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An Interdependence Analysis of the Trade Network of Key Exporting Countries: Focusing on the Asia-Pacific Region (U.S., China, India, Japan, and South Korea)

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ABSTRACT

This paper investigates the impact of economic crises on the trade networks of key economies in the Asia-Pacific region, specifically focusing on both trade volume contraction and structural reconfiguration. Utilizing network theory and a dataset covering 1992-2020, the study examines how crises, such as the Asian Financial Crisis and the Global Financial Crisis, affect the interdependence among the United States, China, Japan, South Korea, and India. We hypothesize that economic crises not only lead to a reduction in trade volumes but also cause a lasting reconfiguration of trade networks, with China's centrality increasing as a result. Our findings confirm that while trade volumes temporarily contract during crises, the structural shifts within the trade network are more enduring. China's role as a sub-hub has significantly strengthened, displacing Japan's previous position in the network, particularly after the 2007-2008 crisis. These results suggest that economic crises permanently alter trade interdependence, with critical implications for global trade dynamics and policy-making. The study contributes to the literature on trade interdependence and offers insights for policymakers navigating post-crisis economic recovery and long-term trade strategy.

Keywords: International Economics, Interdependence, Network Analysis, Economic Crisis, International Trade
JEL Classifications: F140, F150

1. INTRODUCTION

Over the past few decades, the dynamics of international trade have been profoundly shaped by economic, geopolitical, and technological shifts. Nowhere is this more apparent than in the Asia-Pacific region, which has seen its economies grow into major global trading hubs. Countries such as the United States, China, Japan, South Korea, and India have not only expanded their bilateral trade ties but have also become increasingly interconnected through complex networks of trade relationships. These evolving networks reflect more than just the volume of goods exchanged; they embody deeper patterns of interdependence, shaped by the balance of reciprocity and the strategic importance of each nation within the global trade system.

Economic crises, from the Asian Financial Crisis of the late 1990s to the Global Financial Crisis of 2007-2008, have underscored the vulnerability of these networks. Historically, much attention has been given to the contraction in trade volumes during such crises, with studies documenting significant drops in total exports and imports across affected regions. However, the broader impact of crises on the structure of trade networks has received less scrutiny. In particular, how these crises reconfigure the interdependence among major economies remains an open question in the existing literature.

This paper seeks to address this gap by examining how economic crises not only reduce trade volumes but also induce structural shifts in trade networks, fundamentally altering the balance of interdependence among key Asia-Pacific economies. Utilizing network theory and a comprehensive dataset spanning from 1992 to 2020, this study focuses on the interplay between trade contraction and network reconfiguration, with a particular emphasis on China's evolving role in the global economy.

We hypothesize that economic crises not only lead to a contraction in trade volumes but also cause a structural reconfiguration of trade networks, shifting the balance of interdependence among major economies in the Asia-Pacific region, with China's centrality increasing as a result. By quantitatively analyzing the reciprocal and dependent relationships within this trade network, we demonstrate that these crises have catalyzed a shift from a US-Japan-centric network to one increasingly dominated by China. The implications of these findings are crucial, as they suggest that trade networks do not merely recover from crises but are often permanently reshaped, with significant geopolitical and economic consequences.

This research not only contributes to the academic discourse on trade interdependence but also offers practical insights for policymakers. As nations navigate the complexities of post-crisis recovery, understanding the structural changes in trade networks will be critical for formulating strategies that enhance economic resilience and long-term stability.

2. LITERATURE REVIEW

The study of international trade has evolved significantly over the past decades, particularly in response to digital advancements and geopolitical events. Ahmedov (2020) underscores the transformative impact of the digital economy on trade, highlighting how new technologies have reshaped traditional trade dynamics. This shift necessitates rethinking how trade relationships are understood.

Beckman (2018) discusses the interplay between fiscal policies and trade interdependence, showing how domestic economic decisions are increasingly influenced by global trade dependencies. This insight is vital for understanding how major economies, especially in the Asia-Pacific region, adjust their trade policies during crises.

The growing centrality of multinational corporations is highlighted by Bösenberg et al. (2017), who demonstrate the interconnectedness of global firms. This perspective aligns with studies focusing on the role of large economies, like China and the U.S., in shaping global trade networks.

Network analysis has become an essential tool for understanding global trade structures. De Lombaerde et al. (2018) and De Benedictis and Tajoli (2011) introduce network science as a method for capturing trade patterns that traditional models may miss. By applying network theory, they reveal how interconnected trade relationships form complex networks, which is crucial for analyzing shifts during crises.

The concept of "weaponized interdependence," introduced by Farrell and Newman (2019), emphasizes the strategic use of economic interdependence by states, particularly in trade. This aligns with the increasing centrality of China in the global trade network, as nations leverage their trade relationships for geopolitical influence.

Finally, Garlaschelli et al. (2004) and Maluck and Donner (2015) provide valuable insights into the reciprocity and interdependence in trade networks. While Garlaschelli focuses on the balance of trade flows, Maluck extends the analysis by using multi-regional data to show how economic crises disrupt these networks. Their work lays the foundation for understanding how trade relationships shift during economic downturns.

As shown in Table 1, the following gaps are identified.

While several studies have explored various aspects of trade interdependence and network theory, a detailed comparison with our research is provided in Table 1. This table highlights the methodological approaches and key findings of prominent works, and contrasts them with the unique contributions of this study.

For instance, Alves et al. (2022) and Yazawa (2023) focus on centrality within global trade networks, with Alves identifying a pivotal shift in 2007, where China surpassed the U.S. in certain sectors. However, our study extends these analyses by examining interdependence indicators from 1992 to 2020, showing that while China gained importance, it has not yet fully replaced the U.S. as the central hub, acting instead as a sub-hub after 2007.

Garlaschelli et al. (2004) and Maluck and Donner (2015) provide insights into the reciprocity of trade networks, highlighting long-term trends. Our study builds on their findings by introducing interdependence as a composite measure of both reciprocity and dependence, which offers a more comprehensive understanding of how economic crises impact the structural configuration of trade networks.

Finally, Maluck and Donner (2015) used the Hamming distance to measure anomalies in trade patterns during economic crises, but our analysis offers a novel perspective by identifying two distinct crisis impacts: Trade volume contraction and a structural reconfiguration of the network, with clear shifts in interdependence during and after crises.

In summary, Table 1 underscores the gaps in the existing literature—particularly the lack of focus on long-term interdependence shifts and the dual effects of crises—that our study addresses. This comparative analysis reinforces the significance of our findings and highlights the innovative methods and extended timeframe used in this research.

3. METHODS

Trade relationships among multiple countries are best understood through network analysis. This study seeks to identify the type of network that most accurately represents interdependence among these economies. Recent studies increasingly focus on understanding how multiple actors connect within networks.

Table 1: Comparative analysis of existing studies and our research

Articles	Their method	Their key findings	Our methods	Our key findings
Alves et al. (2022)	An eigenvector centrality of graph theory was applied as a common measure for assessing the importance of nodes in a network	2007 marked an inflection point at which new winners and losers emerged and a remarkable reversal of leading role took place between the two major economies, the US and China.	Comparison of the interdependence indicators of each country	From the viewpoint of interdependence, the United States remained the central hub of networks from 1992 to 2020. Until 2007, Japan served as a sub-hub to the United States, but after that, China assumed the role of sub-hub
Yazawa (2023)	Visualization of the time series progression of network structure with arrows whose standard deviation are 55 or greater.	The center of the network has shifted from the US to China in 2007 for all products		
Garlaschelli et al. (2004)	The study of link reciprocity in binary directed networks of global trade a definition of reciprocity as the correlation coefficient between the entries of the adjacency matrix of a directed graph year: 1948-2000	Reciprocity of trade network increased from 0.68 (1948) to 0.9 (2000), resulting in 32 increase	interdependence indicator as composition of reciprocity and dependence Where R (i, j, tl)≡min(X (i, j, tl), X (j, i, tl))/max(X (i, j, tl), X (j, i, tl)) D (i, j, tl) ≡min(X (i, j, tl), X (j, i, tl))	interdependence of trade network increased 12.4 from 1992 to 2020
Maluck and Donner (2015)	multi-regional input-output data to decompose 186 national economies into 26 industry sectors 1990-2010 (a) a definition of reciprocity as $r = \frac{1}{\lvert A\rvert}\mathrm{Tr}[A]^2$ where A is an adjacency matrix	The reciprocity (r) gradually increases in the national partition Cc, but saturating in 2000.		
Yazawa (2023)	The degree of reciprocity within a network, measured by the sum of the squared trade imbalances between each pair of actors	The overall increase in squared trade imbalances led to a 14.3 increase in reciprocity		
Maluck and Donner (2015)	(b) measure the Hamming distance between the international trade network in the present and the preceding year	Hm is an applicable measure to identify anomalies in trade patterns, such as the financial crisis in 2009	The time series changes in total trade volume and network interdependence were analyzed, with particular attention to the behavior of these two indicators during economic crises	The types and characteristics of the impact of economic crises on the network can be measured by two indicators: the first being a contraction of the entire network with a reduction in total trade volume, and the second being a structural shift in the network's configuration with a reduction in network interdependence
Yazawa (2023)	Clustering analysis applying to time vectors	The many substantial alterations in the network structure occurring during such incidents suggest that global trade is significantly susceptible to these crises.		

Source: The author

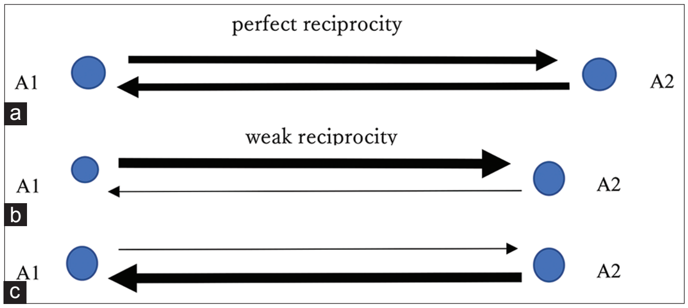
Studies on the reciprocity of weighted networks such as international trade networks and the World Wide Web have recently been published in literature such as De Lombaerde et al. (2018), Squartini et al. (2013), Ruzzenenti et al. (2010), and Garlaschelli and Loffredo (2004). Based on their findings, we focus on the theme of interdependence as the composite of dependence and reciprocity. However, our definition of dependence and reciprocity is partly different from Squartini et al. (2013).

3.1. Reciprocity

Suppose there are n actors A1, A2,…, An. When a link from A1 to A2 and a link from A2 to A1 exist, and both links have the same flow quantity, we say the relation between A1 and A2 is perfectly reciprocai (Figure 1a). On the other hand, when the link from A1 to A2 has a large flow quantity and the link from A2 to A1 has a little flow quantity, we say the relation between A1 and A2 has little reciprocity (Figure 1b).

Figure 1 illustrates the different degrees of reciprocity between two actors in a trade network. Panel (a) depicts perfect reciprocity where the flow quantities between the two actors are equal, representing a balanced relationship. Panel (b) shows weak reciprocity, characterized by a significant difference in the flow quantities between the actors, indicating an imbalanced

Figure 1: Illustration of three types of reciprocity between two actors in a trade network. (a) Perfect reciprocity where trade flows are equal between actors. (b) Weak reciprocity with a significant difference in trade flows. (c) Another example of weak reciprocity emphasizing trade imbalance



Source: Yazawa (2023)

relationship. Panel (c) presents an example of weak reciprocity where the flow from A1 to A2 is substantially larger than the flow from A2 to A1, further emphasizing the imbalance in their trade relationship.

We will quantify the strength of the link and let it have positive real number a. Let the flow quantity of the link from A1 to A2 be F(1,2), and from A2 to A1 be F(2,1). Then we quantify the degree of reciprocity between A 1and A2 as R(1,2) in the following way.

In this subsection, we regard directed links as output flows from actors. In equation (1), $X(1,2,t_0)$ represents the proportion of output flow from A1 to A2 in the total output flow from A1 at the time t_0.

$$X(1,2,t_0)=\frac{F(1,2,\ t_0)}{\sum_{i=2}^{n}F(1,i,\ t_0)} \tag{1}$$

$T(t_1)$ is defined in equation (2)

$$T(t_1)\equiv\sum_{i=1}^{n}\sum_{k\neq i}F(i,k,\ t_1) \tag{2}$$

In general, $X(i,j,t_1)$ is formulated as below (equation (3)).

$$X(i,j,\ t_1)\equiv\frac{F(i,j,\ t_1)}{\sum_{k\neq i}F(i,k,\ t_1)} \tag{3}$$

In equation (3), $X(i, j, t_1)$ represents the proportion of output flow from Ai to Aj in the total output flow from Ai at the time $t= t_1$. Next, we define the reciprocity index (R) between A1 and A2 in the following way.

$R(1,2, t_1) = \min(X(1,2, t_1), X(2,1, t_1)/\max(X(1,2, t_1), X(2,1, t_1))$

Therefore, in general, R(i, j) is formulated as below (equation (4)).

$$R(i,j, t_1)\equiv \min(X(i,j, t_1), X(j,i, t_1))/\max(X(i,j, t_1), X(j,i, t_1)) \tag{4}$$

Note that $0 \le R(i,j,t_1)=R(j,i,t_1) \le 1$

We define the reciprocity index of a network of n nodes in equation (5).

$$R_{net(t_1)}\equiv\frac{1}{2}\sum_{i}\sum_{j,\ j\neq i}|R(i,j,\ t_1)| \tag{5}$$

3.2. Dependence

When a link from A1 to A2 and a link from A2 to A1 exist, and A1 has only one link directed to others which is to A2, and A2 also has only one link directed to others which is to A1, the dependence between A1 and A2 is maximal. On the other hand, when the link from A1 to A2 is non-existent as well as from A2 to A1, the dependence between A1 and A2 is minimal.

Based on the manner of quantification of reciprocity, which we formulated in 3.1, we quantify the degree of dependence as follows.

From equation (3), we define dependence measure (D) between Ai and Aj as equation (6).

$$D(i,j, t_1)\equiv \min(X(i,j, t_1), X(j,i, t_1)) \tag{6}$$

Note that $0 \le D(i,j,t_1) \le 1$ and $D(i,j,t_1) = D(j,i,t_1)$. The larger $D(i,j,t_1)$ is, the stronger the bond between Ai and Aj is. However, $D(i,j,t_1)$ cannot indicate the degree of reciprocity.

We define the dependence index of a network of n elements in equation (7).

$$D_{net}(\ t_1)\equiv\frac{1}{2}\sum_{i}\sum_{j,\ j\neq i}D(i,j,\ t_1) \tag{7}$$

3.3. Interdependence

In this article, we regard interdependence index as composed of reciprocity measure and dependence measure. Therefore, we define interdependence index between Ai and Aj as equation (8).

$$I(i,j,t_1)\equiv D(i,j,t_1)\ R(i,j,t_1) \tag{8}$$

Note that $0 \le I(i,j,t_1) \le 1$ and $I(i,j,t_1) = I(j,i,t_1)$

We define an interdependence index of a node in a network of n nodes in equation (9).

$$I(i,\ t_1)=\sum_{j,\ j\neq i}^{n}I(i,j,\ t_1) \tag{9}$$

We define the interdependence index of a network of n nodes in equation (10).

$$I_{net}(t_1)\equiv\frac{1}{2}\sum_{i}\sum_{j,\ j\neq i}I(i,j,t_1) \tag{10}$$

In this paper, we apply the three indices, which we defined in chapter 3, to a case of international trade of the US, China, India, Japan, and South Korea, using data from WITS database. We calculate dependence, reciprocity, and interdependence indices of the ten links from 1992 to 2020. Thus, $t_0 = 1992$, $t_1 = 1993, \cdots\cdots, t_{28} = 2020$.

3.4. Data and Country Selection

Our decision to employ the World Integrated Trade Solution (WITS) database as the foundation of our research was driven by its unparalleled comprehensiveness and reliability in the realm of international trade data. WITS amalgamates datasets from esteemed organizations, including the United Nations Comtrade database, the World Bank, and the World Trade Organization, making it an exhaustive repository for trade information. The reliability of WITS, supported by its sourcing from reputable international bodies, establishes it as an indispensable resource for scholarly inquiry into global trade.

The temporal scope of our investigation, spanning from 1992 to 2020, was determined by the availability of data within the WITS framework. This period allows for a rigorous longitudinal analysis, providing a comprehensive view of the shifts in global trade networks over nearly three decades. Our analysis focuses on the US, China, India, Japan, and South Korea, the most influential actors in the Asia-Pacific region during the study period. These countries were selected for their significant roles in shaping global trade dynamics and their prominent bilateral trade relationships.

4. ANALYSIS AND RESULTS

4.1. Trends of Interdependence Index of the Links

In this section, following equation (8), we calculate $I(i,j,t_l)$ for each link from 1992 to 2020. Note that $I(i,j,t_l) = I(j,i,t_l)$.

The table highlights significant growth or decline in these indices across various bilateral relationships.

The data reflect fluctuations in interdependence and the impact of key economic events.

Table 2 shows the change rate of D, R, and I from 1992 to 2020 in each link. From Table 3, firstly, during the Asian financial crisis in 1997 and 1998, all the values except for India-China, India-South Korea, India-the US, the US-China, and China-Japan experienced a decrease, with the largest decrease being seen in I(K, J) with a drop of 52.2 in 1998. Moreover, the impact of the Asian Financial Crisis is that the export share from China and Japan to South Korea and that from South Korea to Japan drastically dropped and the export share from the US to South Korea also decreased significantly as well as that from India to China and South Korea. This implies that the interdependence between Japan and South Korea weakened. However, the US's market demand for imports from South Korea did not decline. Secondly, during the 9.11 terrorist attacks in 2001, the values of I(I,C) and I(I,J) decreased by 4.7 and 15.5 respectively. Thirdly, during the Global financial crisis in I(C,J), I(K,C), I(J,U), and I(K, J) decreased by 12.2, 32.0, 10.4, and 24.8 respectively, while the export share from China, Japan, and South Korea to India kept growing as well as that from the US to China. Fourthly, during the Chinese devaluation in 2015, the values of I(C,J), I(J,U), I(C,U), and I(K, J) decreased by 14.4, 8.8, 4.7, and 24.0 respectively.

Table 2: Percentage changes in interdependence (I), dependence (D), and reciprocity (R) for the ten trade links between the US, China, Japan, India, and South Korea from 1992 to 2020

Links	D 2020/1992	R 2020/1992	I 2020/1992
I-C	1142	35	1574
I-J	149	1191	3116
I-K	267	107	661
I-U	284	300	1435
K-C	80	−65	−37
J-U	−64	−28	−74
C-U	348	189	1193
K-J	−26	83	35
J-C	97	124	341
K-U	−6	70	60

Source: The author

From Table 3, I(K,C) is relatively high in 1992, but declining by 37 with values from 0.0620 in 1992 to 0.0388 in 2020. I(J,U) is consistently high but declining by 74, with values from 0.5859 in 1992 to 0.1519 in 2020, making it the most dominant relationship in 1992 and the second strongest in 2020 in the network. I(C,U) is relatively low in 1992, but it is drastically increasing by 1193, with values from 0.0288 in 1992 to 0.3720, which is the strongest link in 2020. I(K,J) is relatively high with a slight increase by 35, with values from 0.0550 to 0.0743. I(K,U) stays relatively high and slightly increasing by 60, with values from 0.0752 in 1992 to 0.1204 in 2020.

According to Table 3, India's most interdependent partner from 1992 to 2020 is South Korea. For South Korea, its most interdependent partner is the United States during the same period. Similarly, Japan's most interdependent partner is also the United States throughout this period. In contrast, the United States' most interdependent partner is Japan from 1992 to 2008 and China from 2009 to 2020. China's most interdependent partner shifts over time: it is South Korea from 1992 to 1997, Japan from 1998 to 2005, and the United States from 2006 to 2020. This implies that China is shifting to a more central role in the network.

4.2. Comparison of Interdependence Index of Countries

It is illustrated how the centrality of these countries in the trade network has evolved, with notable shifts in roles, particularly between Japan and China.

Figure 2 illustrates the trends of the interdependence index for the US, China, Japan, South Korea, and India from 1992 to 2020. It shows the shifting centrality in the trade network, with the US

Figure 2: Trends of interdependence index of countries

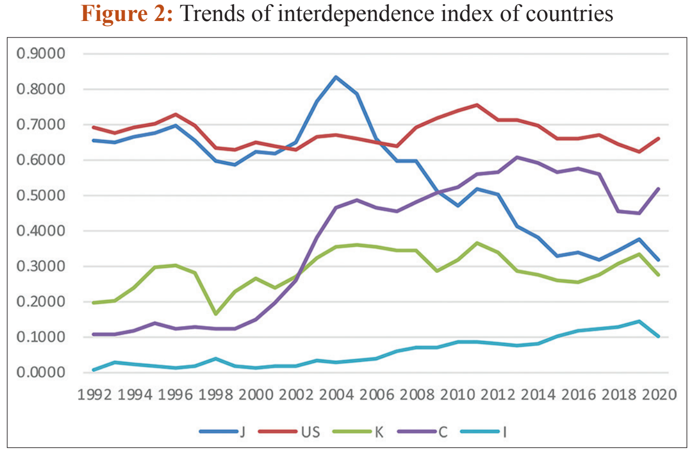


Table 3: Interdependence indicators (I, D, R) for each of the ten trade links between the US, China, Japan, India, and South Korea from 1992 to 2020

year	I (I, C)	I (I, J)	I (I, K)	I (I, U)	I (K, C)	I (U, J)	I (U, C)	I (K, J)	I (C, J)	I (K, U)
1992	0.002	0.000	0.005	0.001	0.062	0.586	0.029	0.055	0.017	0.075
1993	0.001	0.000	0.022	0.002	0.045	0.565	0.029	0.056	0.032	0.080
1994	0.004	0.001	0.018	0.001	0.056	0.571	0.028	0.068	0.029	0.095
1995	0.004	0.001	0.009	0.002	0.069	0.549	0.031	0.093	0.033	0.125
1996	0.002	0.001	0.010	0.001	0.057	0.562	0.030	0.099	0.037	0.135
1997	0.002	0.001	0.010	0.002	0.057	0.534	0.033	0.083	0.039	0.129
1998	0.004	0.001	0.030	0.002	0.029	0.518	0.047	0.040	0.041	0.066
1999	0.004	0.001	0.012	0.002	0.039	0.480	0.036	0.063	0.044	0.114
2000	0.004	0.001	0.008	0.001	0.047	0.481	0.042	0.085	0.056	0.126
2001	0.003	0.001	0.011	0.002	0.045	0.463	0.073	0.080	0.074	0.101
2002	0.004	0.001	0.008	0.002	0.040	0.417	0.095	0.109	0.123	0.113
2003	0.002	0.001	0.025	0.003	0.033	0.408	0.127	0.140	0.216	0.126
2004	0.003	0.002	0.020	0.004	0.034	0.385	0.152	0.171	0.277	0.130
2005	0.004	0.002	0.022	0.006	0.031	0.339	0.175	0.169	0.276	0.140
2006	0.007	0.003	0.020	0.007	0.033	0.287	0.214	0.159	0.212	0.142
2007	0.012	0.004	0.024	0.017	0.036	0.262	0.234	0.156	0.174	0.130
2008	0.017	0.006	0.027	0.017	0.047	0.288	0.261	0.145	0.159	0.124
2009	0.019	0.007	0.026	0.019	0.032	0.258	0.320	0.109	0.139	0.122
2010	0.018	0.007	0.042	0.018	0.032	0.234	0.346	0.102	0.126	0.141
2011	0.025	0.010	0.036	0.015	0.034	0.225	0.367	0.148	0.135	0.147
2012	0.024	0.008	0.037	0.014	0.034	0.206	0.370	0.147	0.140	0.124
2013	0.023	0.007	0.031	0.013	0.033	0.166	0.422	0.108	0.132	0.113
2014	0.030	0.008	0.033	0.011	0.037	0.164	0.410	0.094	0.114	0.111
2015	0.041	0.010	0.039	0.011	0.037	0.150	0.391	0.071	0.097	0.111
2016	0.050	0.011	0.044	0.011	0.036	0.155	0.392	0.074	0.099	0.103
2017	0.046	0.011	0.055	0.013	0.034	0.152	0.392	0.070	0.086	0.117
2018	0.042	0.016	0.050	0.021	0.031	0.172	0.300	0.078	0.079	0.151
2019	0.047	0.018	0.055	0.024	0.041	0.177	0.273	0.090	0.090	0.150
2020	0.030	0.016	0.041	0.016	0.039	0.152	0.372	0.074	0.075	0.120
2020/1992	15.74	31.16	6.61	14.35	−0.37	−0.74	11.93	0.35	3.41	0.60

Annual change rates (%)

year	I (I, C)	I (I, J)	I (I, K)	I (I, U)	I (K, C)	I (U, J)	I (U, C)	I (K, J)	I (C, J)	I (K, U)	
1993	−35.1	−19.8	317.4	101.9	−26.8	−3.6	2.4	1.2	88.9	6.2	
1994	267.0	46.9	−20.2	−46.0	24.2	1.1	−5.2	21.9	−10.0	18.5	
1995	−4.6	33.9	−49.5	31.5	22.0	−4.0	10.4	37.8	12.4	32.1	
1996	−57.9	31.3	13.7	−11.0	−16.4	2.4	−4.3	5.6	12.7	8.3	
1997	24.7	−13.0	2.1	22.0	−1.5	−4.9	10.3	−15.7	6.4	−5.0	Asian crisis
1998	93.3	51.3	183.4	18.6	−47.9	−3.0	44.8	−52.2	4.9	−49.0	
1999	−3.4	−10.6	−60.2	−2.3	31.5	−7.4	−23.4	57.7	7.4	73.7	
2000	−10.2	−19.1	−31.5	−27.0	22.3	0.1	17.0	34.9	26.5	10.8	
2001	−4.7	−15.5	33.4	29.0	−5.2	−3.7	73.2	−5.4	33.6	−20.2	9/11shock
2002	4.6	−6.8	−23.9	27.6	−11.4	−9.9	29.9	35.7	65.5	12.0	
2003	−36.2	55.2	199.9	29.3	−15.9	−2.3	33.9	28.6	75.7	12.0	
2004	39.7	34.1	−20.8	32.0	1.6	−5.5	19.5	22.3	27.9	3.1	
2005	13.9	22.6	13.3	54.4	−8.8	−11.9	15.4	−1.2	−0.1	7.7	
2006	88.5	30.8	−10.0	14.3	6.1	−15.3	22.0	−5.8	−23.3	1.4	
2007	82.2	60.1	21.5	140.6	9.9	−8.9	9.2	−1.8	−18.0	−8.5	Global crisis
2008	37.0	48.0	12.1	3.2	28.7	10.1	11.8	−7.2	−8.8	−4.3	
2009	11.9	11.6	−3.7	8.8	−32.0	−10.4	22.5	−24.8	−12.2	−2.2	
2010	−6.1	6.1	60.0	−6.6	−0.3	−9.4	8.0	−6.4	−9.4	15.5	
2011	38.3	34.7	−14.6	−13.0	7.1	−3.7	6.0	45.1	7.0	4.9	
2012	−5.1	−12.8	2.6	−10.4	0.9	−8.6	0.8	−0.3	3.3	−16.1	
2013	−1.9	−23.0	−14.6	−7.2	−2.2	−19.5	14.1	−26.6	−5.5	-8.6	
2014	28.4	16.7	6.8	−12.7	10.2	−0.9	−2.7	−13.2	−13.8	−1.8	
2015	39.2	33.4	16.3	0.9	0.2	−8.8	−4.7	−24.0	−14.4	0.2	Chinese devaluation
2016	21.1	12.2	12.8	−1.4	−2.2	3.7	0.3	4.2	1.2	−7.3	
2017	−8.4	−5.5	24.7	18.7	−4.4	−2.5	0.1	−6.3	−12.9	13.0	
2018	−7.7	51.6	−9.0	58.2	−9.5	13.5	−23.5	12.2	−7.6	29.5	US−China Trade war
2019	10.9	12.1	11.4	14.9	31.3	3.2	−9.0	15.7	14.0	−0.7	
2020	−35.9	−12.9	−26.2	−31.2	−5.0	−14.4	36.2	−17.8	−16.7	−19.7	

Source: The author

consistently remaining a hub and China increasingly assuming the role of a sub-hub.

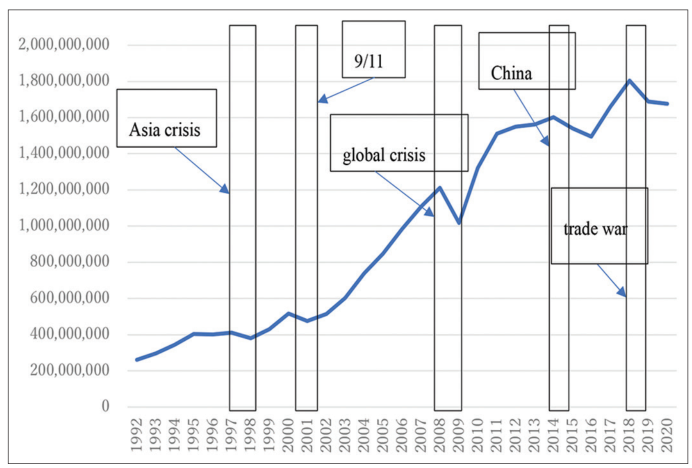
From equation (9), an interdependence index of a country is calculated. From Table 4 and Figure 2, it is observed that the

Table 4: Trends in the interdependence index for the US, China, Japan, South Korea, and India from 1992 to 2020

year	I (I)	I (C)	I (US)	I (J)	I (I)	I (C)	I (US)	I (J)
1992	0.009	0.1096	0.691	0.658				
1993	0.026	0.1082	0.676	0.653	199.3	−1.3	−2.1	−0.8
1994	0.024	0.1176	0.695	0.669	−8.5	8.6	2.8	2.4
1995	0.015	0.1362	0.706	0.676	−35.5	15.9	1.6	1.0
1996	0.014	0.1254	0.728	0.698	−6.8	−8.0	3.1	3.4
1997	0.015	0.1303	0.697	0.657	5.6	3.9	−4.3	−5.9
1998	0.037	0.1217	0.633	0.601	144.9	−6.6	−9.2	−8.6
1999	0.019	0.1229	0.632	0.588	−49.0	1.0	−0.1	−2.0
2000	0.014	0.1489	0.650	0.622	−25.7	21.2	2.9	5.7
2001	0.017	0.1959	0.638	0.618	19.8	31.6	−1.9	−0.6
2002	0.015	0.2616	0.627	0.650	−11.7	33.5	−1.8	5.1
2003	0.031	0.3794	0.664	0.765	109.2	45.0	5.9	17.7
2004	0.028	0.4660	0.671	0.834	−9.2	22.8	1.1	9.1
2005	0.034	0.4866	0.661	0.786	19.6	4.4	−1.5	−5.7
2006	0.036	0.4660	0.651	0.661	7.3	−4.2	−1.6	−15.9
2007	0.058	0.4563	0.642	0.596	58.5	−2.1	−1.3	−9.8
2008	0.068	0.4836	0.691	0.598	17.5	6.0	7.6	0.3
2009	0.071	0.5103	0.719	0.514	4.8	5.5	4.0	−14.1
2010	0.084	0.5217	0.738	0.470	19.3	2.2	2.6	−8.6
2011	0.085	0.5606	0.755	0.518	1.2	7.5	2.3	10.4
2012	0.082	0.5670	0.713	0.502	−3.7	1.1	−5.6	−3.2
2013	0.074	0.6102	0.713	0.413	−10.6	7.6	0.1	−17.7
2014	0.082	0.5905	0.697	0.380	11.1	−3.2	−2.3	−8.0
2015	0.101	0.5667	0.663	0.329	24.1	−4.0	−4.8	−13.4
2016	0.116	0.5768	0.662	0.340	14.6	1.8	−0.3	3.3
2017	0.124	0.5586	0.674	0.318	6.9	−3.2	1.8	−6.4
2018	0.129	0.4530	0.644	0.346	3.8	−18.9	−4.4	8.8
2019	0.144	0.4513	0.624	0.377	11.9	−0.4	−3.0	8.9
2020	0.103	0.5162	0.661	0.318	−28.5	14.4	5.8	−15.7

central part of network structure shifts from the US-Japan to the US-China during the period and India's presence is growing. From Table 4, the largest decrease compared to the previous year during the economic crises was recorded in I(J) in 2009, with a decrease of 14.1. The next largest decrease was recorded in I(J) during the Chinese devaluation in 2015, with a decrease of 13.4. It appears that even though from 2003 to 2005, Japan was temporarily the most interdependent country with other nations, the United States consistently remained at the center of the network during other periods, with high interdependence values ranging between 0.624 in 2019 and 0.755 in 2011. This suggests that the US plays a central role in the network of these five nations. I(J) has also been high, ranging from 0.318 in 2017 and 2020 to 0.834 in 2004, which suggests that Japan also plays a major role in the network. I(C) has been sharply increasing over the years, ranging between 0.108 in 1993 and 0.610 in2013, which suggests that it is becoming more central in the network surpassing Japan from 2010 and South Korea from 2003. However, it is important to note that I(C) has never surpassed I(U). I(K) has increased between 0.165 in 1998 and 0.365 in 2011, steadily increasing until 2011. Although India plays a less central role in the network. I(I) has been quickly increasing, ranging between 0.009 in 1992 and 0.144 in 2019. Consequently, the structure of the network transitioned from one where the US served as the hub and Japan as the sub-hub, to a configuration where the US remains the hub, but China has assumed the role of the sub-hub. The observed shift from a US-Japan-centric trade network to one dominated by US-China relations after 2007 reflects China's rapid economic growth and its strategic positioning within global trade networks. This finding aligns with broader geopolitical trends where China has increasingly challenged US dominance, as seen through initiatives like the Belt and Road.

Figure 3: Trends of total amount of trade within the network Unit: US$ thousand



4.3. Trends of the Network Interdependence from 1992 to 2020

4.3.1. General trends

Figure 1 presents the growth of total trade volume (T) among the US, China, India, Japan, and South Korea from 1992 to 2020. Trade volume generally increased, with notable declines during crises (shaded areas), especially in 1998, 2001, 2009, and 2015, reflecting the impact of the Asian Financial Crisis, 9/11 shock, Global Financial Crisis, and Chinese currency devaluation, respectively.

Figure 3 shows the trend of the total amount of trade (in thousand US dollars) among the US, China, India, Japan, and South Korea from 1992 to 2020. The trade volume increased by 542.3 over this period, with notable declines during economic crises.

Figure 4 presents the trend in the network interdependence index (Inet) from 1992 to 2020. Inet exhibited an increasing trend until 2004, followed by fluctuations and a slight downward trend starting in 2011.

Figure 4: Trend in the network interdependence index

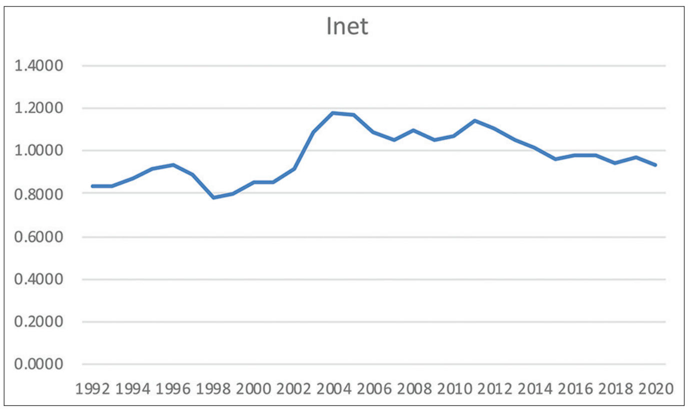


Figure 5: Trend in the network dependence index

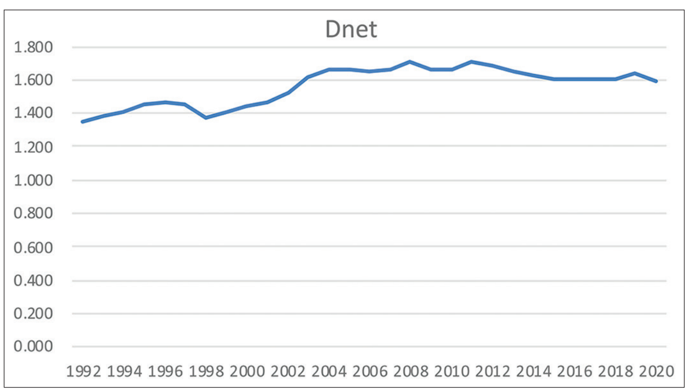


Figure 6: Trend in the network reciprocity index

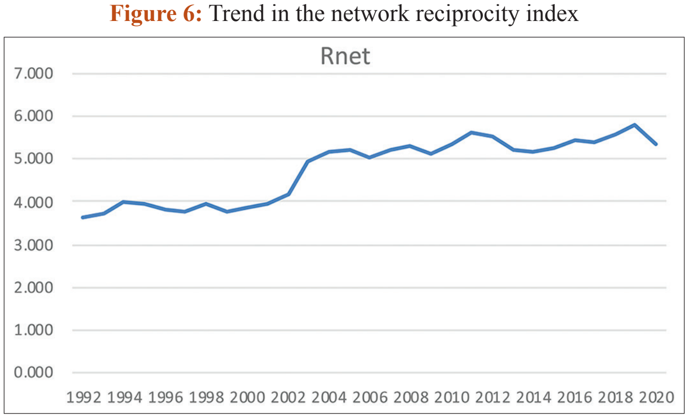


Figure 5 shows the trend in the network dependence index (Dnet) from 1992 to 2020. Dnet increased by 18.7 during this period, with declines during major economic crises.

Figure 6 highlights the trend in the network reciprocity index (Rnet) from 1992 to 2020. Rnet increased by 48.1, reflecting the overall increase in the bidirectionality of trade relationships, despite some fluctuations.

Following equations (2), (5), (7), and (10), we calculate R_{net}, D_{net}, and I_{net} from 1992 to 2020 (Figures 3-6).

$T(t_l)$ increased by 542.3 from 1992 to 2020 (Figure 3), which suggests that from the viewpoint of trade volume, the connection among the five countries got strengthened. It drops by 7.4 in 1998 reflecting the Asia financial crisis, 7.7 in 2001 due to the 9.11 shock, and by 16.0 in 2009 in the Financial crisis of 2007-2008. It also drops by 3.9 in 2015 and 2.9 in 2016 reflecting the Chinese devaluing the yuan in 2015. On the other hand, Inet, Rnet, and, Dnet increase by 12.4, 48.1, and 18.7 respectively from 1992 to 2020. We find that Inet drops in the Asian Financial Crisis, the Financial crisis of 2007-2008, and the Chinese devaluation of the yuan in 2015 (Figures 4-6).

This shows the percentage changes in network interdependence, dependence, reciprocity, their standard deviations, and total trade value during key economic crises, such as the Asian Financial Crisis, 9/11, and the Global Financial Crisis. The data illustrates how these events influenced the trade network.

The network interdependence (Inet) exhibited a slight increasing trend until 2004, after which it experienced minor fluctuations, essentially remaining flat until 2011. From 2011 onwards, there has been a slight downward trend (Figures 4-6 and Table 5), indicating that all trade relationships are not necessarily getting bidirectional (Garlaschelli and Loffredo, 2004), even though they become somewhat more bidirectional in times of financial crisis due to the decrease in the standard deviation of Inet. Moreover, the standard deviation of the values for the link interdependence (Std of Inet) continues to decline until 2007, after which it begins to rise. This trend is primarily attributed to the standard deviation of the reciprocity indices values, which continue to decrease until 2008, before shifting towards an increase thereafter.

Figure 7: Standard deviation of T and Inet from 1992 to 2020

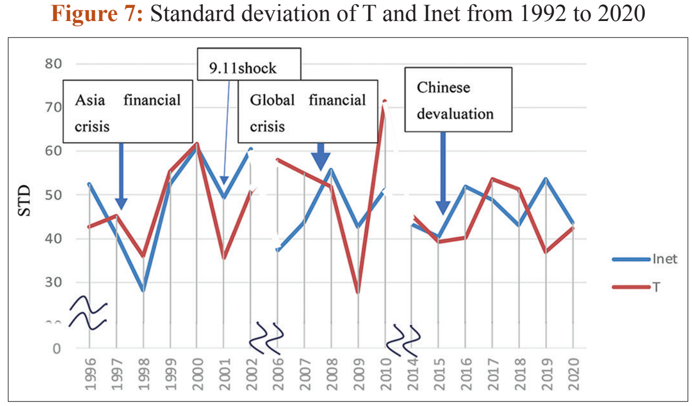


Table 5: Changes in network interdependence (Inet), dependence (Dnet), reciprocity (Rnet), standard deviation, and total trade value (T) during economic crises

Indices	Asian financial crisis		9.11	Global financial crisis				Chinese devaluation
	1997	1998	2001	2007	2008	2009	2010	2015
Inet	−4.8	−12.5	0.2	−3.2	4.0	−3.7	1.3	−5.2
Dnet	−1.1	−5.8	1.6	0.9	2.4	−2.1	−0.1	−1.9
Rnet	−1.2	5.2	1.8	3.0	1.7	−3.0	4.2	1.6
Std of I	−5.2	−3.4	−4.9	−8.1	5.8	5.0	1.5	−6.1
Std of D	−1.4	1.3	−3.7	−7.8	−1.0	3.0	0.5	−1.9
Std of R	−5.0	10.3	−0.5	−8.7	−5.6	−3.6	7.1	−5.5
T	2.4	−7.4	−7.7	12.6	9.3	−16.0	29.9	−3.9

year	US-China trade war			Rate of change 1992/2020
	2018	2019	2020	
Inet	−3.5	2.7	−3.2	12.4
Dnet	−0.3	2.3	−2.8	18.7
Rnet	2.8	4.3	−7.6	48.1
Std of I	−20.5	−9.4	32.5	−39.8
Std of D	−11.5	−6.2	17.8	36.0
Std of R	−3.0	1.2	−3.1	17.1
T	8.7	−6.5	−0.7	542.3

T represents the total trade volume of the network

This figure shows standard deviation of T and Inet from 1992 to 2020. It highlights the variations in total trade volume and network interdependence across different periods, with significant changes during major economic crises.

In general, during economic crises, the network interdependence and standard deviation of interdependence tend to decrease (Figures 4-7, Table 5, Supplement Figures 1-3), resulting in a levelling and reduction of interdependence of the links. When examining the impact of individual economic crises on the networks, firstly, from Table 5 and Figures 3-5, the Asian Financial crisis had a significant negative impact on the Dnet, Inet, and T with drops of 5.8, 12.5, and 7.4, respectively in 1998. However, even though the 9/11 terrorist attacks in 2001 caused a drastic shock to the total trade volume(T) with a drop of 7.7, it did not result in a decrease in Inet. Moreover, the Global Financial crisis in 2008 had a negative effect on all values in 2009, with drops of 2.1, 3.0, 3.7, and 16.0 in Dnet, Rnet, Inet, and T, respectively. The Chinese devaluation in 2015 had a negative impact on Dnet, Inet, and T with changes of 1.9, 5.2, and 3.9, respectively. Finally, US-China trade war had a negative impact on all values in 2020, with drops of 2.8, 7.6, 3.2, and 0.7 in Dnet, Rnet, Inet, and T, respectively. Moreover, unlike other crises, standard deviation of I and D drastically increased, which implies that a movement has arisen that goes against the trend of equalization.

4.3.2. Impact of crises on network measures

This presents the annual growth rates of the total trade volume and network interdependence, highlighting the years where growth rates dropped significantly due to economic crises. The table provides insights into the resilience or vulnerability of the trade network during these periods.

The annual growth rate of total trade volume (T) was calculated, identifying years where this rate fell below a standard deviation score of 40 relative to the average growth rate from 1993 to 2020 (Tables 6 and 7, Figure 3). A similar analysis was conducted for network interdependence (Inet), marking years where the growth rate from the previous year was below the standard deviation score of 40, compared to the average rate over the same period. During the Asian Financial Crisis, both Inet and T experienced a significant drop in growth rates in 1998, falling below the standard deviation score of 40. The decline in Inet's growth rate was more pronounced than during other economic crises, indicating that the initial shock had a substantial impact on the structure of trade networks before reducing trade volume. Following the 9/11 attacks in 2001, T's growth rate dropped to a standard deviation score of 36, similar to the level observed during the Asian Financial Crisis. However, Inet's growth rate remained relatively stable, with a standard deviation score around 50, suggesting that the impact was primarily on trade volume rather than on the structure of the network. During the Global Financial Crisis, Inet's growth rate dropped to a standard deviation score of 37 in 2006, while T's growth rate remained above 50. However, by 2009, Inet's growth

Table 6: Annual growth rates of total trade volume (T) and network interdependence (Inet) during economic crises

Year	Std of growth rate of Inet	Std of growth rate of T
1996	53	43
(Asian crisis) 1997	41	45
1998	28	36
1999	52	55
2000	61	62
(9/11shock) 2001	49	36
2002	60	51
2006	37	58
(Global crisis) 2007	44	55
(Global crisis) 2008	56	52
2009	43	28
2010	51	71
2014	43	45
(Chinese devaluation) 2015	40	39
2016	52	40
2017	49	54
(Trade war) 2018	43	51
(Trade war) 2019	54	37
(Trade war) 2020	44	42

Table 7: Comparison of standard deviation scores before and after economic crises

Crisis	Year (s)	Impact on network interdependence (Inet)	Impact on trade volume (T)
Asian Financial Crisis	1998	Decline in 1998 to a score of 36	Significant drop in growth rate, below standard deviation score of 40
9/11 Shock	2001	Relatively stable, with a standard deviation score around 50	Significant drop in growth rate to a standard deviation score of 36
Global Financial Crisis	2006-2009	Decline in 2006 to a score of 37, slight decline in 2009 to a score of 43	Stable in 2006, significant drop in 2009 to a score of 28
Chinese devaluation	2015-2016	Decline in 2015 to a score of 40, recovered to normal in 2016	Decline in 2015, remained below 40 in 2016
US-China Trade War	2019-2020	Continuous weak structural shock, leading to trade volume decline	Decline below 40 in 2019, significant impact in 2019 and 2020

rate slightly declined to 43, and T's growth rate significantly fell to 28, marking the most substantial drop among the crises studied. This suggests that the Global Financial Crisis had a broader impact, significantly affecting trade volume. In the case of China's currency devaluation in 2015, both Inet and T's growth rates fell below a standard deviation score of 40. By 2016, Inet's growth rate returned to normal levels, but T's growth rate remained below 40, indicating that the devaluation initially affected both the structure and trade volume, with a prolonged impact on trade volume. Finally, during the US-China Trade Crisis, T's growth rate fell below 40 in 2019, indicating a sustained, albeit mild, structural shock, followed by a significant impact on trade volume in both 2019 and 2020.

This table compares the standard deviation scores of interdependence, dependence, and reciprocity before and after major economic crises, reflecting the level of fluctuation in the trade network's stability. The data indicates how certain crises caused more significant disruptions than others.

Tables 5 and 6 show that the 9/11 shock in 2001 differs from all other financial crises primarily in its impact on network interdependence (Inet) compared to trade volume (T). In other words, as for 9/11 Shock, despite the significant impact on trade volume, the network interdependence remained relatively stable during the 9/11 shock, with a standard deviation score around 50. This suggests that the 9/11 shock had a limited effect on the structural interdependence between countries in the global trade network. In contrast, all other financial crises like the Asian Financial Crisis and the Global Financial Crisis had more pronounced effects on network interdependence (Table 7). For example, The Asian Financial Crisis in 1998 led to a significant decline in Inet, indicating a major structural impact, and the Global Financial Crisis also caused notable declines in Inet in both 200VI and 2009.

5. DISCUSSION

This study sought to analyze the dual effects of economic crises on the Asia-Pacific trade network, focusing on both the contraction in trade volumes and the structural reconfiguration of trade interdependence. Our findings demonstrate that economic crises not only reduce trade volumes but also lead to significant structural shifts within the trade network, validating the hypothesis that "economic crises not only lead to a contraction in trade volumes but also cause a structural reconfiguration of trade networks, shifting the balance of interdependence among major economies in the Asia-Pacific region, with China's centrality increasing as a result."

5.1. Trade Volume Contraction and Structural Shifts

Consistent with expectations, major economic crises such as the Asian Financial Crisis (1997-1998) and the Global Financial Crisis (2007-2009) triggered a reduction in total trade volumes among the key economies of the region. However, our network analysis revealed a more profound, longer-lasting impact: a structural reconfiguration of trade relationships. Before 2007, the U.S.-Japan axis dominated the trade network, with Japan serving as a secondary hub. Post-2007, China has increasingly assumed this sub-hub role, reshaping the network's core structure. These findings suggest that economic crises do more than disrupt trade flows temporarily; they induce lasting structural changes that alter the balance of power in trade interdependence.

5.2. China's Increasing Centrality

Our results also highlight the rise of China as a central player within the Asia-Pacific trade network. Although China had always been an important trading partner, its role has become increasingly significant in the aftermath of the Global Financial Crisis, as evidenced by its growing trade interdependence with key economies like the United States and South Korea. While the U.S. remains a central hub in the global trade network, China's rise as a sub-hub reflects broader geopolitical and economic shifts, consistent with existing literature on China's ascendant role in global trade.

5.3. The Role of Economic Crises in Trade Network Reconfiguration

One of the most critical contributions of this study is the identification of two distinct effects of economic crises: (1) a contraction in total trade volumes and (2) a reconfiguration of trade interdependence. Crises not only disrupt existing trade volumes but also catalyze shifts in the structure of trade networks, often solidifying or amplifying the roles of key players like China. These findings align with network theory, which suggests that shocks to complex systems—such as global trade networks—can result in long-term structural realignments rather than a simple reversion to pre-crisis conditions.

5.4. Implications for Trade Policy and Global Economics

The structural shifts observed in this study have important policy implications. Policymakers must recognize that trade networks do not simply revert to their pre-crisis state after recovery; instead, they are often permanently reshaped. China's increased centrality suggests that future trade policies in the Asia-Pacific region will need to account for its growing influence. Similarly, the U.S. and Japan may need to reconsider their strategic approaches to trade and regional partnerships as China continues to cement its role as a dominant player.

5.5. Summary

In sum, this study confirms that economic crises have both immediate and long-term effects on the structure of trade networks. The dual impact of trade volume contraction and structural reconfiguration underscores the complexity of global trade relationships. China's rise as a central player in the Asia-Pacific network following economic crises presents new opportunities and challenges for the region's economies. Future research could explore whether similar structural shifts occur in other regions and whether the COVID-19 pandemic has further accelerated these trends.

6. CONCLUSION

This study has provided a comprehensive analysis of the impact of economic crises on the trade networks of key economies in the Asia-Pacific region, with a particular focus on the interplay between trade volume contraction and the structural reconfiguration of interdependence. By employing network theory and analyzing data from 1992 to 2020, we tested the hypothesis that economic crises not only lead to a contraction in trade volumes but also cause a structural reconfiguration of trade networks, shifting the balance of interdependence, with China's centrality increasing as a result.

Our findings support this hypothesis. First, we observed a significant reduction in total trade volumes during major economic crises such as the Asian Financial Crisis and the Global Financial Crisis. As expected, these crises led to a temporary contraction in trade flows across the region. However, our analysis also revealed a more enduring effect: the structural shifts within the trade network. While the United States and Japan had long dominated the Asia-Pacific trade network, we found that China's centrality within the network increased significantly in the aftermath of these crises. This reconfiguration suggests that crises do not merely disrupt trade volumes but also reshape the underlying structure of global trade relationships.

The implications of these findings are substantial. As China continues to strengthen its role as a central hub in the region, this shift has both geopolitical and economic consequences that extend well beyond the immediate post-crisis recovery periods. Policymakers should recognize that trade networks, once restructured by a crisis, may not revert to their previous configurations, and future trade agreements or economic policies must take these structural changes into account.

Moreover, the dual nature of crises—causing both trade volume contraction and structural shifts—introduces a new dimension to the study of trade interdependence. Traditional models that focus solely on trade flows may overlook these deeper, longer-lasting changes in the global trade network. Our study underscores the importance of considering both immediate and long-term effects when analyzing the impact of economic crises on trade.

In conclusion, this paper not only deepens our understanding of the Asia-Pacific trade network but also contributes to broader discussions on global trade resilience, crisis recovery, and the strategic shifts in economic power. Future research could build on these findings by examining whether similar structural shifts occur in other regions or under different types of economic disruptions, such as the ongoing impacts of the COVID-19 pandemic.

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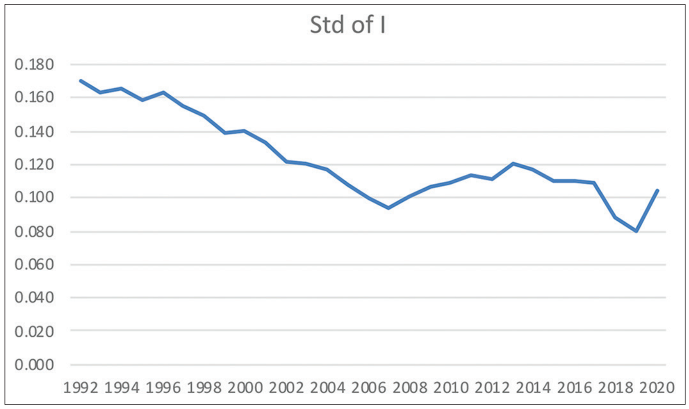
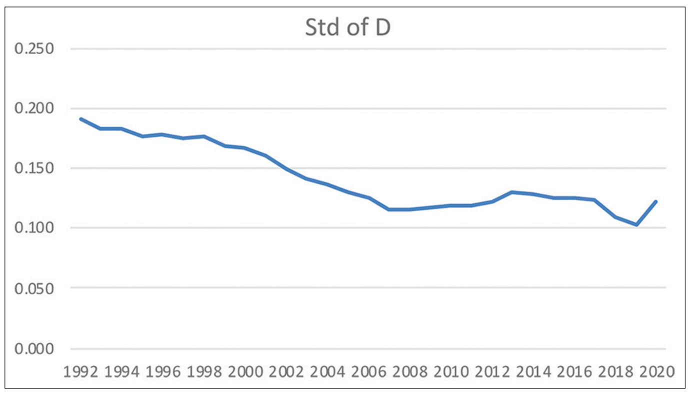
SUPPLEMENTARY FILES

Supplementary Figure 1: Trends of the standard deviation of the network interdependence



Supplementary Figure 2: Trends of the standard deviation of the network dependence



Supplementary Figure 3: Trends of the standard deviation of the network reciprocity