events demand that the ecosystem resist or adapt for survival [3]. Subsequently, the concept of improving industrial ecosystem resilience has emerged as a potential alternative to conventional risk management options [4-7]. A vital component of any resilient system is the development of adaptive capabilities that allow the system to withstand economic shocks [8] structurally. Although conventional risk management strategies have helped reduce the impacts of specific sources of shocks [8, 9], they cannot comprehensively cope with economic dynamics and uncertainty. This study aims to identify the degree of industrial ecosystem resilience and proposes industrial diversification as an adaptive capability. The risk mitigation will combat the industrial ecosystem collapse and systemic shocks across the globe and help in European economy [10].

Industrial ecosystem resilience is broadly defined as the capability of a system to absorb economic shocks and reorganize while changing to retain the same function, structure, identity and feedback [7]. The concept of industrial resilience embraces the fact that every productive industrial ecosystem will always be subject to unprecedented shocks. From the perspective of the industrial ecosystem, scholars defined resilience as an ecosystem that has developed adaptive capabilities after having experienced unexpected economic disruptions [11]. System resilience, a theory originating from socio-ecological studies investigated by Huang, Shi [12], is the ability of a system to withstand any shocks structurally, predicted, or unpredicted. From this perspective, industrial sector producers have already implemented resilience techniques into their risk management strategies for many years. Yet, in terms of reasonable risk management practices, applications of system resilience in the industrial sector are still evolving [13]. Survival in the turmoil of the present global economy, industrial sectors need to improve their processes, systems, and technologies to be dynamic and flexible and meet the ongoing changes in the global market [14].

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Nowadays, robust industrial interaction leads to a high industrial ecosystem risk of uncertainty. If these risks become real, they can negatively impact the system resulting in deformed. Many studies have shown that modern industrial ecosystems are at greater risk than their managers recognize [15, 16].

A. Resilience Quantification and Industrial Diversification as an Adaptive Capability

Measuring and analyzing industrial ecosystem resilience is essential in strategically locating critical facilities as network operations strategies. In support of this, we introduce the adopted resilience triangle approach [17] to analytically quantify the underlying resilience degrees that unveil the characteristics of industrial resilience discussed above. The approach investigates the industrial ecosystem's robustness against initial loss and the rapidity of the recovery process. In this study, we discuss the background of the resilience triangle introduced by Bruneau [18]. We then define the notion of predicted industrial ecosystem resilience as an analytic measure and provide a simple approach to calculating its value. The resilience value depends on the behavioral patterns of the industrial revenue volatility. This behavior of industrial revenue dynamics can be illustrated with the resilience triangle (see Fig. 1).

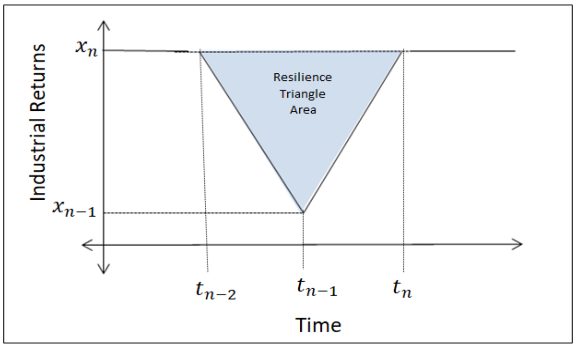

Figure 1. Graphical representation of the resilience triangle framework

The concept of the triangle of resilience can represent the loss of functionality of the industrial ecosystem from harm and discomfort. The resilience triangle helps visualize the industrial ecosystem shocks and system performance. It is helpful to investigate the resilience of an industrial ecosystem after an unexpected disorder. This represents a measure of the loss of functionality of an ecosystem after a disaster and the amount of time it takes for the ecosystem to return to normal performance levels. Resilience enhancement measures are designed to reduce the size of the resilience triangle area by improving performance. This paper proposes a triangle resilience quantitative approach for measuring the resilience of the industrial network components and the network itself. This study introduces a conceptual framework featuring the ability of the industrial ecosystem to adopt alternative plans when a part is disrupted. As a first step toward measuring industrial ecosystem resilience, the resilience is defined and quantified as a function of criticality, disruption frequency, disruption impact, and recovery capability. This quantification approach reflects the effect of component-level disruption on the ecosystem during disruptive events. Hence, it is proposed that the industrial ecosystem resilience is measured by the resilience of the network component having the lowest resilience index [17]. The proposed approach can help decision-makers assess the network resilience status and compare other ecosystems, identify and promote industrial resilience, evaluate the cost of resilience improvement, and determine the extent of enhancement achieved under a given budget constraint.

This study brings together the resilience and strategic settings of industrial ecosystems. Ongoing regulatory reforms in the industrial ecosystem urge a joint analysis of such complementary domains better to understand industrial sectors' environment and strategic behavior. We address the interrelationship between regulatory, industrial resilience and industrial diversification. Both play a part in alleviating default industrial risks [19, 20]. Industrial diversification is a strategy that involves choosing to industrial structure operation in a manner that promotes involvement in a wide range of revenue-producing activities. As a part of this evolution, researchers have acknowledged that industrial diversification is a management practice that can potentially lead to higher levels of industrial ecosystem resilience [21]. Diversified industrial sectors may have to do with the production of goods and services associated with the trade activity or may focus more on how the ecosystem arranges its investment portfolio. The goal of any industrial diversification is to increase the chances of industrial revenue by diversifying or spreading assets over a broader range of activities while also helping to mitigate the economic risks triggered by industrial defaults.

This study contributes to the literature in determining whether industrial diversification drives the increase in industrial ecosystem resilience. The contribution is explored in two fold. First, applying the adopted stochastic system model and resilience triangle framework in the industrial ecosystem dynamics context introduces the system resilience perspective to existing risk management literature in this field. Second, the empirical outcomes provide valuable insights for informing policy and industrial-level decision-making in the face of increasingly volatile industrial revenue caused by the COVID-19 and Ukraine-Russia war.

The remainder of this paper is structured as follows. The following section portrays the related literature review and knowledge gaps. Section three quantifies industrial ecosystem resilience using the adopted stochastic model system and resilience triangle. This section also explains the data and the industrial sectors under study. Section four presents the simulation results. Section five discusses the results, and the final section concludes the study and provides future recommendations.

II. Literature Review

Industrial ecosystem resilience has been broadly studied by Tan, Hu [22] during the last decades based on the different perspectives of resilience in the various disciplines to which the resilience concept is relevant. The recent studies associated, in fact, resilience with the ability of systems to absorb regional industrial changes, as opposed to stability as the ability of the latter systems to return to a state of equilibrium after a temporary disruption [19]. In connection to the social point of view, Duchek [5] studied organizational resilience. They conceptualized resilience as a meta-capability and decomposed the construct into its sections. The process-based studies suggest three successive resilience stages (anticipation, coping, and adaptation) and give a framework of underlying capabilities that form organizational resilience. Iannacone, Sharma [23] developed a novel dynamic model to investigate the effects of infrastructure deterioration on their time-varying ability to recover after disruptive events. By unifying available models for deterioration and recovery, the research proposed developing resilience measures to quantify the temporal and spatial variations of infrastructure's ability to recover from shocks.

Numerous metrics have been applied to quantify resilience over a range of industrial ecosystems. However, the way resilience is measured the degree to which different trajectories of industrial ecosystem recovery from disturbance are portrayed as resilient, precluding a comparison of risk responses across ecosystems and their properties and functions. To approach a broadly comparative assessment of ecosystem resilience, Ingrisch and Bahn [24] suggested using a bivariate framework that jointly considers the disturbance impact and the recovery rate, both normalized to the undisturbed state of a system. The scholars further demonstrated the framework's potential for attribution and integration across the various components underlying resilience. Moreover, ecosystem resilience has been quantitatively analyzed by measuring indicators. Indicators used to quantify resilience are either objective or subjective. Subjective indicators are quantified through the rates given to them by people [25-27]. Using a case study of potable water networks as a demonstrating tool, Yarveisy, Gao [28] proposed a demand-based framework for resilience assessment under disruptions to address the measuring of ecosystem resilience. Linkov, Carluccio [29] used broader resilience conceptualizations to introduce the resilience matrix and three-tiered resilience assessment that can be applied within value chain analyses to better safeguard long-term business feasibility despite a context of increasing risks. In this study, we adopt the resilience triangle approach to quantify the resilience of industrial ecosystems as discussed by the scholars [17, 30]. The other scholars who quantified the ecosystem resilience are Bevilacqua, Ciarapica [31]. They offered a modularization of the Supply Chain Resilience Triangle (SCRT), an intuitive tool for examining the performance of a Supply Chain during a shock through an accurate study of the various factors affecting the resilience of the Supply Chain. Fischer, Škorić [32] used the triangle resilience to demonstrate its usefulness in the containment problem of the square of a Hamilton cycle.

Researchers have posited that industrial diversification is an adaptive capability to enhance industrial ecosystem resilience [7]. Umutlu and Yargı [20] argued that a diversified industrial ecosystem could withstand simultaneous disturbances to several sectors and promote and maintain viability and productivity. Previous studies have shown that the diversification of industrial sector production can enhance the ability to respond to changes in consumer preferences and weather financial shocks [21]. However, the literature on industrial ecosystem resilience in general and the effect of diversification on industrial sector resilience is still relatively underdeveloped. This study attempts to fill this gap by presenting an empirical examination of the role that industrial diversification can play in enhancing the strength of the industrial ecosystem. Specifically, it utilizes 21 years of industrial revenue-level data from the OECD member countries database to examine the effect of diversification on industrial ecosystem resilience. Iversen and Herstad [33] studied industrial diversification using the trademark data approach to research regional diversification. They developed a regional trademarking-intensity measure to shed new light on how different regions diversify while accounting for changing industrial structures and revenue levels. The approach revealed that density moderately affects trademarking sale intensity and confirms the strong relationship between new industrial sector formation and regional diversification. These impacts are found to vary by sector and to be sensitive to industry-level employment and turnover.

Recent researchers investigated whether industrial ecosystem diversification generally provides a tax advantage and how the convexity of the tax system contributes to this benefit. The results showed that multi-industry operations lower a firm's taxes and income volatility relative to single industry operations. Still, the benefit is not universal [34]. Yiğit, Kartaltepe-Behram [35] investigated whether there is a significant difference between types of diversification and performance values in Turkey and Italy and found that organizational performance values are high for single businesses. Unrelated diversification in Turkey, organizational performance is high for dominant businesses and related diversification in Italy. In the study of diversifying crop rotations strengthens agroecosystem services and resilience conducted by Liu, Plaza-Bonilla [36], it was found that diversified crop mixtures improve ecosystem resilience.

This paper is the first to investigate the quantification of industrial ecosystem resilience using both the resilience triangle and stochastic model theory and suggests industrial diversification as an adaptive capability. First, our adopted stochastic model system incorporates the mean-reversion rate, which quantifies the speed with which the process returns to the average value aftershock. Second, it empirically unveils the triangles which examine the industrial ecosystem resilience dynamics in the period from 1995 to 2015. Third, we introduce a resilience triangle approach to quantify the degree of the industrial ecosystem during the 2008-2009 global crisis. Finally, we compute the diversification index followed by using Ordinary Least Squares (OLS) to examine the statistical significance between diversification and resilience. These concepts have been encompassed in a single study, which other scholars have not discussed.

III. Methods and Materials

This study is carried out in the following four steps. Firstly, we adopt the stochastic system model approach to examine the system's behavior and use a model parameter to quantify the resilience of the industrial ecosystems. The model system highlights industrial returns' residues (volatility) by exhibiting the resilience triangle areas. In this work, we present a stochastic methodological approach to studying resilience. For the rest of this study, we adopt the following definition for industrial ecosystem resilience: The speed at which an industrial ecosystem returns to equilibrium after an economic shock. Therefore, in our framework, we argue that an industrial ecosystem is more or less resilient depending on whether it recovers rapidly or slowly from economic perturbations. We assume that the state of the ecosystem can be determined by some quantifiable industrial revenue returns that exhibit stochastic behavior. In this approach, we adopt the perspective that the economic risks that disrupt the functioning of the ecosystem are assumed to be random. The perturbation caused by the shock in the next time interval has a Wiener process with mean μ and volatility σ. For these assumptions, we use a stochastic model of the form;

$$\text{system state} = \text{recovery} + \text{random shock}$$

And attempt to measure the recovery rate, thus quantifying the resilience of the industrial ecosystem. Furthermore, we assume that as the shock propagates and is absorbed in the ecosystem, it always aims to improve or bounce back to normal functioning, thereby unveiling a phenomenon called mean-reversion of the industrial ecosystem. The standard mean-reversion model with deterministic and stochastic terms in literature [37] is adopted.

$$dX(t) = \alpha\big(\big(\mu(t) - X(t)\big)dt + \sigma(t)dW(t) \qquad (1)$$

Where

$X(t)$ = the state of the ecosystem (revenue of the industrial sector)

α = the mean-reversion rate which quantifies the speed with which the process returns to the average value aftershock.

$\mu(t)$ = the time-dependent mean level

$\sigma(t)$ = the standard deviation that describes the volatility (controls of randomness in the industrial revenue.

$W(t)$ = the Brownian motion (Wiener process)

From Eq (1), we see that the first term the mean-reversion rate and the mean-reversion level govern (drift term). The mean-reversion rate term captures the ability of an industrial ecosystem to recover from random shocks. Suppose the value of $X(t) > \mu(t)$, the drift becomes negative and pulls the economic process down towards the mean-reversion level at a rate α. Conversely, if $X(t) < \mu(t)$, the drift term becomes positive and thus, pushes the economic process upwards towards the mean-reversion level. Therefore the above model and the parameter α provide a new methodology to quantify the resilience of industrial ecosystems that exhibit stochastic behavior.

Secondly, this work adopts the resilience triangle approach [17, 18]. This approach highlights the industrial resilience quantification by calculating the resilience indexes of the industrial ecosystems. This is achieved by adopting the resilience index equation to obtain the degree to which the industrial ecosystem withstands the economic disruption during the shocks. Here we adopt the resilience triangle model to get

$$R = 1 - \left[\sum_{t_0}^{t_n} \left(1 - {x_{t_n}}/{x_{t_0}}\right) \Big/ (t_n - t_0) \right] \qquad (2)$$

R represents the industrial ecosystem resilience index, x_{t_n} is the expected revenue at time shock t_n, x_{t_0} is an expected revenue at the first shock during the time t_0 and $t_n - t_0$ is the total time during the shocks.

The rationale behind adopting the resilience triangle approach is to calculate the resilience index during the shock model to depict the degree of shock exhibited from the stochastic model system. This approach is essentially quantifying the area of the 2008-2009 economic crisis. Although it is not a perfect triangle (due to the nature of net industrial revenue), it creates a measure that includes both the degree of impact of the industrial ecosystem shock and the length of time to recovery.

Thirdly, we adopt the diversification approach to calculate the industrial diversification index in 2008-2009 industrial ecosystems. Here we have

$$D_e = \left(\sum_{t_0}^{t_n} \left(\sum_{i=1}^{N} \left({x_i}/{x_T}\right)^2\right)\right) \Big/ (t_n - t_0) \qquad (3)$$

where D_e is the industrial ecosystem diversification index, x_i is the revenue at industrial sector i, x_T is the total revenue of all industrial sectors in the ecosystem at the time t_n and $t_n - t_0$ is the total time during the shocks. Finally, we investigate the relationship between industrial resilience and its corresponding diversification degree. This is achieved by adopting the Ordinary Least Squares (OLS) approach to examine the influence of industrial diversification on the resilience of the industrial ecosystem. Here we have the adopted regression model;

$$R_{ei} = \alpha + \beta_1 D_{ei} + \varepsilon_i \quad (4)$$

where R_{ei} and D_{ei} are the resilience and diversification indexes of industrial ecosystem i, and α β_1 ε_i are the corresponding model parameters.

A. *Numerical Simulation*

1995-2015 industrial sales of OECD countries provide information about the industrial return in 33 industrial sectors in four economic zones. Thus, in these industrial transactions, we obtain the empirical values of time-dependent mean level and volatility that exhibit the economic trends of industrial ecosystems. This section presents the details of our study on the profitability and accuracy of this method to quantify the degree of the industrial ecosystem during the perturbation (during the 2008-2009 global crisis). The numerical simulation was conducted by selecting data from 33 industrial sectors from 1995 to 2015, including the 2008–2009 global crisis. The data 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: estimating the value of the mean-reversion rate, and then using the MATHEMATICA V09 tool, we apply stochastic developed Eq (1) to simulate the Wiener process as described in the methodological section.

B. *Data Structure*

The data structure investigates the role of industrial diversification on the resilience of industrial ecosystems. To calibrate the model, we selected 33 industries and relied on industrial transaction data sources. First, we obtained input-output (I.O. table) data for 62 OECD country economies from 1995 to 2015, sourced from the OECD database (https://data.oecd.org/). The list of industrial sectors and countries is summarised in Tables A and B, respectively (see *Appendix A*). The selected data involve 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 maximum value of the sample size as "*Report for Selected Country Groups and Subjects (PPP valuation of country GDP)*" Retrieved 9 May 2018 (Chai, 2020). These two values of GDP and purchasing power parity (PPP) portray the required information in the study of industrial ecosystem structure. Moreover, the OECD countries contribute the most significant value of countries' economic sophistication (Economic Complexity Index) as studied by recent scholars (Lapatinas et al., 2019). This measure portrays good results for the investigation of industrial ecosystem dynamics.

IV. Simulation Results

A. *Resilience Index and Stochastic Triangle Areas*

The area of the shaded triangle defines the extent of an industrial ecosystem's resilience (see Fig. 1). This study aims to quantify the degree of resilience of the industrial ecosystem from 1995 to 2018. Different ecosystems experienced different average mean levels and volatilities, as summarized in Table B1 (see *Appendix B*), which quantified the degree of resilience. From a global perspective, the results show that the resilience of the industrial ecosystem determined using the resilience triangle approach is 0.9945.

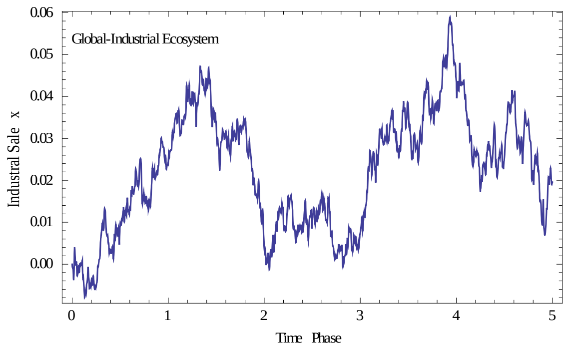

Figure 2. A stochastic modeling of global- industrial ecosystem using 1995-2015 industrial sale data.

Corresponding to the worldwide resilience degree, Fig. 2 shows the global ecosystem's stochastic volatility that exhibits the role of the mean level and volatility of industrial sales towards the resilience degree. The figure shows that the industrial sales were random within the ecosystem. The random distribution of sales is investigated using the Wiener process of the stochastic differential system [37]. That reveals the best results of resilience triangles of the industrial ecosystem, as shown in the figure.

Furthermore, the figure displays many resilience triangles because the lower position triangles indicate the time of major industrial ecosystems shock. In comparison, the larger size triangles indicate the longest time of shocks. Here we see that phases 2 (in 2008) and 3 (in 2009) experienced the greatest industrial shocks compared to other phases of industrial ecosystems.

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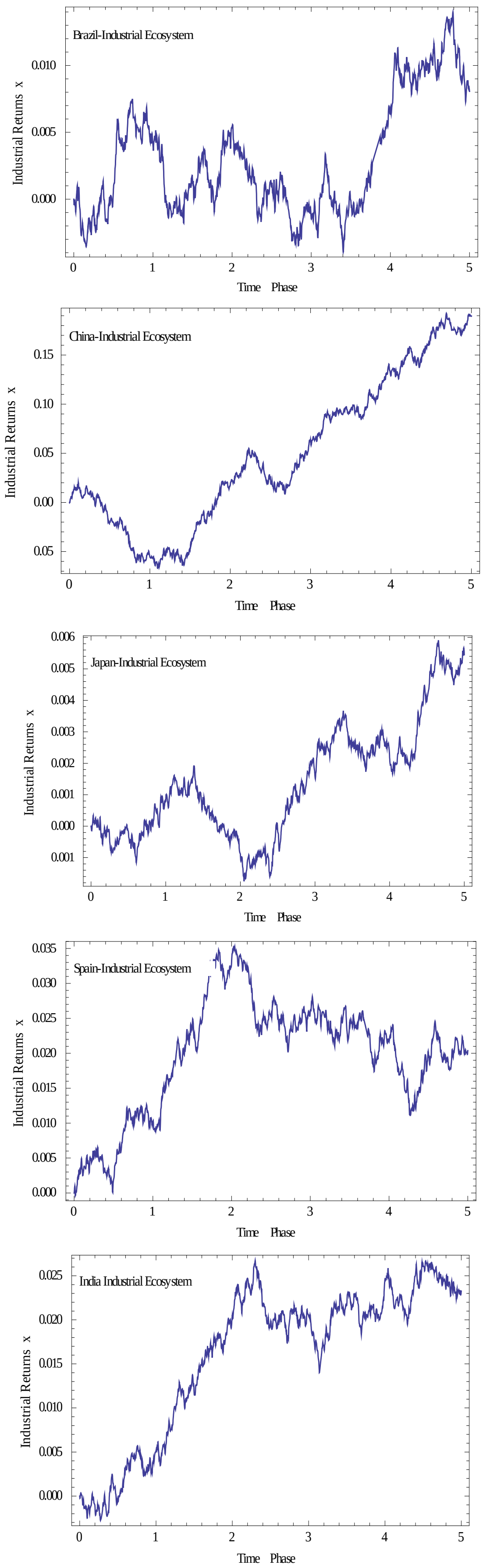

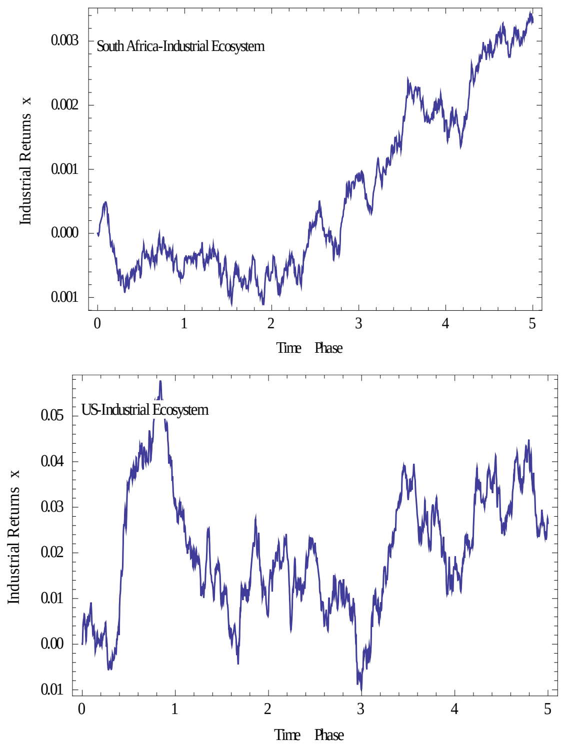

Figure 3. A stochastic modeling of the country- industrial ecosystem using 1995-2015 industrial sale data

B. Industrial Diversification

Depending on the dynamic behavior of the industrial returns, the stochastic approach unveiled the resilience triangles as explained in section 3. We obtained the resilience index using the resilience triangle approach and the corresponding industrial diversification index of global and seven-industrial ecosystems from the resilience triangle. Table I shows that China's industrial ecosystem was most resilient during this shocking period with a resilience index of 1.1765, followed by India and the U.S. with a resilience index of 1.0602 and 0.9987, respectively. Spain and South Africa were the least resilient country-industrial ecosystems, with a resilience index of 0.7489 and 0.7825, respectively. Additionally, we find that industrial ecosystems along the globe experienced a slight industrial resilience during the 2008-2009 shock with averaging resilience index of 0.9945. Having calculated the resilience index for the industrial ecosystems, we then want to identify a significant relationship between industrial resilience and industrial diversification. This is achieved using the OLS method to determine the correlation coefficient that unveils the degree of the relationship. Using the calculated diversification index of eight industrial ecosystems summarized in Table I and then the OLS method, the results show a positive correlation between industrial resilience and industrial diversification with a correlation coefficient of 0.33 (see *Appendix C*). The rationale behind the positive correlation is that diversification enhances the industrial resilience of the economic system.

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TABLE I. EMPIRICAL OUTCOMES OF 1995-2015 RESILIENCE INDEX (R) AND INDUSTRIAL DIVERSIFICATION INDEX (D_e)

Empirical Outcomes of 1995-2015 Resilience Index (R) and Industrial Diversification Index (D_e)								
Ecosystem	Global	Brazil	China	Japan	Spain	India	South Africa	US
R	0.9945	0.7807	1.1765	0.8255	0.7489	1.0602	0.7825	0.9987
D_e	0.0058	0.0546	0.1235	0.0579	0.0543	0.0629	0.0505	0.0661

Source: *Author computation*

TABLE II. DESCRIPTIVE STATISTICS OF STATISTICS FOR MEAN LEVEL (Μ) AND STANDARD DEVIATION (Σ)

	μ	σ
Mean	0.059450	0.971675
Median	0.056250	0.996600
Maximum	0.123500	1.188400
Minimum	0.005800	0.748900
Std. Dev.	0.032003	0.171330
Skewness	0.501810	-0.050000
Kurtosis	3.910362	1.568530
Jarque-Bera	0.612004	0.686368
Probability	0.736385	0.709508
Sum	0.475600	7.773400
Sum Sq. Dev.	0.007169	0.205478
Observations	8	8

Source: *Eviews simulation*

V. DISCUSSION

The results confirm that the varying diversification index of industrial ecosystems reveals the different degrees of industrial ecosystem resilience. Moreover, resilience quantification was investigated. The results from the stochastic state function showed that the industrial revenue volatility exhibits many resilience triangles that unveil the different degrees of shocks, as shown in Figs. 2 and 3. The figures further show that the area of the resilience triangles in all industrial ecosystems was more extensive during the 2008-2009 shock compared to the other industrial ecosystem phases. This indicates that the ecosystems experienced the most remarkable economic shocks during 2008-2009, as verified by recent scholars [38].

From a global perspective, the industrial ecosystem experienced an average mean level and volatilities of 0.0075 and 0.0188 billion dollars, which quantified the degree of resilience. The results unveil that the resilience of the industrial ecosystem determined using the resilience triangle approach is 0.9945, corresponding with a diversification index of 0.0058. Fig. 3 shows the revenue residues of seven country-industrial ecosystems. The results compare with the industrial ecosystem resilience index as summarized in Table I and the weighted mean and volatility summarized in Table B1 (see *Appendix B*) of each country-industrial ecosystem. The results in Table I further show that China's industrial ecosystem was most resilient during the 2008-2009 shock with a resilience index of 1.1765, followed by India and the U.S. with a resilience index of 1.0602 and 0.9987, respectively. Spain and South Africa were the least resilient country-industrial ecosystems, with a resilience index of 0.7489 and 0.7825, respectively. The results unveil the positive relationship between industrial resilience and industrial diversification with a correlation coefficient of 0.33. This indicates that industrial diversification improves industrial ecosystem resilience, as revealed in Table I. Additionally, China's industrial ecosystem experienced the most significant degree of diversification with a value of 0.1235, followed by the U.S. (Diversification Index=0.0661). Furthermore, Spain and South Africa experienced the lowest industrial diversification with the index degree of 0.0543 and 0.0505, respectively. The other three country-industrial ecosystems experienced moderate industrial diversification with the index degree of 0.0546 (Brazil), 0.0579 (Japan), and 0.0629 (India).

VI. CONCLUSIONS

There is a significant positive correlation between diversification and resilience of the industrial ecosystems. This is to say that; industrial diversification enhances the resilience of industrial ecosystems. This work proposes a theoretical framework for revealing the quantification of industrial resilience degree and the impact of diversification on improving resilience during shocks. Our adopted model is based on the stochastic system model theory. The model incorporates the mean-reversion rate and Wiener process (Brownian motion) that affects the resilience of industrial ecosystems. In this paper, we further argue that our adopted model is the model that applies the stochastic system model theory followed by using the adopted resilience triangle approach to quantify the resilience index. This methodological approach bridges the resilience quantification analysis of industrial ecosystems and the role of diversification in improving ecosystem resilience. Many recent scholars, such as [12, 37], discussed the stochastic system model on the financial spikes and ecology and the corresponding resilience quantification using the triangle resilience approach [17, 18]. Iversen and Herstad [33] pointed out the effect of industrial diversification on industrial ecosystem structures using the trademark data approach. Applying the stochastic system model theory and the resilience triangle approach to quantify the resilience of the industrial ecosystem followed by the OLS method approach to measure a significant relationship between resilience and diversification gives the study novelty. We demonstrate that industrial diversification boosts the resilience degree within the industrial ecosystem. The results unveiled show that the industrial ecosystem is more likely to crash when industries are less diversified. Moreover, we confirm that the industrial system is susceptible to industrial diversification. Smaller diversification degree exerts a tremendous negative impact on the resilience of the industrial ecosystem and triggers industrial system collapse.

Our study sheds light on several concerns for economic regulators, managers, and policymakers. First, from an ex-ante perspective, economic regulators can improve the resilience of the industrial ecosystem by regulating the degree of industrial diversification formed by transaction interconnectedness between industries. This improvement can be achieved by promoting the diversified trade activity enhancement [20]. This outcome will make the industrial structure strong. Again, make it focused on withstanding the economic collapse, the risk of crisis in the industrial ecosystem, and its spillover to the economy. Second, stressed scenarios can be generated by economic shocks. This work contributes an intuitive and straightforward way to quantify the resilience degree that can push the industrial ecosystem towards growth. Thus, policymakers and regulators can suggest an appropriate industrial diversification strategy as a system control method. We hope that our adopted stochastic system model system and resilience triangle approach and analysis trigger the interest of future economic researchers from diverse disciplines. The theory approach includes investigating financial spikes and industrial ecosystems, thereby helping to have a deeper insight into other global economies.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, methodology, software, Akwer Eva.; validation, Akwer Eva and Joseph David Madasi formal analysis, Joseph David Madasi investigation, Akwer Eva resources, Akwer Eunice.; data creation, Akwer Eva.; writing—original draft preparation, Akwer Eva.; writing—review and editing, Joseph David Madasi and Akwer Eunice; visualization, Akwer Eunice.; supervision, Joseph David. Madasi; project administration, Akwer Eva; funding acquisition, N/L.

References

[1] M. H. Dungey, et al., *Industrial Firms and Systemic Risk.* Available at SSRN 3555836, 2020.

[2] S. Pettersson, V. M. Savage, and M. Nilsson Jacobi, "Predicting collapse of complex ecological systems: quantifying the stability–complexity continuum," *Journal of the Royal Society Interface*, vol. 17, no. 166, p. 20190391, 2020.

[3] V. C. Westmont, "Assessing the adaptive resilience of twentieth-century post-industrial fishing landscapes in Siglufjörður, Iceland," *Landscape Research*, vol. 46, no. 5, pp. 693-712, 2021.

[4] N. C. Dormady, et al., "The cost-effectiveness of economic resilience," *International Journal of Production Economics*, vol. 244, p. 108371, 2022.

[5] S. Duchek, "Organizational resilience: a capability-based conceptualization," *Business Research*, vol. 13, no. 1, pp. 215-246, 2020.

[6] R. J. Floetgen, et al., "Introducing platform ecosystem resilience: leveraging mobility platforms and their ecosystems for the new normal during COVID-19," *European Journal of Information Systems*, vol. 30, no. 3, pp. 304-321, 2021.

[7] S. M. Grabner and M. Modica, "Industrial resilience, regional diversification and related variety during times of crisis in the US urban–rural context," *Regional Studies*, pp. 1-13, 2021.

[8] T. Saeed, E. Bouri, and D. K. Tran, "Hedging strategies of green assets against dirty energy assets." *Energies*, vol. 13, no. 12, pp. 3141, 2020.

[9] X. Sun, et al., "Assessing the extreme risk spillovers of international commodities on maritime markets: A GARCH-Copula-CoVaR approach," *International Review of Financial Analysis*, vol. 68, p. 101453, 2020.

[10] M. Simoens and R. V. Vennet, "Does diversification protect European banks' market valuations in a pandemic?" *Finance Research Letters*, vol. 44, p. 102093, 2022.

[11] Q. Zhou, et al., "Achieving resilience through smart cities? Evidence from China," *Habitat International*, vol. 111, p. 102348, 2021.

[12] Y. Huang, et al., "A stochastic predator–prey model with Holling II increasing function in the predator," *Journal of Biological Dynamics*, vol. 15, no. 1, pp. 1-18, 2021.

[13] A. P. Browning, et al., "Persistence as an optimal hedging strategy," *Biophysical Journal*, vol. 120, no. 1, pp. 133-142, 2021.

[14] O. Khlystova, Y. Kalyuzhnova, and M. Belitski, "The impact of the COVID-19 pandemic on the creative industries: A literature review and future research agenda," *Journal of Business Research*, vol. 139, pp. 1192-1210, 2022.

[15] H. An, et al., "Early warning system for risk of external liquidity shock in BRICS countries," *Emerging Markets Review*, 2022, p. 100878.

[16] M. S. Rizwan, G. Ahmad, and D. Ashraf, "Systemic risk: The impact of COVID-19," *Finance Research Letters*, vol. 36, p. 101682, 2020.

[17] N. Ahmadian, et al., "A quantitative approach for assessment and improvement of network resilience," *Reliability Engineering & System Safety*, vol. 200, p. 106977, 2020.

[18] C. Li, et al., "Time-dependent resilience analysis of a road network in an extreme environment," *Transportation Research Part D: Transport and Environment*, vol. 85, p. 102395, 2020.

[19] A. Soroka, et al., "Measuring regional business resilience," *Regional Studies*, vol. 54, no. 6, pp. 838-850, 2020.

[20] M. Umutlu and S. G. Yargı, “To diversify or not to diversify internationally?” *Finance Research Letters*, vol. 44, p. 102110, 2022.
[21] S. Li and C. Wang, “Network structure, portfolio diversification and systemic risk,” *Journal of Management Science and Engineering*, vol. 6, no. 2, pp. 235-245, 2021.
[22] J. Tan, et al., “Industrial structure or agency: What affects regional economic resilience? Evidence from resource-based cities in China,” *Cities*, vol. 106, p. 102906, 2020.
[23] L. Iannacone, et al., “Modeling time-varying reliability and resilience of deteriorating infrastructure,” *Reliability Engineering & System Safety*, vol. 217, p. 108074, 2022.
[24] J. Ingrisch and M. Bahn, “Towards a comparable quantification of resilience,” *Trends in Ecology & Evolution*, vol. 33, no. 4, pp. 251-259, 2018.
[25] B. O. K. Lokonon, “Farmers’ vulnerability to climate shocks: Insights from the Niger basin of Benin,” *Climate and Development*, vol. 11, no. 7, pp. 585-596, 2019.
[26] V. O. Oladokun, D. G. Proverbs, and J. Lamond, “Measuring flood resilience: A fuzzy logic approach,” *International Journal of Building Pathology and Adaptation*, 2017.
[27] S. Woolf, et al., “Towards measurable resilience: A novel framework tool for the assessment of resilience levels in slums,” *International Journal of Disaster Risk Reduction*, vol. 19, pp. 280-302, 2016.
[28] R. Yarveisy, C. Gao, and F. Khan, “A simple yet robust resilience assessment metrics,” *Reliability Engineering & System Safety*, vol. 197, p. 106810, 2020.
[29] I. Linkov, et al., “The case for value chain resilience,” *Management Research Review*, 2020.
[30] Q. Zhao, et al., “Resilience index system and comprehensive assessment method for distribution network considering multi-energy coordination,” *International Journal of Electrical Power & Energy Systems*, vol. 133, p. 107211, 2021.
[31] M. Bevilacqua, F. Ciarapica, and G. Marcucci, “A modular analysis for the supply chain resilience triangle,” *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1528-1535, 2018.
[32] M. Fischer, et al., “Triangle resilience of the square of a Hamilton cycle in random graphs,” arXiv preprint arXiv:1809.07534, 2018.
[33] E. J. Iversen and S. J. Herstad, “Dynamics of regional diversification: A new approach using trademark data,” *Regional Studies*, vol. 56, no. 2, pp. 276-289, 2022.
[34] K. Wentland, “The effect of industrial diversification on firm taxes,” in *Proc. Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association*, JSTOR, 2016.
[35] İ. Yiğit, N. Kartaltepe-Behram, and E. İşçi, “An assessment of the diversification–performance linkage: An empirical comparison between Turkish and Italian firms,” *Tékhne*, vol. 11, no. 2, pp. 76-82, 2013.
[36] C. Liu, et al., “Diversifying crop rotations enhances agroecosystem services and resilience,” *Advances in Agronomy*, pp. 299-335, 2022.
[37] L. Catania, “A stochastic volatility model with a general leverage specification,” *Journal of Business & Economic Statistics*, pp. 1-23, 2020.
[38] J. Nikkinen, V. Piljak, and T. Rothovius, “Impact of the 2008–2009 financial crisis on the external and internal linkages of European frontier stock markets,” *Global Finance Journal*, vol. 46, p. 100481, 2020.

APPENDIX A

TABLE A1. LIST OF INDUSTRIES

AGR: Agriculture, hunting, forestry and fishing	EGW: Electricity, gas and water supply
FOD: Food products, beverages and tobacco	WRT: Whole sale and retail trade
TEX: Textiles, textile products and leathers	CON: Construction
MIN: Mining and quarrying	HTR: Hotels and restaurant
WOD: Wood products and cork	TRN: Transport and storage
PAP: Pulp, paper and printing	PTL: Post and telecommunication
PET: Coke, refined petroleum	FIN: Financial intermediaries
CHM: Chemicals and chemical products	M.Q.: Renting of machinery and equipment
NMM: Nonmetallic mineral products	R REA: Real Estate
RBP: Rubber and plastic products	ITS: Computer and related activities
MET: Basic metals	OBZ: Research and development
FBM: Fabricated metal products except machinery and equipment	GOV: Public admin
MEQ: Machinery and equipment	EDU: Education
ELQ: Electrical machinery	HTH: Health and social work
XCEQ: Electrical and optimal equipment	OTS: Other community, social and personal activities.
MTR: Motor vehicles, trailers and semi-trailers	OTM: Manufacturing and recycling
TRQ: Other transport equipment	

TABLE A2. COUNTRIES UNDERSTUDY

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

APPENDIX B

TABLE B1. GLOBAL AVERAGE OF FOREIGN DIRECT INVESTMENT AND GLOBAL AVERAGE EXCHANGE RATE

Empirical Outcomes of 1995-2015 weighted average (μ) and volatility (σ) in …Dollars								
Ecosystem	Global	Brazil	China	Japan	Spain	India	South Africa	US
μ	0.0075	0.0024	0.0218	0.0100	0.0049	0.0035	0.0007	0.0235
σ	0.0188	0.0048	0.0242	0.0129	0.0063	0.0046	0.0008	0.0360

Source: *Author Computation*

APPENDIX C: MODEL ADAPTATION ANALYSIS AND PARAMETER DETERMINATION

A. *Stochastic Model Derivation*

Here we assume that W_t is the standard Brownian motion, $\alpha > 0$ and $\sigma > 0$ are constants, and μ_t is a deterministic function that gives the time-dependent mean level. By substituting

$Y_t = e^{mt}X_t$, then using Ito's Lemma [37], we substitute

$$dY_t = me^{mt}X_t dt + e^{mt}dX_t, \tag{C1}$$

into Eq (1) to get

$$dY_t = me^{mt}X_t dt + e^{mt}(\alpha(\mu_t - X_t)dt + \sigma dW_t) \tag{C2}$$

This can further expanded to get

$$dY_t = e^{mt}(\alpha\mu_t - \alpha X_t dt + mX_t)dt + e^{mt}\sigma dW_t) \tag{C3}$$

Let $m = \alpha$. Then

$$dY_t = e^{\alpha t}\alpha\mu dt + e^{\alpha t}\sigma dW_t \tag{C4}$$

This implies that

$$Y_t - Y_0 = \int_0^T e^{\alpha t}\alpha\mu_t dt + \int_0^T e^{\alpha t}\sigma dW_t$$

Here we see that the first integral is a purely deterministic function. The second integral is an Ito integral function. Using stochastic calculus we have

$$\int_0^T e^{\alpha t}\sigma dW_t = \lim \sum_{j=1}^{N} e^{\alpha t_j} \sigma N(0, t_j - t_{j-1}) \tag{C5}$$

Thus,

$Y_t - Y_{t-1}$ has a normal distribution with mean $= \int_t^{t+1} e^{\alpha t}\alpha\mu_t dt$ *and*

variance $= \int_t^{t+1} e^{2\alpha t}\sigma^2$ similar to

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$$Y_{t+1} = Y_t + \int_0^T e^{\alpha t} \alpha \mu_t dt + \left(\sqrt{\int_t^{t+1} e^{2\alpha t} \sigma^2}\right) \epsilon \quad \text{(C6)}$$

where $\epsilon \sim N(0,1)$

From Ito's study, we see that the transition probabilities of a diffusion process $X_t = (X_t^1, \ldots, X_t^n)$ A Euclidean space satisfies a linear second-order parabolic (Kolmogorov's equation). The equation tells us that the coefficients $\sigma^{ij}(t,x)$ of the second-order part and $\mu^i(t,x)$ of the first-order term of the equation is characterized by

$$\begin{aligned} &\text{(i) } E\left[X_{t+h}^i - X_t^i \middle| X_t = x\right] = \mu^i(t,x)h + o(h), \\ &\text{(ii) } E\left[\left(X_{t+h}^i - X_t^i\right)\left(X_{t+h}^j - X_t^j\right) \middle| X_t = x\right] = \sigma^{ij}(t,x)h + o(h) \end{aligned} \quad \text{(C7)}$$

In words, the transition probabilities of the industrial diffusion process should be determined by the above infinitesimal mean $\mu^i(t,x) = \left(\mu^1(t,x), \ldots, \mu^n(t,x)\right)$ and the infinitesimal covariance $\sigma^{ij}(t,x)$ of the industrial revenue diffusion process. Using Eq (C7) to simplify Eq (1) to get

$$dX_t = \alpha \mu_t dt + \sigma dW_t \quad \text{(C8)}$$

B. *Parameter Determination*

From model Eq (4) and using the statistical results in Table II, we calculate the coefficient of correlation using the equation defined below

$$r_{\sigma\mu} = \sum_{i=1}^{N} (\mu_i - \bar{\mu})(\sigma_i - \bar{\sigma}) \Big/ \sqrt{\sum_{i=1}^{N} (\mu_i - \bar{\mu})^2 \sum_{i=1}^{N} (\sigma_i - \bar{\sigma})^2} \quad \text{(C9)}$$

where $r_{\sigma\mu}$ is the correlation resilience index and industrial diversification index and $\overline{R}$ and $\overline{D_e}$ are their mean values, respectively.

$$r_{\sigma\mu} = \sum_{i=1}^{8} (\mu_i - 0.0595)(\sigma_i - 0.9717) \Big/ \sqrt{\sum_{i=1}^{N} (\mu_i - 0.0595)^2 \sum_{i=1}^{N} (\sigma_i - 0.9717)^2} = 0.33 \quad \text{(C10)}$$

From Eq (2), we get the resilience index of Brazil during the global crisis as

$$R_{Brazil} = 1 - \left[\left(\left(1 - {4.42}/{11.79}\right) + \left(1 - {13.99}/{11.79}\right)\right) \Big/ 2\right] = 0.78 \quad \text{(C11)}$$

and the Eq (3) to get

$$D_{Brazil} = \left((3.9 \times 10^{-3}, \ldots, +2.16 \times 10^{-5}) + (3.4 \times 10^{-3}, \ldots, +2.33 \times 10^{-5})\right) \Big/ (t_{2010} - t_{2008}) = 0.0546 \quad \text{(C12)}$$

Similarly, the calculation is carried out for other remaining industrial ecosystems and summarized in Table I.

Data Availability Statement: All data outcomes used in this paper (see *https://data.oecd.org/*)