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A global trade supply chain vulnerability in COVID-19 pandemic: An assessment metric of risk and resilience-based efficiency of CoDEA method

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ABSTRACT

The COVID-19 pandemic has an adverse impact on the global trade supply chain. Countries where the economy is driven by global trade, either as exporters or importers and are faced with the problem of declining imports and exports. This is due to the interruption of the main players of the global supply chain (i.e., production, logistics and transportation sector) as well as the slow-down in consumption of overseas customers. This paper presents the development of an efficiency related metric from the Coherent Data Envelopment Analysis (CoDEA) method for assessing the vulnerability (or conversely, the robustness) levels of the supply chain system of six ASEAN countries. The results reveal that Thailand is most vulnerable to international supply chain issues indicated by its lowest efficiency score. This is due to Thailand's severe disruption of logistics and transportation systems compared with its neighboring countries. In contrast, Vietnam is the most robust because of its efficiency in the exports sector. Our research reveals that trading partners with a lower risk and the ability to rapidly recover their import volume reflect their less vulnerable supply chains. This research provides the associated strategies to establish a resilient global supply chain in spite of the COVID-19 pandemic.

1. Introduction

The global pandemic of coronavirus disease 2019 (COVID-19) is a highly infectious respiratory virus that poses a great threat to humans. The epidemic of COVID-19 has spread with a disturbing velocity, bringing economic activities and supply chains to a near standstill as many countries tighten movement restrictions to curb the spread of the virus. The World Bank (2020) stated that the baseline forecast envisions a 5.2 percent contraction in global gross domestic product (GDP) in 2020. Due to lower investment, the fragmentation of global trade and supply linkages, an erosion of human capital occurs with the loss of jobs and schooling. These affect the international merchandise and trade services of the global supply chain system. According to the December 2020 nowcast of The United Nations Conference on Trade and Development (UNCTAD, 2020), it predicted the value of global merchandise trade to fall by 5.6 percent in 2020 as compared with that in 2019. The predicted decline in trade services is higher and is likely to fall by 15.4 percent in 2020 as compared with that in 2019. The supply chains around the world face major disruptions and difficulties and are adjusting to the new demands and needs of a locked-down world to prevent the spread of COVID-19 (Zhu, Chou, & Tsai, 2020). For example, Asian countries where the greater span of global supply chains are because of their comparative advantage in production and distribution are affected e.g., China which is the *workshop of the world* paused to supply industrial parts and components. In Asia, India, Korea and Japan idled as the *hubs of factory* in their information and communication technology sectors (Vidya & Prabheesh, 2020). The Association of Southeast Asian Nations (ASEAN) countries are undertaking a swift mechanical transformation in their agricultural domains which is the source of numerous *agricultural-based food products for the globe* (Fan, Teng, Chew, Smith, & Copeland, 2021). Therefore, this pandemic has unearthed the vulnerability and risks of global supply chains by disrupting national nodes and internal supply networks (Golan, Jernegan, & Linkov, 2020).

Vulnerability, risk, and resilience of supply chains have gained considerable attention since the start of the COVID-19 pandemic. Vulnerability is used to quantify system susceptibility to threat scenarios which is different from the risk that focuses on the severity of

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consequences due to uncertain events and their probabilities (Ezell, 2007). On the other hand, resilience involves the ability of speedy recovery of the system to continue operating (Bryce, Ring, Ashby, & Wardman, 2020). From the risk management standpoint, the risk assessment process is important for the development of a robust supply chain. The outcome of risk assessment also allows the supply chain partners know their level of risk or vulnerability. As such, they can generate the necessary risk mitigation or resilient strategies for recovery. It is important to be conscious of the features and current vulnerability levels when it comes to developing strategies to close the weakness in various operations. While developing the appropriate metrics is a difficult challenge, a major problem is neglecting the use of the appropriate metrics to develop strategies. Further, the quantification of supply chain vulnerabilities was not incorporated and aligned with the defined elements of the supply chain. This situation is aggravated by the confusion over the measurements of vulnerability, risk and resilience of which each has significantly different perspective.

Reliable metrics and statistics are required to track the vulnerability, risk and resilience of the entire global supply chain in order to maximize the effectiveness of the mitigation strategies for addressing the impact of COVID-19 pandemic or similar threats that may arise in the future. In this study, the main objective is to develop the metrics to assess supply chain vulnerability based on risk and resilience perspectives in the COVID-19 pandemic in the economics setting. It introduces the risk mitigation scenarios to elucidate a global trade supply chain vulnerability. This study examines two main research questions: first, the proposed metric of applying the evaluation of the economic risk and resilience-based efficiency using CoDEA and whether it is reflective of the global trade supply chain vulnerability in the COVID-19 pandemic scenario? Second, is the result of the efficiency score of CoDEA method applicable for guiding risk mitigation or resilience policy for vulnerability closure in the ASEAN global trade supply chain?

Our research applied the basis of DEA to evaluate the efficiency score of the supply chain to represent the level of vulnerability of the risk rate and recovery rate (resilience) which are assigned as direct input and direct output respectively (Pournader, Rotaru, Kach, & Hajiagha, 2016). We enhanced this evaluation using the CoDEA model which is based on the traditional DEA calculation that encapsulates an intramural structure for the evaluation of the efficiency score of the supply chain (Chen & Yan, 2011). CoDEA avoids the intermediate measures between nodes and the virtual intermediate measure or the efficiency score of previous nodes are replaced (Jomthanachai, Wong, & Lim, 2021). CoDEA is the alternative for the evaluation of the supply chain performance in any perspective where vulnerability can be applied. CoDEA serves as an alternative for evaluating supply chain efficiency, which is different as compared with the two or multistage DEA model. Moreover, the main advantage of the CoDEA which is a traditional based DEA method is its flexibility in choosing appropriate inputs from the crucial information pertaining to the set of DMU under evaluation. In the context of supply chain vulnerability, the supply nodes are a vital resource of a network. Therefore, the supply vulnerability which presents as the efficiency score is defined as one of the inputs of CoDEA. It represents the critical resources of the system under evaluation, which can affect the vulnerability of the entire supply chain. The prior stage vulnerability score is expressed as the output, i.e., the last node of the network which indicates the level of the robustness chain of the global trade. As such, efficient supply countries with their logistics and transport sectors and the international customers that can deliver a low vulnerability form an integral part in developing a robust global trade supply chain. This crucial factor is taken into consideration in the application of CoDEA. Our research is motivated by the need to develop a useful metric for vulnerability assessment which strengthens the scientific platform of the vulnerability discipline by providing new insights into the relationships between vulnerability, risk, and resilience. The metric addresses the whole supply chain and its outcome is to provide the necessary strategies for realizing a resilient global supply chain especially for ASEAN trade.

2. Literature review

2.1. Vulnerability, risk, and resilience – concepts

The definition of vulnerability is a measure of susceptibility of a system to threat scenarios. Vulnerability studies are commonplace to identify weaknesses in the system. However, in the literature of vulnerability, the word is frequently confused with risk. Vulnerability emphasizes the perception of susceptibility to a scenario, while risk highlights the severity of consequences within the scenario context (Ezell, 2007). Incidentally, resilience and vulnerability are closely related concepts. Resilience involves the ability of the system to continue functioning and, if corrupted, to 'bounce back' (Bryce et al., 2020) within acceptable degradation factors and to recuperate within an acceptable time, composite costs and residual risk (Aven, 2011). Consequently, resilience is considered as a component or subset of the system capacity to respond in determining how vulnerable a system is (Elleuch, Dafaoui, Elmhamedi, & Chabchoub, 2016). In addition, the uncertainty (probability) dimension is included for the risk definition but not for vulnerability and resilience (Aven, 2011). From our knowledge, the characteristic of system vulnerability, risk, and resilience of a threat event is presented in Fig. 1 portraying the relationships of vulnerability, risk and resilience. Aven (2011) mentions that a vulnerable system means that the vulnerability is deemed high. The vulnerability is high if the conditional risk is high. We could infer that if there is high severity of consequences and greater occurrences of uncertain events, the vulnerability rate will increase. Moreover, in the depiction of vulnerability and resilience (Fig. 1), the system vulnerability decreases as resilience increases (Pettit, Fiksel, & Croxton, 2010).

There are different perspectives of vulnerability, risk, and resilience. Vulnerability assessments are unlike risk or resilience assessments. Assessments of risks are utilized to help understand what can go erroneous, estimate the likelihood (occurrence) and the consequences (severity), and develop risk mitigation strategies. An important part of risk assessment is ascertaining a system's vulnerability (Ezell, 2007). Moreover, the resilience assessment complements the conventional risk assessment and management by explicitly focusing on the draw-down and draw-up post-disruption process (Gasser et al., 2019). Regularly

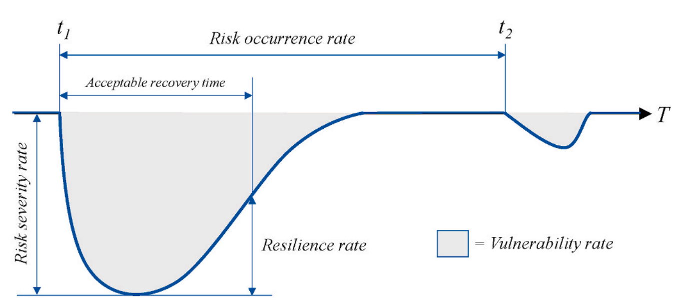

Fig. 1. The characteristics of system vulnerability, risk, and resilience. Source: Modified from the theory of resilience curve of Gasser et al., 2019 and supply chain resilience triangle of Singh, Kumar, Panchal, & Tiwari, 2020.

and for a long time, academicians have adopted a framework for risk assessment. Recently, there is an increased in popularity of vulnerability and resilience research in various disciplines across several industries to demonstrate the risk profile of different disruptive events. For example, Mantha and de Soto (2019) study cybersecurity risks and vulnerability assessment in the construction industry. Singh, Sinha, Vijhani, and Pahuja (2018) research vulnerability assessment of urban road networks from urban flood risk. Zhang, Wolshon, and Murray-Tuite (2019) propose the basis for demonstrating and measuring risk and resilience in evacuation transportation systems. da Mata Martins, da Silva, and Pinto (2019) develop an indicator-based methodology for measuring resilience in urban mobility related to at-risk trips. Espinoza et al. (2020) explore risk and resilience assessment of electric power systems subject to earthquakes. Nowadays, vulnerability and resilience awareness are heightened since the COVID-19 pandemic is disruptive with an entirely unprecedented magnitude. The pandemic tests the vulnerability and resilience of systems, the global supply chain included. These have prompted research into the relatively unexplored measurement metrics of the supply chain vulnerability, risk and resilience.

2.2. Vulnerability, risk and resilience – the COVID-19 research gap

The events and reactions of COVID-19 are unprecedented in affecting the supply chain, both the regional and global supply chains. The resilience and sustainability of supply chain are complementary, and both aspects function cooperatively (Sarkis, 2020). The resilience capability provides recovery from various uncertain situations and contributes to the long-term sustainability of a supply chain. From the lessons of COVID-19, the supply chain risk management (SCRM) is an essential area in contemporary supply chain management. El Baz and Ruel (2020) found SCRM has a mediating role in influencing supply chain resilience and robustness. These results could guide organizational and supply chain partners' behaviour such as the COVID-19 pandemic by introducing mitigation policies.

Since the outbreak of COVID-19, many researchers have published the application of SCRM which covers each part of the risk management perspective in literature. The main goal was to present methods that could help mitigate the impact of COVID-19 threats and propose appropriate strategies to enhance resilience capacity and strengthen the supply chains. Corresponding to the supply chain risk triggered by COVID-19, most publications report the identification of the supply and demand risks (Ivanov & Das, 2020; McMaster et al., 2020; Sharma, Shishodia, Kamble, Gunasekaran, & Belhadi, 2020; Singh et al., 2020), distribution, logistics and infrastructure risks (Sharma et al., 2020; Ivanov & Das, 2020; Singh et al., 2020), as well as financial, management and operational, policy and regulation, and biological and environmental risks (Sharma et al., 2020). Various strategies to deal with the supply chain disruptions of COVID-19 are suggested, such as increasing safety stock and the integration of warehouses (Singh et al., 2020; Zhu et al., 2020), adoption of Industry 4.0 technologies (Sharma et al., 2020), implementation of a triple bottom line (Sarkis, 2020; Sharma et al., 2020), and introduction of a novel business model (Choi, 2020). One key strategy is supply chain collaboration which is flexible enough to respond and share responsibility (Aday & Aday, 2020; El Baz & Ruel 2020; Sharma et al., 2020). Indeed, the COVID-19 disruptions demand the needs for network collaborations, inter-organizational capabilities and resource sharing. Eventually, for firms intending to broaden the latitude of their SCRM practices, they would have to cooperate with their supply chain partners to address different disruption scenarios that a single corporation cannot mitigate (El Baz & Ruel, 2020). In addition to collaboration between all related organizations, the private and public sectors need to work in unity to overcome the substantial economic obstacles that COVID-19 presents (Love, Ika, Matthews, & Fang, 2020).

Some researchers study the tools for vulnerability and resilience related to risk assessments. For instance, Fuzzy Linguistic Quantifier Order Weighted Aggregation (FLQ-OWA) is used to investigate the impact of risks and to create resilient agricultural supply chain organizations (Sharma et al., 2020). This metric mainly focuses on the severity of COVID-19 organizations. For the simulation-based models, Ivanov and Das (2020) propose learning how to strengthen the resilience of their global supply chains to tackle disruptions. The simulation model is used to analyze the pandemic supply risk mitigation measures and potential recovery paths. Additionally, a study by Singh et al. (2020) highlights the importance of a resilient supply chain during a pandemic. In their simulation model, the factors related to the severity (damping rate) and the resilience (recovery rate). Studies on vulnerability and resilient supply chains primarily contemplate a conceptual framework for both chains to describe different phases of their risk management. Despite a large number of conceptual studies on vulnerable and resilient supply chains, quantitative studies are limited (Behzadi, O'Sullivan, & Olsen, 2020). Furthermore, SCRM requires appropriate metrics in which vulnerability that primarily disrupts the performance and revenue generation of firms (Karwasra, Soni, Mangla, & Kazancoglu, 2021) and rapidity (speed of recovery) are investigated as the two key indicators reflect COVID-19 disruption. This is the critical research gap as effective metrics that can be applied to the global trade supply chain for vulnerability, risk, and resilience which are not yet available in literature. Our study presented in this paper contributes towards this major research gap.

2.3. The DEA and network DEA

The Data Envelopment Analysis (DEA) is a mathematical programming method broadly used to compute the inter-related set of efficiency of Decision Making Units (DMUs). The DEA method applies a set of inputs to yield the outputs (Kao & Hwang, 2008), or multiple performance measures (Charnes, Cooper, & Rhodes, 1978). Efficiency is oriented towards successful input transformation into outputs (Bartuševičienė & Šakalytė, 2013). The efficiency score is the result of the DEA method. Efficiency scores for production units are defined as the ratio of actual to the frontier value of (the net value of) outputs and inputs (McDonald, 2009). In other words, productive efficiency implies whether the firm's internal resources (input) are used to produce operational product or service (output) capacity effectively (Huang, Ho, & Chiu, 2014). The efficient DMU is typically related to its ability to minimize input usage in the production of given outputs, or to maximize output production with given inputs (Fried, Lovell, Schmidt, & Yaisawarng, 2002). The theory is similar to the DEA approach which DEA input-oriented models try to minimize input utilization without forgoing output, while DEA output-oriented models target at maximizing output without intensifying the inputs. The realization of DEA models requires the inputs and outputs selection. Numerous norms are generally engaged in this selection. Regarding the nature of selected criteria, the concurrent inputs decrease and outputs increase are considered (Karami, Ghasemy Yaghin, & Mousazadegan, 2020).

Since its initiation by Charnes et al. (1978), countless DEA models have been studied. In the early phase, DEA models are recognized as "black boxes" because the relationships between multiple performance measures are unknown (Chen & Zhu, 2004). As such, DEA models have been extended to several studies (Tone & Tsutsui, 2009). One popular extension is to examine the performance of a two- or multi-stage process, namely a network structure (Chen, Li, Liang, Salo, & Wu, 2016). This extended model offers a fundamental concept for application to the supply chain structure. From the supply chain perspective, computational algorithms have been established for DEA models to deal with sizable volumes of data (inputs, outputs, and DMUs) especially the colossal and valuable secondary data. These DEA models attempt to obtain valuable information hidden in big data embodied within the network structures. These network structures, such as transportation, logistics, and supply chain system, involve a comprehensive range of *inter-linked* metrics (Zhu, 2020). Various network DEA models have been improved to deal with the complex supply chains which include a coherent DEA (CoDEA) model from previous research that operates on the *virtual inter-linked* concept (Jomthanachai et al., 2021).

Moreover, DEA and its extended models are popular for addressing supply chain risk management issues. These models are usually applied to the risk assessment process. According to the review of Ho, Zheng, Yildiz, and Talluri (2015) on supply chain risk management, supplier evaluation and selection is a topic that has attracted the most attention in DEA studies. These researchers usually assign the supplier nodes as the DMUs in traditional DEA models. It means the risks of supplier represent the supply chain risk, which is deemed unrealistic because the risks of other nodes can also contribute to the overall risk of a supply-chain. From the vulnerability, risk and resilience management perspective, this is a limitation when applied to network DEA structures to deal with complex supply chains. In this research, we undertake this challenge by employing an extended network DEA structure (i.e., CoDEA) and developing a metric to assess the vulnerability based on risk and resilience of all the nodes in the entire supply chain structure in this pandemic.

2.4. CoDEA and supply chain – the research model and theory

CoDEA is proposed for evaluation of the global supply chain efficiency. This method could evaluate a complex supply chain without the presence of intermediate measures (Jomthanachai et al., 2021). The concept of CoDEA (Fig. 2) is to reach a network efficiency in the final stage. In step one, CoDEA calculates the efficiency of DMUs of the original supply node by employing the traditional DEA model. Step two uses the efficiency score of related DMU in a single preceding supply node as the input or virtual intermediate measure to the next customer's node in the supply chain when the conventional DEA model is executed. Based on these, the CoDEA running steps are repeated until the final customer node in the chain is reached.

A popular definition of a supply chain is "*a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and information from a source to a customer*" (Mentzer et al., 2001). As a complex supply chain, the global trade contains multiple upstream and downstream players. In assessing

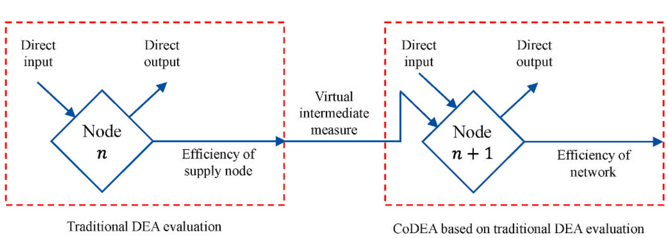

Fig. 2. The concept of coherent DEA (CoDEA).

the vulnerability based on risk and resilience perspective of the global trade supply chain, the research model (Fig. 3) and its extension (Fig. 4) and the theoretical underpinnings are assembled as follows.

In the COVID-19 pandemic, the interruption of the main components of the global supply (i.e., production, logistics, and transportation), as

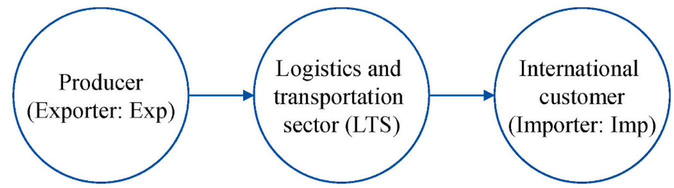

Fig. 3. A global trade supply chain.
Source: Modified from the physical and support supply chain of Carter, Rogers, and Choi (2015).

well as the slow-down in consumption of overseas customers have significantly disrupted the global trade network (Kumar, Luthra, Mangla, & Kazançoğlu, 2020). In this study, the global trade supply chain structure is categorized into three main critical components, as shown in Fig. 3. Firstly, the producer node represents a network of its members. This node plays the role of exporters. Secondly, the node of logistics and transportation sector plays the role of mediators in the supply chain. It is a supporter of the product flow. Importantly, the logistics and transporter sectors stand as an essential enabler to global trade (Tang & Abosedra, 2019). Thirdly, the international customers node plays the role of importers.

In business operations, the evaluation of supply chain efficiency using CoDEA relies on the concept that the previous node's (exporter) efficiency affects the next node (logistics and transportation sector) while the efficiency of the logistics and transportation sector affects the next node in the chain. As an example, the capability of exporters affects the logistics providers' return of investment. The exporter's efficiency score is considered as an input when evaluating the linked sub-chains which can be assumed as the *virtual intermediate measure*. In the evaluation process of a global supply chain, the efficiency score of the export network can affect the benefits of the importers, i.e., high efficiency of the export network provides a lower logistics cost and time which increases the demand for imported products and the satisfaction level of importers. Consequently, the export network efficiency is considered as an input, together with other direct inputs and the outputs of importers for evaluating the global trade supply chain efficiency. Fig. 4 shows the fundamental research model. It depicts the supply chain of Exporter (Exp)-Logistics & Transport Sector (LTS)- Importer (Imp). This figure is modified to accommodate the efficiency related metric and the global trade supply chain vulnerability. In this paper, the supply chain which consists of several focal firms adopts the stakeholder theory (Freeman, 1984) for the relationships of a focal firm to its suppliers and customers in the chain. For clarity, the theory suggests stakeholders as "any group or individual who can affect or is affected by the achievement of the firm's objectives" (Freeman, 1984) making each focal firm a stakeholder in the supply chain. This theory would explicitly depict the efficiency of a supplier and customer could influence the interest (efficiency) of the focal firm. In placing this theory in the Covid-19 scenario, the stakeholder theory operationalises as (i) the suppliers' output as the input to a focal firm and (ii) focal firm's output as the input to the customer. These culminate as the global trade supply chain efficiency (Fig. 4). In summary, CoDEA measures the efficiency of each accumulated previous stage and uses it as an input in the next stage. This overcomes the limitation in undertaking complex supply chains where the authentic intermediate measure is difficult to obtain for evaluation purposes.

3. Methodology and data

3.1. CoDEA parameters for vulnerability assessment of a global supply chain

CoDEA improves the traditional DEA model. In the traditional DEA method, a set of DMU j is formed, utilizing quantities of inputs $X \in x^m$ to deliver quantities of outputs $Y \in y^s$, where m and s indicate the numbers

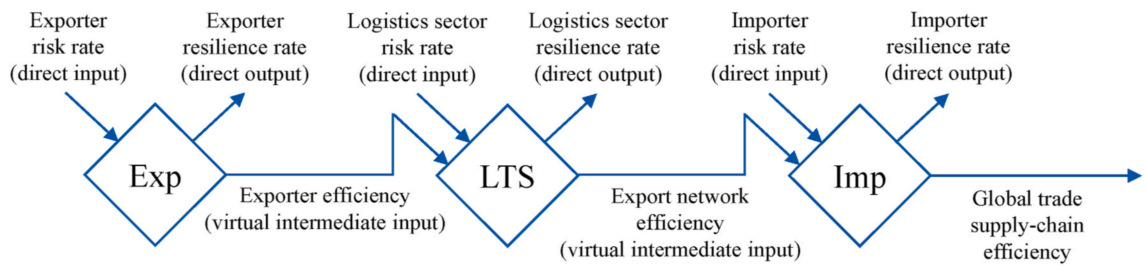

Fig. 4. Evaluation of vulnerability of a global supply chain with CoDEA.

of the inputs and outputs. Specifically, x_{ij} denotes the amount of the i th input used and y_{rj} the amount of the r th output produced. The efficiency score of each DMU, θ, is measured as:

$$\theta=\frac{\sum_{r=1}^{s}\mu_r y_r}{\sum_{i=1}^{m}\upsilon_i x_i} \tag{1}$$

when μ_r and υ_i are the output and input weights respectively (Charnes et al., 1978). The envelopment formulation of an input-oriented mechanism to illustrate the constant returns of scale (CRS) situation (Zhu, 2000) is shown in model 2:

$$\begin{aligned} &\min\theta-\varepsilon\Big(\sum_{i=1}^{m}s_i^-+\sum_{r=1}^{s}s_r^+\Big)\\ \text{s.t.}\ &\sum_{j=1}^{n}\lambda_j x_{ij}+s_i^-=\theta x_{i0},\ i=1,\ \dots,\ m,\\ &\sum_{j=1}^{n}\lambda_j y_{rj}-s_r^+=y_{r0},\ \ r=1,\ \dots,s;\ \ j=1,\ \dots,n,\\ &\lambda_j,s_i^-,s_r^+\ \geq 0, \end{aligned} \tag{2}$$

where n is the number of members in a set of DMUs in which the subscript $_{i0}$ or $_{r0}$ represents the evaluating DMU, λ_j is a nonnegative scalar, ε is non-Archimedean infinitesimal, and s_i^- and s_r^+ are the slacks of the input and output respectively. Model 2 is an input-oriented DEA model where the objective function and its constraints are minimizing the inputs while maintaining the outputs at their current levels (Zhu, 2009). With an optimality result ($\theta=1$) and all slacks are zero, the DMU is said to be CRS-efficient and is operating on the CRS frontier. Otherwise, the DMU is CRS-inefficient, and an improvement is required by decreasing the input and/or increasing the output (Charnes et al., 1978).

For CoDEA, the initial or upstream node efficiency is evaluated using model 2. Then, the sub-chain and overall supply chain efficiency scores are computed, leading to model 3:

$$\begin{aligned} &\min\Phi-\varepsilon\Big(\sum_{i=1}^{u}s_i^-+\sum_{t=1}^{p}z_t^-+\sum_{r=1}^{v}s_r^+\Big)\\ \text{s.t.}\ &\sum_{j=1}^{h}\rho_j\widehat{x}_{ij}+s_i^-=\Phi\widehat{x}_{i0},\ i=1,\ \dots,\ u,\\ &\sum_{j=1}^{h}\rho_j\widehat{\theta}_{tj}+z_t^-=\Phi\widehat{\theta}_{t0},\qquad t=1,\ \dots,\ p,\\ &\sum_{j=1}^{h}\rho_j\widehat{y}_{rj}-s_r^+=\widehat{y}_{r0},\qquad r=1,\ \dots,\ v;\ j=1,\ \dots,h,\\ &\rho_j,s_i^-,z_t^-,s_r^+\ \geq 0, \end{aligned} \tag{3}$$

where h is the number of midstream or downstream nodes in a set of DMUs with index j, $\widehat{\theta}_t$ is the transformation of θ_t, which is the efficiency of each initial or sub-chain p. In model 3, the transferred value of θ_t from model 2 is treated as one of the inputs to a traditional DEA model. However, from the perspective of a traditional DEA model, the input should be a decreasing factor for efficiency evaluation (Zhu, 2009). In evaluating the efficiency, θ_t needs to increase to enhance the sub-chain or overall supply-chain efficiency. As a result, θ_t is transformed to $\widehat{\theta}_t=\frac{1}{\theta_t}$. This is a non-linear monotonic decreasing transformation that changes an undesirable input (need to increase) to a desirable input (need to decrease) (You & Yan, 2011). Besides that, z^- is a slack of the transformed value. Model 3 can be used to evaluate any sub-chain with a dual-stage link, such as the only sub-chain of the midstream and downstream without any upstream (see Jomthanachai et al., 2021). The properties of CoDEA and simulation run are shown in Appendix A.

The theoretical vulnerability, risk, and resilience integrated into CoDEA are applied as the conceptual framework in this study. As shown in Fig. 1, risk is referred as the possibility of human activities or natural events leading to outcomes that affect the aspects of what humans value. The definition of risk contains three elements: (i) outcomes that affect what humans value (severity rate), (ii) possibility of uncertainty (occurrence rate), and (iii) a formula to combine both elements (Renn, 1998). The risk, which represents a risk value, is the result of a function pertaining to the degree of uncertainty and its impact (Sinha, Whitman, & Malzahn, 2004). Moreover, the degree and impact have some quantifiable measures (Waters, 2011). Then to evaluate the risk rate which aggregates both risk elements by multiplying the severity rate with the probability of the occurrence is the popular method (Renn, 1998). In terms of resilience, the ability to recover rapidly and effectively from a disruption is not uniformly standard over the restoration period (Behzadi et al., 2020). Without considering time, the concept of resilience cannot be fully addressed. Hence, the recovery time is appropriate as a quantitative resilience metric (Simchi-Levi, Schmidt, & Wei, 2014). Recall Fig. 1, at the end of an acceptable recovery time, the distance between maximum severity of risk event and the residual gap represented the resilience rate of this study.

When CoDEA was applied to assess the global trade supply chain vulnerability, the assignment of parameters, e.g., inputs and outputs related to the abovementioned theoretical DEA input and output selections are necessary. The design of the CoDEA accommodates inputs and outputs for evaluation of a global supply chain vulnerability (Fig. 4). This is an economic risk and resilience-based efficiency evaluation. We selected the risk rate as the direct input and the resilience rate as the direct output. Then the GDP value of export, logistics, and transport sectors of export countries along with the import sectors of countries of the international customers are used to compute the risk and resilience rate. The details of these input and output rate calculations will be shown in the next sub-section. The design of this research method is expected to answer the question: Is the proposed metric in the evaluation of the economic risk and resilience-based efficiency using CoDEA reflective of the global trade supply chain vulnerability in the COVID-19 pandemic scenario?

In Fig. 4, for all nodes, i.e., Exp, LTS, and Imp, the direct inputs of CoDEA are signified by the risk rate associated with the node. According to the theoretical risk, the risk factors are severity and occurrence of disaster. The linear programing function of traditional DEA method is used to combine both severity and occurrence. In this study, the disaster of COVID-19 pandemic is analyzed, and it is assumed that the occurrence of this catastrophe is a constant value at the global level. However, the degree of severity varies from country to countries. Hence, the direct input of CoDEA is the value of severity that represents the operation risk of each node. For the direct output of all nodes in CoDEA, when the traditional DEA model is used solely from the risk assessment perspective, the DEA model without the outputs, or constant outputs equals to one is usually applied (Barnum, Johnson, & Gleason, 2016; Chang & Paul Sun, 2009; Garcia, Leal Junior, & Oliveira, 2012; Rezaee, Yousefi, Eshkevari, Valipour, & Saberi, 2020). However, some studies applied other alternative output values, e.g., cost and duration of treatment which are considered as two extra undesirable outputs (Yousefia, Alizadeha, Hayatia, & Baghery, 2018). We also apply the alternative of a non-constant output as the risk recovery or resilience rate. The details of direct inputs and output are explained in the next section.

3.2. The global trade supply chain and data of countries

According to the research questions, is the result of the efficiency score of the CoDEA method applicable for guiding risk mitigation or resilience policy to vulnerability closure for the ASEAN global trade supply chain? In this study, six of ten ASEAN countries were chosen for evaluation. They are Singapore, Thailand, Malaysia, Indonesia, Vietnam and the Philippines. We selected these six countries because they have the highest export activity among ASEAN countries. Similarly, global trade is the main driver of their economies. These countries are characterized by the speedy growth of the economy and their active involvement in the world economy (Nguyen & Almodóvar, 2018). Moreover, using a benchmarking tool of DEA approach which avoids the other major factor pertaining to the capability of global trade e.g., continent geography and the large difference of global trade scale, this study then chose to focus on the ASEAN region. The complexity of the global trade supply chain structure of each country is shown in Fig. 5. The worldwide economics panel data are sourced from the

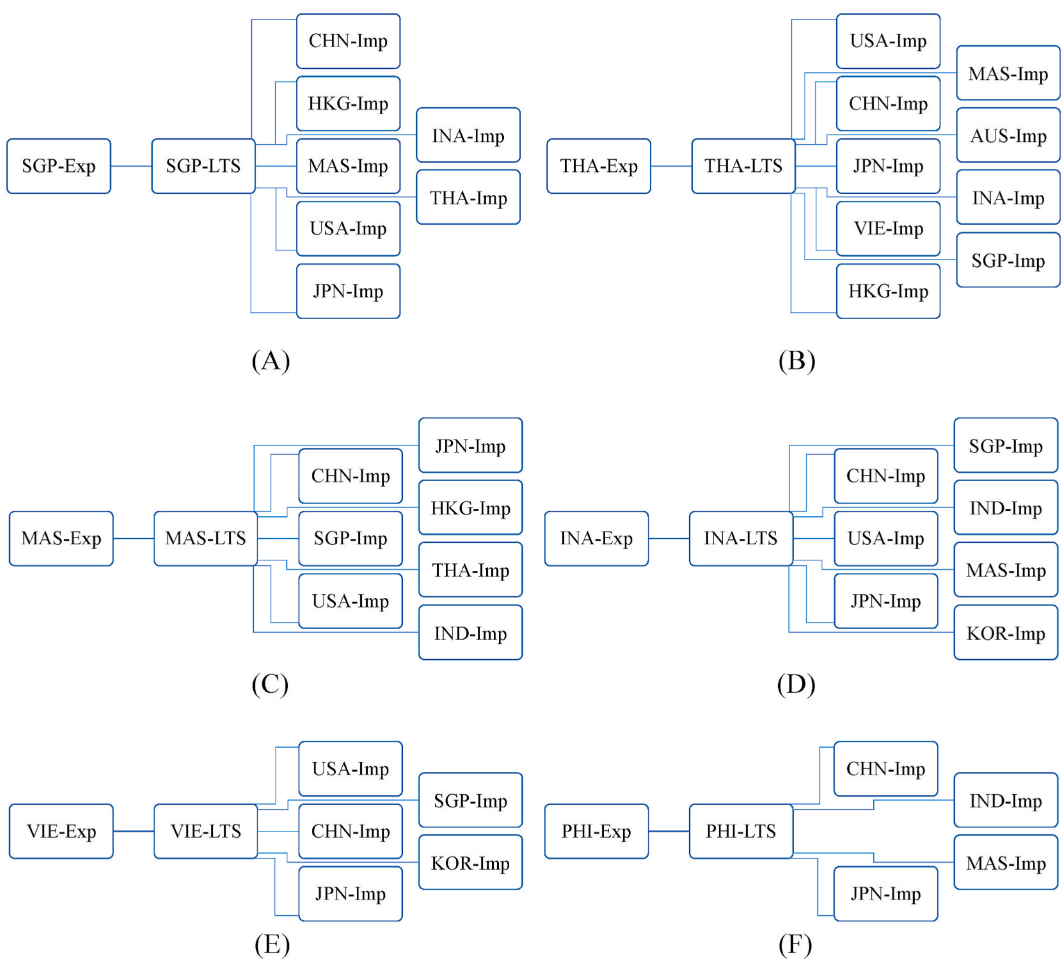

Fig. 5. The global supply chain of six countries: (A) Singapore, (B) Thailand, (C) Malaysia, (D) Indonesia, (E) Vietnam, and (F) Philippines. Source: www.tradingeconomics.com. Note: AUS = Australia, CHN = China, HKG = Hong Kong, INA = Indonesia, IND = India, JPN = Japan, KOR = South Korea, MAS = Malaysia, SGP = Singapore, THA = Thailand, USA = United, VIE = Vietnam.

Table 1
Mapping of six exporters and importers with percentage of import amount.

	CHN	USA	JPN	HKG	SGP	MAS	INA	THA	KOR	IND	VIE	AUS	Total
SGP	14	9.2	4.7	12		11	7.3	4.1					62.3
THA	12	13	10	4.8	3.6	4.4	3.7				5.1	4.1	60.7
MAS	15	10	6.9	7	14			5.9		4			62.8
INA	17	11	9.8		7.9	5.5			4.4	7.2			62.8
VIE	17	20	10		7.7				7.7				62.4
PHI	14	17	16	14									61.0

Source: www.tradingeconomics.com

TRADINGECONOMICS (2020) website. All the six selected countries have manifold export partners. The number of countries used for this downstream is therefore based on a percentage of the total cumulative export of approximately sixty percent, as shown in Table 1.

Based on the data from TRADINGECONOMICS (2020), a brief information for six ASEAN countries are follows:

Singapore derives most of its revenues from foreign trade. Machinery and equipment take up 43 percent of its exports. The country also exports 19 percent petroleum, 13 percent chemical products, 8 percent miscellaneous manufactured articles, 7 percent and oil bunkers. On average, Singapore's main exporter partners are China, Hong Kong, Malaysia, the United States, Indonesia and Japan.

Thailand is an export-oriented economy with exports amounting to about 65 percent of its GDP. The country primarily exports 86 percent of manufactured goods consisting of 14 percent electronics, 13 percent vehicles, 7.5 percent machinery and equipment, and 7.5 percent food stuff. Agricultural goods (mainly rice and rubber) account for 8 percent of total shipments. The major export partners of Thailand are the United States, China, Japan, and the European Union. Others include Vietnam, Hong Kong, Malaysia and Australia.

Malaysia's exports are supported by the entry of foreign direct investments and have been one of the most important factors driving Malaysia's GDP growth in recent years. Malaysia's main exports are 36 percent of electrical and electronics products, 7.1 percent of chemicals, 7.0 percent petroleum products, 6 percent liquefied natural gas, and 5.1 percent palm oil. Malaysia's main export partners are China, Singapore, the United States, Hong Kong and Japan.

Indonesia's exports have been an engine of economic growth. However, after reaching a peak in 2012, it has been in a steady decline due to lower commodity prices and dwindling global demand. The major exports are 12.4 percent oil and gas (of those, 6.9 percent is gas, 4.3 percent crude oil and 1.2 percent oil products), 14 percent animal and vegetable fats and oils, and 10.45 percent electrical equipment and machinery. The major export partners are China, United States, Japan, Singapore and India.

Vietnam's exports in the last few years have doubled as the competitive minimum wage and low costs of utilities boost foreign direct investments in the manufacturing sector. Vietnam's main exports are 21 percent telephones, mobile phones, and parts thereof and 12 percent textiles. Others include 12 percent computers and electrical products, 7 percent shoes and footwear and 6 percent machinery, instruments, and accessories. The main export partners are the United States, China, Japan, Singapore and South Korea.

Exports in the Philippines account for nearly a third of its GDP. The major exports are 42 percent electronic products, 10 percent other manufactures, and 6 percent woodcrafts and furniture. The Philippines is also the world's largest producer of coconut, pineapple, and abaca. The main export partners are the United States, Japan, China and Hong Kong.

Recall that the inputs and outputs of CoDEA are specified earlier in Fig. 4. In this section, the numerical values for such inputs and outputs are described. Firstly, we classify the COVID-19 pandemic into three phases, as shown in Fig. 6. The data indicate the export amounts of the six ASEAN countries with respect to the three phases. The first phase is before and early stages of the pandemic i.e., the fourth quarter of 2019 to the first quarter of 2020 which is defined as the base data. The second or high impact phase covers the second quarter of 2020, while the third phase or recovery phase is the third quarter of 2020.

Table 2 is the export data of the six studied countries presented in months. By referring to the three phases, the average value of each phase is computed. As an example, the average export amounts of the first, second, and third phases of Singapore are 44.08, 38.52, 41.37 SGD billion respectively. Then the percentage of change is calculated for comparison with the base data or the average data of the first phase. The change of the second phase is (38.52 / 44.08 =) 87.38 percent (lower than the base data by 12.62 percent.) This indicates that the average impact rate pertaining to the export amount of Singapore in the period of high impact of COVID-19 is 12.62 percent. The value of 12.62 percent represents the export risk rate of Singapore exporters, and it is the direct input into CoDEA that needs to decrease with respect to the exporter node of Singapore. Next, the change of the third phase is (41.37 / 44.08 =) 93.77 percent (still lower than the base data by 6.23 percent.) This indicates that by the end of the third quarter of 2020, Singapore has a limit to recover the impact of COVID-19 in the export sector by an average recovery rate of 93.77 percent. The value of 93.77 percent represents the export recovery rate of Singapore exporters, and it is the direct output (need to increase) of CoDEA with respect to the exporter node of Singapore. This direct input and output assignment concept is used for all the studied countries. This concept is similar to the logistics and transportation sector of the six ASEAN countries. The quarterly GDP of transport data are provided in Table 3. Table 4 shows the import data of partner countries with respect to the six ASEAN countries based on the monthly import amounts.

4. Computation results

The computational process for the efficiency scores is carried out using the DEA Frontier program developed by Zhu (2009), which is based on the Excel Solver platform. The results are presented in the following sub-sections.

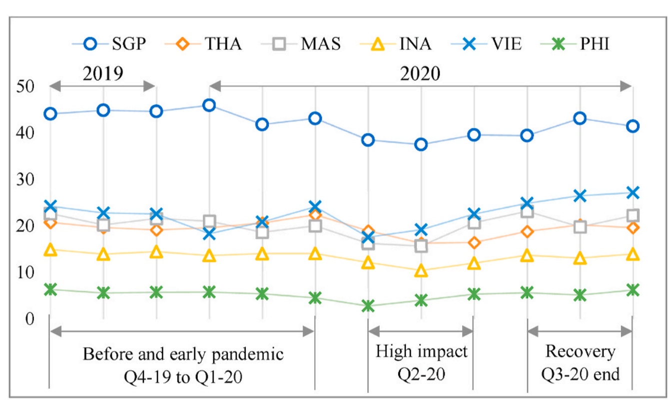

Fig. 6. Three phases of data (based on the export amounts: US$). Source: www.tradingeconomics.com

Table 2
Export data of countries.

Phase	Month-year	SGP Export amount (SGD Billion)	SGP Phase average (SGD Billion)	SGP Changed (Per cent)	THA Export amount (MYR Billion)	THA Phase average (MYR Billion)	THA Changed (Per cent)	MAS Export amount (USD Billion)	MAS Phase average (MYR Billion)	MAS Changed (Per cent)
Before and starting pandemic	Oct-19	44.10	44.08	–	20.76	20.37	–	90.56	82.75	–
	Nov-19	44.87			19.66			80.87		
	Dec-19	44.63			19.15			86.37		
	Jan-20	45.95			19.63			84.08		
	Feb-20	41.82			20.64			74.50		
	Mar-20	43.12			22.40			80.10		
High impact of pandemic	Apr-20	38.48	38.52	87.38	18.95	17.22	84.54	64.92	70.14	84.77
	May-20	37.51		(−12.62)	16.28		(−15.46)	62.69		(−15.23)
	Jun-20	39.57			16.44			82.82		
Recovery	Jul-20	39.43	41.37	93.77	18.82	19.55	95.96	92.56	86.87	104.98
	Aug-20	43.14		(−6.23)	20.21		(−4.04)	79.13		(+4.98)
	Sep-20	41.44			19.62			88.91		

Phase	Month-year	INA Export amount (USD Billion)	INA Phase average (USD Billion)	INA Changed (Per cent)	VIE Export amount (USD Billion)	VIE Phase average (USD Billion)	VIE Changed (Per cent)	PHI Export amount (USD Billion)	PHI Phase average (USD Billion)	PHI Changed (Per cent)
Before and starting pandemic	Oct-19	14.93	14.19	–	24.23	22.15	–	6.33	5.57	–
	Nov-19	13.95			22.79			5.60		
	Dec-19	14.47			22.56			5.74		
	Jan-20	13.63			18.32			5.79		
	Feb-20	14.06			20.85			5.40		
	Mar-20	14.07			24.13			4.53		
High impact of pandemic	Apr-20	12.16	11.54	81.35	17.58	19.78	89.30	2.78	4.03	72.48
	May-20	10.45		(−18.65)	19.19		(−10.70)	3.99		(−27.52)
	Jun-20	12.01			22.56			5.33		
Recovery	Jul-20	13.7	13.59	95.78	24.87	26.18	118.20	5.65	5.67	101.83
	Aug-20	13.1		(−4.22)	26.50		(+18.20)	5.13		(+1.83)
	Sep-20	13.96			27.16			6.22		

Source: www.tradingeconomics.com

Table 3
Transportation sector data of six studied countries.

Phase	Quarter-year	SGP GDP from transport (SGD Billion)	SGP Phase average (SGD Billion)	SGP Changed (Per cent)	THA GDP from transport (THB Billion)	THA Phase average (THB Billion)	THA Changed (Per cent)	MAS GDP from service* (MYR Billion)	MAS Phase average (MYR Billion)	MAS Changed (Per cent)
Before and starting pandemic	Q4-19	8.10	7.78	–	187.59	187.22	–	216.95	209.01	–
	Q1-20	7.45			186.84			201.07		
High impact of pandemic	Q2-20	4.93	4.93	63.41 (−36.59)	110.62	110.62	59.09 (−40.91)	167.44	167.44	80.11 (−19.89)
Recovery	Q3-20	5.67	5.67	72.93 (−27.07)	136.14	136.14	72.72 (−27.28)	200.02	200.02	95.70 (−4.30)

Phase	Quarter-year	INA GDP from service* (USD Billion)	INA Phase average (IRD K-Billion)	INA Changed (Per cent)	VIE GDP from transport (VND K-Billion)	VIE Phase average (VND K-Billion)	VIE Changed (Per cent)	PHI GDP from transport (PHP Billion)	PHI Phase average (PHP Billion)	PHI Changed (Per cent)
Before and starting pandemic	Q4-19	53.58	52.97	–	111.68	66.58	–	68.31	118.18	–
	Q1-20	52.36			21.48			168.04		
High impact of pandemic	Q2-20	44.97	44.97	84.90 (−15.10)	45.28	45.28	68.01 (−31.99)	87.79	87.79	74.29 (−25.71)
Recovery	Q3-20	48.53	48.53	91.62 (−8.38)	72.79	72.79	109.33 (+9.33)	121.29	121.29	102.64 (+2.64)

Note: * = Transportation sector included.
Source: www.tradingeconomics.com

Table 4
Import data of partner countries.

Phase	Month-year	CHN			USA			JPN		
		Import amount (USD KHML)	Phase average (USD KHML)	Changed (Per cent)	Import amount (USD Billion)	Phase average (USD Billion)	Changed (Per cent)	Import amount (JPY K-Billion)	Phase average (JPY K-Billion)	Changed (Per cent)
Before and starting pandemic	Oct-19	1.70	1.68	–	253.93	249.49	–	6.56	6.34	–
	Nov-19	1.84			251.49			6.47		
	Dec-19	1.91			258.09			6.73		
	Jan-20	1.50			253.79			6.74		
	Feb-20	1.50			247.48			5.21		
	Mar-20	1.65			232.16			6.35		
High impact of pandemic	Apr-20	1.55	1.55	92.28 (−7.72)	200.69	202.92	81.33 (−18.67)	6.14	5.43	85.60 (−14.40)
	May-20	1.44			199.12			5.02		
	Jun-20	1.67			208.95			5.13		
Recovery	Jul-20	1.75	1.85	109.70 (+9.70)	231.67	236.98	94.98 (−5.02)	5.36	5.24	82.61 (−17.39)
	Aug-20	1.76			239.04			4.98		
	Sep-20	2.03			240.22			5.38		

Phase	Month-year	HKG			SGP			MAS		
		Import amount (HKD Billion)	Phase average (HKD Billion)	Changed (Per cent)	Import amount (SGD Billion)	Phase average (SGD Billion)	Changed (Per cent)	Import amount (MYR Billion)	Phase average (MYR Billion)	Changed (Per cent)
Before and starting pandemic	Oct-19	379.12	347.30	–	40.02	41.16	–	73.27	70.52	–
	Nov-19	385.44			41.49			74.26		
	Dec-19	383.77			40.43			73.88		
	Jan-20	299.99			44.34			72.08		
	Feb-20	277.11			40.72			61.80		
	Mar-20	358.35			39.94			67.80		
High impact of pandemic	Apr-20	332.80	334.35	96.27 (−3.73)	36.02	34.53	83.90 (−16.10)	68.42	60.89	86.35 (−13.65)
	May-20	331.34			32.99			52.27		
	Jun-20	338.90			34.58			61.97		
Recovery	Jul-20	358.28	369.81	106.48 (+6.48)	36.22	37.10	90.14 (−9.86)	67.38	66.75	94.67 (−5.33)
	Aug-20	359.11			36.66			65.92		
	Sep-20	392.04			38.41			66.96		

Phase	Month-year	INA			THA			KOR		
		Import amount (USD Billion)	Phase average (USD Billion)	Changed (Per cent)	Import amount (USD Billion)	Phase average (USD Billion)	Changed (Per cent)	Import amount (USD Billion)	Phase average (USD Billion)	Changed (Per cent)
Before and starting pandemic	Oct-19	14.76	13.96	–	20.25	19.44	–	41.40	41.27	–
	Nov-19	15.34			19.11			40.73		
	Dec-19	14.50			18.56			43.69		
	Jan-20	14.27			21.18			42.72		
	Feb-20	11.55			16.74			37.20		
	Mar-20	13.35			20.81			41.87		
High impact of pandemic	Apr-20	12.54	10.58	75.78 (−24.22)	16.49	15.45	79.47 (−20.53)	37.94	35.99	87.20 (−12.80)
	May-20	8.44			15.03			34.42		
	Jun-20	10.76			14.83			35.60		
Recovery	Jul-20	10.46	10.92	78.24 (−21.76)	15.48	16.24	83.55 (−16.45)	38.69	37.92	91.89 (−8.11)
	Aug-20	10.74			15.86			35.73		
	Sep-20	11.57			17.39			39.34		

Phase	Month-year	IND			VIE			AUS		
		Import amount (USD Billion)	Phase average (USD Billion)	Changed (Per cent)	Import amount (USD Billion)	Phase average (USD Billion)	Changed (Per cent)	Import amount (AUD Billion)	Phase average (AUD Billion)	Changed (Per cent)
Before and starting pandemic	Oct-19	37.39	37.32	–	22.37	20.89	–	36.16	34.56	–
	Nov-19	38.11			21.34			35.15		
	Dec-19	38.61			22.30			35.91		
	Jan-20	41.14			18.60			34.91		
	Feb-20	37.50			18.58			33.40		
	Mar-20	31.16			22.15			31.82		
High impact of pandemic	Apr-20	17.12	20.14	53.98 (−46.02)	18.52	19.14	91.61 (−8.39)	28.71	28.14	81.42 (−18.58)
	May-20	22.20			18.18			27.72		
	Jun-20	21.11			20.71			27.98		
Recovery	Jul-20	28.47	29.42	78.83 (−21.17)	22.10	23.10	110.57 (+10.57)	29.89	29.33	84.88 (−15.12)
	Aug-20	29.47			23.00			30.00		
	Sep-20	30.31			24.20			28.11		

Source: www.tradingeconomics.com

Table 5
The results of exports and logistics and transportation sector.

DMU	Country	Export sector				Logistics and transportation sector			
		Input	Output	Efficiency score	Rank	Input	Output	Efficiency score	Rank
1	SGP	12.62	93.77	0.6726	2	36.59	72.93	0.3285	5
2	THA	15.46	95.96	0.5619	4	40.91	72.72	0.2982	6
3	MAS	15.23	104.98	0.624	3	19.89	95.7	0.793	2
4	INA	18.65	95.78	0.4649	5	15.1	91.62	1	1
5	VIE	10.7	118.2	1	1	31.99	109.33	0.5633	4
6	PHI	27.52	101.83	0.335	6	25.71	102.64	0.658	3

Source: www.tradingeconomics.com

Table 6
The results of export network of the countries.

DMU	Country	Input	Transferred efficiency of export sector (input)	Output	Efficiency score without dummy	Rank	Efficiency score with dummy	Rank
1	SGP	36.59	1.49	72.93	0.5412	5	0.4477	5
2	THA	40.91	1.78	72.72	0.478	6	0.3737	6
3	MAS	19.89	1.6	95.7	1	1	0.6645	3
4	INA	15.1	2.15	91.62	1	1	0.838	2
5	VIE	31.99	1	109.33	1	1	1	1
6	PHI	25.71	2.98	102.64	0.7215	4	0.5514	4
Dummy-1	IDMU	15.1	1	109.33	–	–	1	–
Dummy-2	ADMU	40.19	2.98	72.72	–	–	0.2455	–

4.1. Efficiency scores of exports and logistics and transportation sectors

The efficiency scores of exports and logistics and transportation sectors of the countries are computed using Model 2 as shown in Table 5. The high-efficiency scores reflect the low vulnerability of sectors. In contrast, the low-efficiency scores reflect the high vulnerability. The counties are ranked from low to high vulnerability.

Based on Table 5, for the export sector, Vietnam has the lowest vulnerability with an efficiency score of 1. The reason is Vietnam faces the lowest impact at a rate of 10.7. Moreover, Vietnam can recover to the highest average rate at 118.2 in the third quarter of 2020. For the Philippines, it has the greatest vulnerability in the export sector since the efficiency score is only 0.335. The Philippines faces the highest risk rate at 27.52, which is a wide gap as compared with those of neighboring countries even though she could recover at the rate of 101.83. When considering the logistics and transportation sector, Indonesia has the lowest vulnerability with an efficiency score of 1. In contrast, Thailand has the highest vulnerability with the lowest efficiency score of 0.2982. This is due to the similar reason related to the value of input and output rates.

4.2. Export network efficiency of studied countries

The efficiency of export networks of the studied countries refers to the efficiency of sub-chains of exporters and logistics and transportation sector. Its efficiency is computed using model 3. The results are shown in Table 6 and Fig. 5.

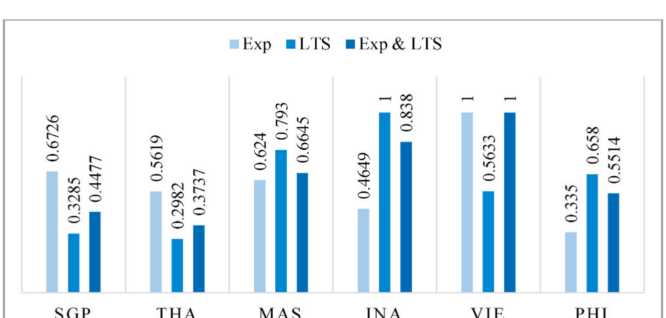

Fig. 7. Comparison of the exports system.

Due to the addition of input i.e., the efficiency of the previous stage, the number of three times with respect to the total input and output becomes larger than total number of DMUs. Therefore, dummy DMUs are applied. According to Wang and Luo (2006), two dummy DMUs can be used: Dummy-1 or "Ideal DMU (IDMU)" and Dummy-2 or "Anti-ideal DMU (ADMU)". An IDMU means the DMU contains the lowest value of the inputs and the highest value of the outputs from a set of actual data of each DMU. It is used to deal with the shortcoming of loss of discrimination power in the traditional DEA model when a small number of DMUs is computed. The results of the efficiency score when applying dummy DMUs as compared with those without dummy DMUs are shown in Table 6. It can be observed that the method without dummy DUMs has lower classification power in three out of six countries that achieved an efficiency score of 1.

Table 6 indicates the efficiency of the export network of countries that represent the vulnerability of their global supply task. With the dummy DMU method, Thailand has the highest vulnerability because of the major effect on the low efficiency of their logistics and transportation sector when compared to each country. Vietnam has the lowest vulnerability because it is the strongest in the export sector and ranked 4th in the logistics and transportation sector (Table 5). Moreover, the results of Vietnam reflect that the efficiency of the previous stage (exporters node) contributes to their export system. Fig. 7 depicts the efficiency of the export system (a deep blue bar of Exp & LTS) based on both sector of Exp and LTS for all study countries.

4.3. Efficiency of imports and overall global supply chains

The efficiency of import countries is compared using model 2. The results are shown in Table 7. The import countries sorted by the highest to lowest vulnerability are Hong Kong, China, Vietnam, South Korea, Malaysia, Japan, Singapore, the United States, Thailand, Indonesia and India. Note that only Hong Kong achieved the efficiency score of 1 and has a very broad gap of efficiency score as compared with other importing countries. According to an in-depth analysis of the data, the ratio of the import sector of Hong Kong is 49 percent orders from China.

Table 7
The results of the import countries.

DMU	1	2	3	4	5	6	7	8	9	10	11	12
Import country	CHN	USA	JPN	HKG	SGP	MAS	INA	THA	KOR	IND	VIE	AUS
Input	7.72	18.67	14.4	3.73	16.1	13.65	24.22	20.53	12.8	46.02	8.39	18.58
Output	109.7	94.98	82.61	106.48	90.14	94.67	78.24	83.55	91.89	78.83	110.57	84.88
Efficiency score	0.4978	0.1782	0.201	1	0.1961	0.243	0.1132	0.1426	0.2515	0.06	0.4617	0.16
Rank	2	8	6	1	7	5	11	10	4	12	3	9

Table 8
The results of the overall global supply chain.

DMU	Linked countries of global supply-chain		Input	Transferred efficiency of export sector (input)	Output	Efficiency score	Rank
1	SGP	- CHN	7.72	2.23	109.7	0.6304	18
2		- USA	18.67	2.23	94.98	0.3885	31
3		- JPN	14.4	2.23	82.61	0.3694	32
4		- HKG	3.73	2.23	106.48	1	1
5		- MAS	13.65	2.23	94.67	0.4341	28
6		- INA	24.22	2.23	78.24	0.32	37
7		- THA	20.53	2.23	83.55	0.3417	34
8	THA	- CHN	7.72	2.68	109.7	0.5557	21
9		- USA	18.67	2.68	94.98	0.3407	35
10		- JPN	14.4	2.68	82.61	0.3344	36
11		- HKG	3.73	2.68	106.48	1	1
12		- SGP	16.1	2.68	90.14	0.3471	33
13		- MAS	13.65	2.68	94.67	0.3921	30
14		- INA	24.22	2.68	78.24	0.2666	39
15		- VIE	8.39	2.68	110.57	0.5463	22
16		- AUS	18.58	2.68	84.88	0.3052	38
17	MAS	- CHN	7.72	1.50	109.7	0.8059	10
18		- USA	18.67	1.50	94.98	0.5754	20
19		- JPN	14.4	1.50	82.61	0.5004	25
20		- HKG	3.73	1.50	106.48	1	1
21		- SGP	16.1	1.50	90.14	0.546	23
22		- THA	20.53	1.50	83.55	0.5061	24
23		- IND	46.02	1.50	78.83	0.4775	26
24	INA	- CHN	7.72	1.19	109.7	0.9156	6
25		- USA	18.67	1.19	94.98	0.7256	12
26		- JPN	14.4	1.19	82.61	0.6311	17
27		- SGP	16.1	1.19	90.14	0.6886	16
28		- MAS	13.65	1.19	94.67	0.7232	13
29		- KOR	12.8	1.19	91.89	0.702	15
30		- IND	46.02	1.19	78.83	0.6022	19
31	VIE	- CHN	7.72	1	109.7	1	1
32		- USA	18.67	1	94.98	0.8658	7
33		- JPN	14.4	1	82.61	0.7531	11
34		- SGP	16.1	1	90.14	0.8217	9
35		- KOR	12.8	1	91.89	0.8376	8
36	PHI	- CHN	7.72	1.81	109.7	0.7203	14
37		- USA	18.67	1.81	94.98	0.4774	27
38		- JPN	14.4	1.81	82.61	0.4152	29
39		- HKG	3.73	1.81	106.48	1	1

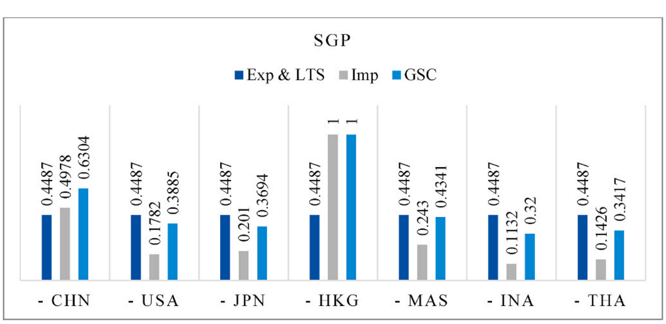

Fig. 8. Comparison of the supply chain vulnerability of Singapore.

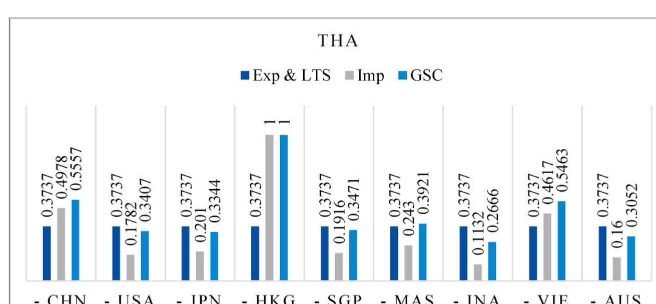

Fig. 9. Comparison of the supply chain vulnerability of Thailand.

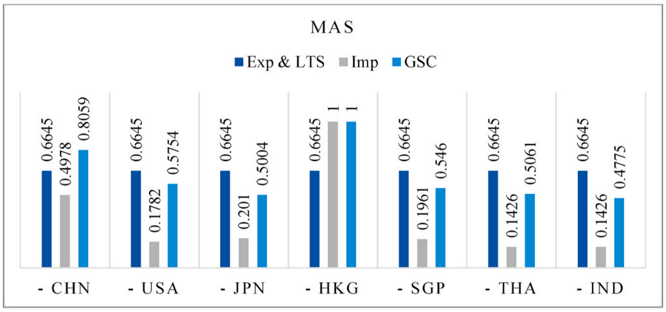

Fig. 10. Comparison of the supply chain vulnerability of Malaysia.

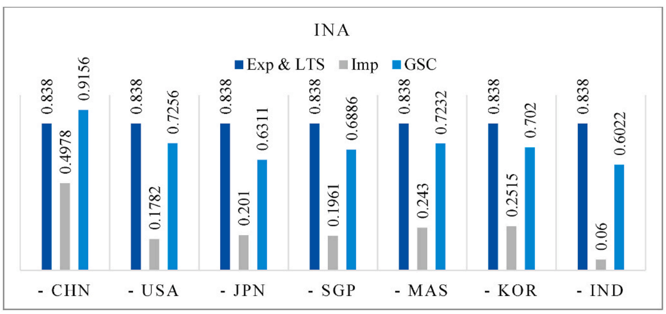

Fig. 11. Comparison of the supply chain vulnerability of Indonesia.

In the second quarter of 2020, China was in a recovery phase, which had rising export volumes. China has recovered from a critical period of the COVID-19 outbreak since the first quarter of 2020. These results show an increase in Hong Kong imports during that time.

The overall efficiency scores of the global supply chain computed using model 3 are shown in Table 8, while Figs. 8–13 depict the associated bar charts of each country. Based on Table 8, five linked countries of the global supply chain reached the efficiency score of 1, i.e., SGP-HKG, THA-HKG, MAS-HKG, VIE-CHN, and PHI-HKG. Four of five of the high efficiency score are related to the high level of imports of Hong Kong, where it has a large gap compared with that of another import country. Another is Vietnam which has the highest export system that is linked to China (China is ranked second in terms of imports). In summary, Figs. 8–13 denote that trading partners with lower risk rate and the ability to quickly recover the import volumes, and reaching high efficiency scores, have made the entire supply chain of linked countries less vulnerable, such as, THA-HKG in Fig. 9. In contrast, INA-IND in Fig. 11 is more vulnerable.

According to the results in Table 8, the summary of the overall global supply chain vulnerability is shown in Table 9. The weighted average of the global supply chain's efficiency scores of the countries are calculated based on the relative weights in Table 3 since the import ratio of each country is different. As an example, in the case of Singapore:

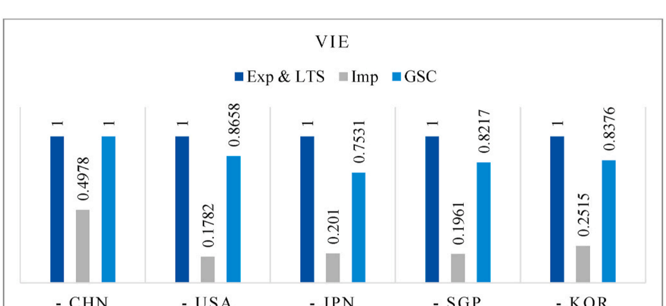

Fig. 12. Comparison of the supply chain vulnerability of Vietnam.

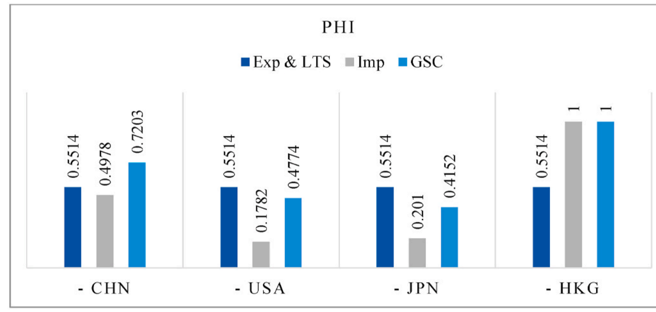

Fig. 13. Comparison of the supply chain vulnerability of the Philippines.

$$
\begin{aligned}
0.5561 = {} & [14 \times 0.6304 \text{ (of SGP} - \text{CHN)} + 9.2 \times 0.3885 \text{ (of SGP} - \text{USA)} \\
& + 4.7 \times 0.3694 \text{ (of SGP} - \text{JPN)} + 12 \times 1 \text{ (of SGP} - \text{HKG)} \\
& + 11 \times 0.4341 \text{ (of SGP} - \text{MAS)} + 7.3 \times 0.32 \text{ (of SGP} - \text{INA)} \\
& + 4.1 \times 0.3417 \text{ (of SGP} - \text{THA)}]/62.3
\end{aligned}
$$

In summary, the country ranking of the global trade supply chain vulnerability with respect to COVID-19 based on the exports from the lowest to highest are Vietnam, Indonesia, Malaysia, the Philippines, Singapore and Thailand.

5. Discussion

5.1. Conceptual and theoretical

This study applies the economic risk and resilience-based efficiency evaluation for metrication. This metric is used to assess a global trade supply chain vulnerability in the COVID-19 pandemic. Vulnerability has a positive relationship with risk, but a negative correlation with resilience. The efficiency is evaluated using the DEA method for assessing the vulnerability of the global trade supply chain. Sample countries where there are economic consequences of the COVID-19 outbreak were established. The concept of metric is not merely a measure of the overall GDP of a country. Rather, it is a measure of the GDP of the important sector of a global supply chain that consists of exports, logistics, and transport sectors of exporting countries along with the international customers The CoDEA model is applied to measure the efficiency of the supply chain. The results of CoDEA for global trade supply chain vulnerability show that Vietnam's global trade supply chain is most robust. When comparing the results to the country's 2020 GDP, only Vietnam's GDP grew (+2.90%). Vietnam's exports accounted for a larger proportion of GDP reaching 97.3% of GDP in 2017 (Kuo, Lu, & Le, 2020). In contrast, the Philippines which ranked fourth in robustness of a global trade supply chain operations, its exports accounted for nearly a third of GDP which is inadequate to ameliorate their negative GDP at −9.44.

Furthermore, the strength of Vietnam's main international customer

Table 9
Summary of overall global supply chain vulnerability.

Country	SGP	THA	MAS	INA	VIE	PHI
Countries' exports network efficiency	0.4487	0.3737	0.6645	0.838	1	0.5514
Weighted average of countries' global supply-chains efficiency	0.5561	0.4397	0.6502	0.7416	0.8754	0.6368
Robustness rank	5	6	3	2	1	4
2020 GDP growth[a] (%)	−5.39	−6.19	−5.59	−2.03	+2.90	−9.44
GDP growth rank	3	5	4	2	1	6

[a] Source: S&P Global.

like China (GDP of 2020 growth = +2.30% (S&P Global, 2021)) can reinforce the robustness of the global trade supply chain of Vietnam. Theoretically, the level of supply chain vulnerability is related to the supply chain design. The supply chain design characteristics include density, complexity, and node criticality (Monostori, 2021). Firstly, density correlates to the node's geographical positioning e.g., Vietnam is geographically connected to China. Secondly, complexity is related to the sum of the number of nodes and connections in which Vietnam also has an appropriate variety of international customers. Lastly, node criticality is the importance of nodes within the supply chain such as the two main international customers of Vietnam were China and the United States and the total exports of both countries reached 37% balancing offshore and nearshore partners. In summary, this proposed metrics of applying the evaluation of the economic risk and resilience-based efficiency using CoDEA is reflective of the global trade supply chain's vulnerability in the COVID-19 pandemic scenario.

5.2. Managerial implications and impacts on policies

In terms of managerial implications, the results in which the metric can be used to generate the resilience scenarios related to *risk treatment* strategies are as follows. The proposed strategies created are based on the supply chain collaboration perspective (Aday & Aday, 2020; El Baz & Ruel 2020; Sharma et al., 2020). According to the results, the vulnerability of global supply chain is dependent on the vulnerability of the export system of each country together with the inefficiencies of their import countries. As such, the selection of partners is necessary. It is recognized that having multiple export partners in multiple regions can help mitigate the risk in each region. This implies that the risks must not occur simultaneously around the world like the case of the COVID-19 outbreak. Therefore, each country can consider a new concept of trading partner collaboration by balancing offshore and nearshore partners. In other words, the country redesigns its global trade supply chain considering its node criticality. This is related to the concept of novel business models under COVID-19 by Choi (2020), which highlights the "bring-service-near-your-home" (BSNYH) concept. Vietnam and China have less vulnerability as their global supply chain countries are closer to them. The business model of BSNYH can decrease the effect of the lost value of the logistics and transportation sector. Cross-border freight transportation is more flexible than other modes of transportation especially by air freight since COVID-19 causes many airlines to stop their operations. However, for BSNYH to be competitive, it requires cooperation between neighboring countries which must be cooperative in both the public and private sectors (Love et al., 2020). Neighboring collaborative countries must work together to change the policy of locking down national borders to locking down regional borders. Moreover, the contactless border trade operations which is supported by a high technology system should be recommended. These collaborative countries also need to agree on the coordination of the trade-off pertaining to the economies of both countries based on mutual responsibility and resource sharing. This policy requires balancing the impact of the national economic stability and health security of their population as the spread of other diseases may occur in future. As mentioned earlier, the results of the efficiency scores of the CoDEA method is applicable for guiding risk mitigation or resilience policy to vulnerability closure for ASEAN global trade supply chain.

5.3. Limitations and future research

This metric may be limited to the data obtained from this analysis. For example, this metric only focuses on the economics. However, the vulnerability of the global supply chain under the COVID-19 pandemic could relate to other dimensions such as the rate of disease outbreaks per population in each country and these can be assigned as the input in the DEA approach. For future work, we will be providing the improvement metric for evaluating the results more comprehensively by considering the enhancement of supply chain structure. Such as the preceding node, it can be expanded to a partner country which is the material provider. Moreover, to directly enhance the power of DEA classification, the addition of several DMU should be considered. Under the continent geography factor control, the DMU may extend to East Asian countries e.g., Hong Kong and Taiwan. Moreover, the metric may be used in other regions which the selected DMU countries should be considering with comparable features e.g., all DMU which are coastal countries and which can offer water freight transportation.

6. Conclusions

In this paper, we have proposed the application of CoDEA integrated with the supply chain risks and resilience management concept for vulnerability assessment. We divided the members of the global supply chain into three main parts that relied on the supply chain definition, namely an upstream node of a producer which plays the role of the exporters; a midstream node of the logistics and transportation sector which plays the role of mediator; and a downstream node of international customers which plays the role of the importers. When we compute the vulnerability level of the supply chain (which is represented by the low efficiency score), the vulnerability of the supply networks of countries is related to the inefficient export operations of organizations as well as the logistics and transportation of service providers. When we calculate the vulnerability of the global supply chain of each export country, the vulnerability of the global supply chain is dependent on the vulnerability of the export system of each country together with the inefficiencies of their international customers. The results show that the metric is suitable to assess an entire global supply chain in which the vulnerability of every node from upstream to downstream is reflected in the overall global supply chain vulnerability.

CRediT authorship contribution statement

Suriyan Jomthanachai: Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft. **Wai-Peng Wong:** Writing – review & editing, Methodology, Validation, Supervision. **Keng-Lin Soh:** Writing – review & editing, Validation. **Chee-Peng Lim:** Writing – review & editing.

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Appendix A

The properties of CoDEA are based on the CRS traditional DEA model in which each node efficiency is independent. Individual node efficiency changes have no detrimental impact on the individual efficiency of other connected nodes. In contrast, if the efficiency of the associated node is increased when CoDEA is utilized, a positive influence on network efficiency can be noticed. Furthermore, CoDEA network efficiency scores are typically greater than the overall efficiency of a two-stage process as a multiplication of stage one and stage two. We further run a simulation using the data of 24 non-life insurance companies in Taiwan (Kao & Hwang, 2008) as shown in Table A1.

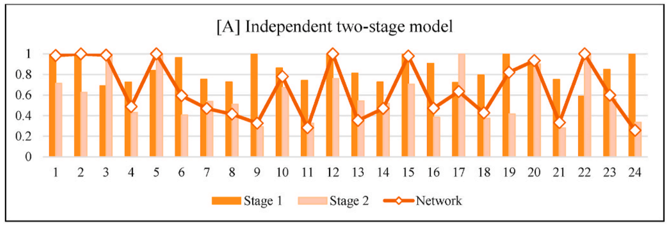
Table A.1
Inputs and outputs of the 24 non-life insurance companies in Taiwan

Company	Operation expenses	Insurance expenses	Direct written premiums	Reinsurance premiums	Under-writing profit	Investment profit
Taiwan Fire	1,178,744	673,512	7,451,757	856,735	984,143	681,687
Chung Kuo	1,381,822	1,352,755	10,020,274	1,812,894	1,228,502	834,754
Tai Ping	1,177,494	592,790	4,776,548	560,244	293,613	658,428
China Mariners	601,320	594,259	3,174,851	371,863	248,709	177,331
Fubon	6,699,063	3,531,614	37,392,862	1,753,794	7,851,229	3,925,272
Zurich	2,627,707	668,363	9,747,908	952,326	1,713,598	415,058
Taian	1,942,833	1,443,100	10,685,457	643,412	2,239,593	439,039
Ming Tai	3,789,001	1,873,530	17,267,266	1,134,600	3,899,530	622,868
Central	1,567,746	950,432	11,473,162	546,337	1,043,778	264,098
The First	1,303,249	1,298,470	8,210,389	504,528	1,697,941	554,806
Kuo Hua	1,962,448	672,414	7,222,378	643,178	1,486,014	18,259
Union	2,592,790	650,952	9,434,406	1,118,489	1,574,191	909,295
Shingkong	2,609,941	1,368,802	13,921,464	811,343	3,609,236	223,047
South China	1,396,002	988,888	7,396,396	465,509	1,401,200	332,283
Cathay Century	2,184,944	651,063	10,422,297	749,893	3,355,197	555,482
Allianz President	1,211,716	415,071	5,606,013	402,881	854,054	197,947
Newa	1,453,797	1,085,019	7,695,461	342,489	3,144,484	371,984
AIU	757,515	547,997	3,631,484	995,620	692,731	163,927
North America	159,422	182,338	1,141,950	483,291	519,121	46,857
Federal	145,442	53,518	316,829	131,920	355,624	26,537
Royal & Sun alliance	84,171	26,224	225,888	40,542	51,950	6491
Asia	15,993	10,502	52,063	14,574	82,141	4181
AXA	54,693	28,408	245,910	49,864	0.1	18,980
Mitsui Sumitomo	163,297	235,094	476,419	644,816	142,370	16,976

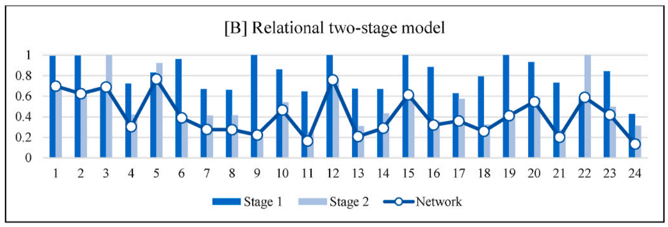
The production process in the non-life insurance sector is typically two-stage. The marketing of insurance is the first sub-process which involves attracting clients to pay direct writing premiums and receiving reinsurance premiums from other insurance firms. Investment is the second sub-process, in which premiums are invested in a portfolio to make a profit. Operating expenses and insurance expenses are the first stage inputs. The first stage produces two outputs: direct writing premiums and reinsurance premiums both of which are also inputs to the second stage which are namely intermediate measures. The second stage outputs are underwriting profit and investment profit.

Table A.2
The efficiency score of independent and relational two-stage model compared to CoDEA

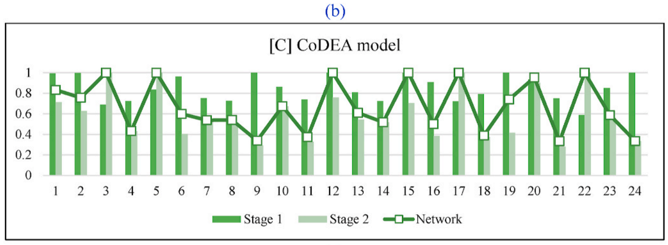
Company	Independent two-stage			Relational two-stage			CoDEA		
	Stage 1	Stage 2	Network	Stage 1	Stage 2	Network	Stage 1	Stage 2	Network
Taiwan Fire	0.993	0.713	0.984	0.993	0.704	0.699	0.993	0.713	0.833
Chung Kuo	0.998	0.627	1	0.998	0.626	0.625	0.998	0.627	0.757
Tai Ping	0.69	1	0.988	0.69	1	0.69	0.69	1	1
China Mariners	0.724	0.432	0.488	0.724	0.42	0.304	0.724	0.432	0.433
Fubon	0.838	1	1	0.831	0.923	0.767	0.838	1	1
Zurich	0.964	0.406	0.594	0.961	0.406	0.39	0.964	0.406	0.599
Taian	0.752	0.538	0.47	0.671	0.412	0.277	0.752	0.538	0.538
Ming Tai	0.726	0.511	0.415	0.663	0.415	0.275	0.726	0.511	0.54
Central	1	0.292	0.327	1	0.223	0.223	1	0.292	0.338
The First	0.862	0.674	0.781	0.862	0.541	0.466	0.862	0.674	0.674
Kuo Hua	0.741	0.327	0.283	0.647	0.253	0.164	0.741	0.327	0.373
Union	1	0.76	1	1	0.76	0.76	1	0.76	1
Shingkong	0.811	0.543	0.353	0.672	0.309	0.208	0.811	0.543	0.61
South China	0.725	0.518	0.47	0.67	0.431	0.289	0.725	0.518	0.518
Cathay Century	1	0.705	0.979	1	0.614	0.614	1	0.705	1
Allianz President	0.907	0.385	0.472	0.886	0.362	0.32	0.907	0.385	0.501
Newa	0.723	1	0.635	0.628	0.574	0.36	0.723	1	1
AIU	0.794	0.374	0.427	0.794	0.326	0.259	0.794	0.374	0.389
North America	1	0.416	0.822	1	0.411	0.411	1	0.416	0.74
Federal	0.933	0.901	0.935	0.933	0.586	0.547	0.933	0.901	0.953
Royal&Sun alliance	0.751	0.28	0.333	0.732	0.274	0.201	0.751	0.28	0.333
Asia	0.59	1	1	0.59	1	0.59	0.59	1	1
AXA	0.85	0.56	0.599	0.843	0.499	0.42	0.85	0.56	0.587
Mitsui Sumitomo	1	0.335	0.257	0.429	0.314	0.135	1	0.335	0.335
Maximum	1	1	1	1	1	0.767	1	1	1
Minimum	0.59	0.28	0.257	0.429	0.223	0.135	0.59	0.28	0.333
Mean	0.849	0.596	0.651	0.801	0.516	0.416	0.849	0.596	0.669



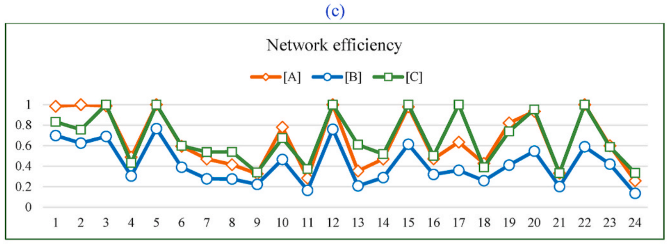
(a)



(b)



(c)



(d)

Fig. A1. Comparison of the independent and relational two-stage model to CoDEA.

Table A2 and Figure A1 illustrate the results of the simulation comparing CoDEA to Kao and Hwang's (2008) independent and relational two-stage models. For the independent two-stage model, the DMUs computed the stage one and stage two efficiencies independently using the traditional DEA in the individual efficiency of stage one and stage two of CoDEA and are identical to the independent two-stage model. The network efficiencies of the independent two-stage model are then calculated by the traditional DEA using stage one inputs (operational expenses and insurance expenses) and stage two outputs (underwriting profit and investment profit) which avoid the intermediate measures, hence indicating that the independent model may produce unusual results for several companies (Kao & Hwang, 2008). As a result, DMU network efficiency differs from CoDEA, which overwhelms these unusual calculations that maintains the beneficial input/output of direct writing premiums and reinsurance premiums but does not apply as intermediary measures. For the relational two-stage model, after the DMUs network efficiencies and the efficiencies of the second stage have been determined using relational two-stage approach deploying these intermediate measures. The first stage's efficiencies then are calculated by dividing the network efficiencies by the second stage efficiencies. Putting this another way, network efficiency is the product of stage one multiplied by stage two. Furthermore, the efficiencies of the different stages are interdependent and changes in one stage may impact the efficiencies of other idle stages. This does not resemble the nature of the supply chain, in which different nodes independently maintain or improve their performance since the individual efficiency evaluation is more appropriate. Furthermore, the multiply or divide rule has the potential to lower the value of network efficiency. CoDEA on the other hand, provides network efficiencies by balancing both stages' efficiency which does not provide a value lower than the efficiencies of each stage. CoDEA could generate an alternate suitable model for dealing with network structures such as a supply chain from this simulated example.

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