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Shock Propagation in Global Value-Added Trade: A Network-Based Simulation of Supply and Demand Crises

(*Penyebaran Kejutan dalam Perdagangan Nilai Ditambah Global: Simulasi Krisis Bekalan dan Permintaan Berasaskan Rangkaian*)

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ABSTRACT

This study examines countries' exposure to supply- and demand-side shock propagation in the global trade-in-value added (TiVA) network, with a particular focus on shocks originating from China and the United States using the 2008 and 2018 baseline networks. The study applies network metrics and the Trade Network Shock Propagation (TNSP) model to bilateral TiVA data covering 49 countries from 2008 to 2020. Under the 2018 baseline, supply shocks from China or the United States affect 93.8% of countries in the network. Demand-shock simulations show rising systemic exposure: in 2008, the United States triggered the largest avalanche, while by 2018, China produced an avalanche ratio of 97.9%, matching that of the United States. These findings indicate that both supply- and demand-side disruptions originating from core economies can generate extensive contagion throughout the global TiVA network. The study extends trade network analysis by integrating value-added trade data with scenario-based shock-propagation modelling. Policymakers should monitor concentrated supplier-buyer dependencies, diversify supplier and market exposure, and strengthen regional trade coordination.

Keywords: Global value chains; trade network; value-added trade; network analysis.

ABSTRAK

Kajian ini meneliti negara yang terdedah kepada penyebaran kejutan dari sisi penawaran dan permintaan dalam rangkaian perdagangan nilai ditambah (TiVA) global, dengan tumpuan khusus terhadap kejutan yang berpunca dari China dan Amerika Syarikat berdasarkan rangkaian asas tahun 2008 dan 2018. Kajian ini menggunakan metrik rangkaian dan model Penyebaran Kejutan Rangkaian Perdagangan (TNSP) terhadap data TiVA dua hala yang meliputi 49 negara bagi tempoh 2008 hingga 2020. Berdasarkan rangkaian asas tahun 2018, kejutan penawaran dari China atau Amerika Syarikat memberi kesan kepada 93.8% negara dalam rangkaian. Simulasi kejutan permintaan menunjukkan peningkatan pendedahan sistemik: pada tahun 2008, Amerika Syarikat mencetuskan gelombang penularan terbesar, manakala pada tahun 2018, China menghasilkan nisbah avalanche sebanyak 97.9%, menyamai Amerika Syarikat. Dapatan ini menunjukkan bahawa gangguan dari sisi penawaran dan permintaan yang berpunca daripada ekonomi kor boleh menyebabkan penularan meluas dalam rangkaian TiVA global. Kajian ini memperluas analisis rangkaian perdagangan dengan mengintegrasikan data nilai ditambah dengan simulasi model penyebaran kejutan berasaskan senario. Pembuat dasar perlu memantau kebergantungan terhadap pembekal-pembeli, mempelbagaikan pembekal dan pasaran, serta memperkukuh penyelarasan perdagangan serantau.

Kata kunci: Nilai rantaian global; rangkaian perdagangan; perdagangan nilai ditambah; analisis rangkaian.

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INTRODUCTION

Global value chains (GVCs) have deepened the economic interdependence of countries, linking dispersed production stages into a tightly connected trade network. This interconnectedness improves efficiency but also increases vulnerability, as shown by the 2009 global financial crisis (GFC), the US-China trade war, and the COVID-19 pandemic, all of which caused contractions in value-added trade (Ayadi et al. 2022; Benguria & Taylor 2020). These crises also highlight the importance of distinguishing between different types of disruptions. The GFC largely took the form of a demand shock driven by collapsing consumption and credit constraints (Yu 2024). The US-China trade war combined supply and demand effects as tariffs reshaped cost structures and rerouted trade flows (Fajgelbaum & Khandelwal 2022). COVID-19 produced simultaneous supply disruptions through production and transport shutdowns, alongside severe demand contractions caused by lockdowns and uncertainty (Hayakawa & Mukunoki 2021). These differences matter because each type of shock propagates through the value-added network in distinct ways.

Despite growing interest in trade networks, most studies examine single crises or rely on gross trade statistics. Research that integrates bilateral trade in value-added (TiVA) data with network metrics and shock-propagation simulations remains limited. This study addresses this gap by examining how structural positions in the global TiVA network shape countries' exposure to potential supply- and demand-side shock propagation. The analysis does not attempt to reproduce realised crisis outcomes. Instead, it uses descriptive network analysis for selected crisis-related years and applies the deterministic, threshold-based TNSP model to the 2008 and 2018 baseline networks to assess how shocks may propagate through the pre-existing value-added trade structure.

Network simulations of food, resource, and production systems show that indirect connections can amplify disruptions beyond first-order partners (Demir et al. 2024; Grassia et al. 2022). This highlights the need to reassess systemic exposure using updated value-added data, particularly as the global trade centre of gravity has shifted toward Asia (Benguria & Taylor 2020). This study contributes in three ways. First, it constructs a directed and weighted global value-added trade network using ADB TiVA flows for 49 countries from 2007 to 2022. Second, it tracks network structure using degree, strength, eigenvector, and closeness centrality. Third, it extends the TNSP model of Wang et al. (2021) by comparing supply-side and demand-side shock propagation from China and the United States in the 2008 and 2018 baseline networks. Within this framework, the core-periphery lens serves as an interpretive layer to explain why shocks originating from core countries can generate disproportionate exposure among peripheral partners.

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methods. Section 4 presents the results and discussion, while Section 5 outlines key policy implications and concluding remarks.

LITERATURE REVIEW

The growing fragmentation of production has exposed the limits of gross trade statistics, which often obscure where value is actually created within global supply chains. TiVA accounting provides a clearer view of cross-border value creation by separating domestic and foreign value-added components, thus offering a more accurate basis for analysing GVC interdependence (Koopman et al. 2014). Although some gaps remain in sectoral and temporal coverage, TiVA data capture underlying trade dependencies more effectively than conventional measures.

Participation in GVCs enhances efficiency but also increases exposure to external shocks. Countries with concentrated export baskets or that rely heavily on a few suppliers tend to suffer more severe disruptions (Coveri & Zanfei 2023). Evidence from the 2008 crisis shows that highly embedded countries experienced deeper contractions, particularly those dependent on imported intermediates (Yu 2024). Network structure plays a central role, as well-connected hubs can transmit shocks widely (Coquidé et al. 2020; Iloskics et al. 2021), underscoring how limited diversification and concentrated trade patterns amplify vulnerability.

Network analysis provides a useful framework for examining how shocks spread across TiVA linkages. By modelling countries as nodes connected through weighted value-added flows, researchers employ centrality and connectivity measures to identify critical transmission points. Recent studies highlight gateway nodes whose disruptions disproportionately affect downstream partners (Sun et al. 2022) and show that concentrated topologies can accelerate contagion (Kim & Yun 2022; Wang et al. 2021), though dense connections may also create alternative adjustment paths (Iloskics et al. 2021). These findings indicate that a country's network position strongly shapes its exposure to crises.

The most closely related studies to the present paper are Coquidé et al. (2020) and Kim & Yun (2022), both of which examine shock propagation in the world trade network using network-based methods. Coquidé et al. (2020) analyse crisis contagion in global trade, while Kim & Yun (2022) examine risk propagation through world trade linkages. However, these studies rely mainly on gross trade networks and do not explicitly distinguish between supply-side from demand-side propagation in a value-added trade setting. The present study differs by constructing the network from bilateral TiVA flows,

comparing supply-side and demand-side shocks within the same TNSP framework, and using pre-crisis baseline networks to assess how systemic vulnerability changed between the global financial crisis and the US-China trade war.

TABLE 1. Summary of related studies on trade networks and shock propagation

Study	Data type	Shock type	Method	Research gap
Coquidé et al. (2020)	Gross trade	Crisis contagion	Network contagion analysis	Does not examine TiVA-based production dependence and does not distinguish between supply-side and demand-side shock propagation.
Kim & Yun (2022)	Export data	Trade risk propagation	Personalized PageRank	Examines risk propagation in trade networks but does not use bilateral value-added trade flows or compare pre-crisis baseline structures.
Iloskics et al. (2021)	Trade and sectoral network data	Economic contagion channels	Network-based contagion analysis	Highlights sectoral and directional channels, but does not apply a TiVA-based TNSP model to compare supply-side and demand-side shocks originating from systemic country hubs.
Grassia et al. (2022)	Food trade network	Trade shock exposure and vulnerability	Network-based simulation	Focuses on food trade rather than aggregate value-added trade and does not examine global TiVA linkages across major pre-crisis baselines.
Kang et al. (2024)	International trade network	Cascading failure	Network cascade simulation	Provides evidence on cascading failures, but does not specifically model bilateral TiVA flows or distinguish between China- and US-origin supply-side and demand-side shocks.

Historical crises illustrate these mechanisms. The 2008 GFC triggered a collapse in global demand, exacerbated by credit tightening that constrained firms' ability to maintain production and exports (Benguria & Taylor 2020; Yu 2024). Manufacturing exporters, in particular, faced abrupt order reductions (Zhang 2023), although some emerging markets mitigated these losses by adjusting trade patterns (Bashir & Regupathi 2022). The 2018 US-China trade war introduced both supply-side and demand-side shocks, with tariffs raising production costs, reconfiguring supply chains, and generating regional spillovers (Fajgelbaum & Khandelwal 2022; Zeng et al. 2022). Temporary gains from trade diversion were quickly eroded by uncertainty. The COVID-19 pandemic produced simultaneous supply- and demand-side shocks. Lockdowns and port closures restricted the supply of intermediate inputs (Hayakawa & Mukunoki 2021), while global demand declined sharply due to mobility and income losses (Liu et al. 2022). Countries with highly concentrated supplier bases were affected most severely (Li et al. 2021; Mendoza 2021).

Distinguishing supply- from demand-side shocks remains empirically challenging because international spillovers blur theoretical categories. A production halt may appear as a demand shock in downstream economies (Mumtaz & Smith 2023). Identification strategies using SVAR, Bayesian methods, or CGE models (Huang et al. 2013; Inoue & Todo 2021; Zheng et al. 2023) provide alternative approaches but rely heavily on modelling assumptions and can produce varying results. To navigate this complexity, this study adopts a crisis-based classification grounded in widely accepted macroeconomic interpretations, treating the 2008 GFC as a demand shock (Fontagné & Santoni 2022), the 2018 US-China trade war as a mixed shock (Zeng et al. 2022), and COVID-19 as a combined supply-and-demand shock (Liu et al. 2022). This classification serves as an analytical simplification for scenario design rather than a formal empirical identification of realised crisis shocks.

Despite substantial research, three gaps remain. First, many trade-network studies of shock propagation rely on gross trade flows, which may overstate systemic exposure because they include repeated cross-border movements of intermediate goods. Second, prior studies rarely compare supply- and demand-side propagation in a value-added trade setting. Third, limited evidence exists on how pre-crisis TiVA structures shape exposure to shocks originating from major core economies. Although stochastic, agent-based, input-output, and multilayer approaches can capture uncertainty, substitution, inventories, and price-mediated transmission more explicitly, they often require stronger assumptions or more detailed data than are available in aggregate bilateral TiVA networks. This study, therefore, uses the TNSP model as a transparent, threshold-based framework for structured simulations of potential exposure rather than to formally identify realised crisis outcomes.

METHODOLOGY

This study utilises bilateral TiVA data from the ADB, covering 49 countries. Each observation represents the TiVA flow from an exporter to an importer, allowing construction of a directed and weighted international TiVA network. Data from 2007 to 2022 are used to analyse global TiVA network characteristics. For network analysis, five years (2008, 2009, 2018, 2019, and 2020) are selected to represent pre-crisis and crisis-period structures. To avoid network saturation, which can result in a complete graph that masks structural asymmetries, a USD 1 billion trade-flow threshold is applied (Serrano & Boguñá 2003; Wang et al. 2023). A sensitivity analysis shows that this cut-off retains approximately 97.0% to 97.4% of total TiVA while reducing the number of edges to around 30% to 34% of all possible bilateral links. The TNSP simulation is applied to the 2008 and 2018 baseline networks because they represent the value-added trade structure immediately before the 2009 global financial crisis and the 2019 escalation of the US-China trade war, whereas crisis-year networks already reflect realised shock effects.

NETWORK ANALYSIS

The global TiVA network is represented as a directed and weighted graph $G(N, E)$, where nodes correspond to countries and edges represent bilateral TiVA flows. The adjacency matrix $X = [x_{ij}]$ contains the TiVA flow from the exporter *i* to importer *j*, with $x_{ii} = 0$ (domestic flows are excluded). Because $x_{ij} \neq x_{ji}$ in most cases, the network is asymmetric. The analysis is conducted using R, UCINET, and Gephi 0.10.1.

Four centrality indicators are used to characterise each country's structural role:

i. Degree centrality - Out-degree and in-degree capture the number of export destinations and import sources, respectively (Newman et al. 2006),

$$\begin{aligned} d_i^{out} &= \sum_{j=1}^{n} a_{ij} \\ d_i^{in} &= \sum_{j=1}^{n} a_{ji} \end{aligned} \tag{1}$$

ii. Strength centrality - Out-strength and in-strength represent total value-added exports and imports (Sun et al. 2022).

$$\begin{aligned} s_i^{out} &= \sum_{j=1}^{n} x_{ij} \\ s_i^{in} &= \sum_{j=1}^{n} x_{ji} \end{aligned} \tag{2}$$

iii. Eigenvector centrality - This measure captures a country's influence by weighting its connections by the importance of its partners (Newman et al. 2006),

$$c_i = \lambda^{-1} A x \tag{3}$$

where x is the weighted adjacency matrix and λ the leading eigenvalue.

iv. Closeness centrality - To measure accessibility in a weighted network, bilateral flows are transformed into distances $d_{ij} = 1/x_{ij}$. Shortest paths are computed using Dijkstra's algorithm, and the symmetric economic distance $d_{ij}^* = \min(d_{ij}, d_{ji})$ is used to calculate closeness centrality (Wasserman & Faust, 1994):

$$C_i = \frac{N-1}{\sum_{j \neq i} d_{ij}^*} \tag{4}$$

High closeness indicates countries that can transmit or receive shocks rapidly.

v. Core-periphery structure - Following Prell (2016), countries forming dense, mutually connected clusters are identified as core countries, while sparsely linked countries are classified as peripheral.

TRADE NETWORK SHOCK PROPAGATION (TNSP) MODEL

China and the United States are selected as the shock origins since all three major crises examined, the GFC, the US-China trade war, and COVID-19, either originated in or were amplified through these two countries. To assess how shocks propagate, this study applies the TNSP model developed by Wang et al. (2021). Each country can exist in either a susceptible, *S*(*t*), or infected, *I*(*t*), state, and transitions follow Equation (5):

$$\begin{cases} \dfrac{dS(t)}{dt} = -kS(t)I(t) \\ \dfrac{dI(t)}{dt} = kS(t)I(t) \\ k_i = a_i / b_i \end{cases} \quad i = 1, 2 \tag{5}$$

Here, a_i denotes the trade reduction proportion (shock intensity), b_i is the infection threshold reflecting a country's capacity to absorb losses, and k_i is the resulting shock propagation coefficient for supply-side (i=1) and demand-side (i=2) scenarios. The infection threshold is fixed at b=5% for all countries, meaning that a country becomes infected when the value-added trade loss exceeds 5% of its relevant total trade exposure. A uniform threshold maintains comparability across simulations, although it does not capture heterogeneous national resilience, such as differences in inventories, substitution capacity, or policy responses. The shock intensity (a) ranges from 10% to 100%, accordingly the propagation coefficient (k) corresponds to (k=2, 4, …, 20).

A country becomes infected when the value-added loss from an upstream partner exceeds its resilience capacity, $a_i x_{ij} > b_i T_j$, where T_j denotes country j's total export or import, depending on the type of shock (Figure 1). Once a node becomes infected, the shock propagates recursively through its downstream or upstream links until no further infections occur.

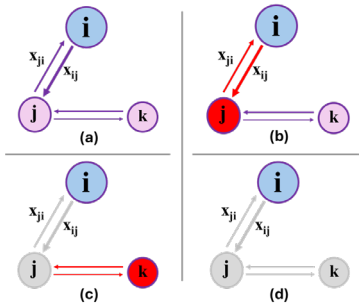


FIGURE 1. Trade network shock propagation model

Two measures summarise outcomes, of which the avalanche scale represents the number of infected countries, whereas the avalanche ratio represents the proportion of the network affected. These indicators are used to assess whether a shock originating from a core country can cascade through the entire TiVA system.

RESULTS AND DISCUSSION

TIME SERIES GLOBAL TRADE IN VALUE-ADDED

Figure 2 compares global trade measured in value-added terms with conventional gross flows from 2007 to 2022. Both series follow broadly synchronous trajectories, although the TiVA curve remains consistently below the gross trade measure because value-added accounting removes intra-industry double counting that inflates gross trade statistics (Koopman et al. 2014). Both indicators display three clear downturns that coincide with the GFC in 2009, the escalation of the US-China trade war in 2019, and the COVID-19 pandemic in 2020. During the GFC, gross trade fell from USD 18.1 trillion to USD 15.1 trillion, while TiVA declined from USD 13.0 trillion to USD 11.3 trillion. Both series then recovered to new peaks in 2018, before falling again in 2019 and 2020. By 2022, gross trade and TiVA had rebounded to USD 28.7 trillion and USD 20.2 trillion, respectively. This comparison is descriptive and is not intended as a formal decomposition of the gap between gross trade and TiVA. Rather, it demonstrates the relevance of TiVA because value-added flows better reflect the study's focus on production-based trade linkages and potential shock propagation.

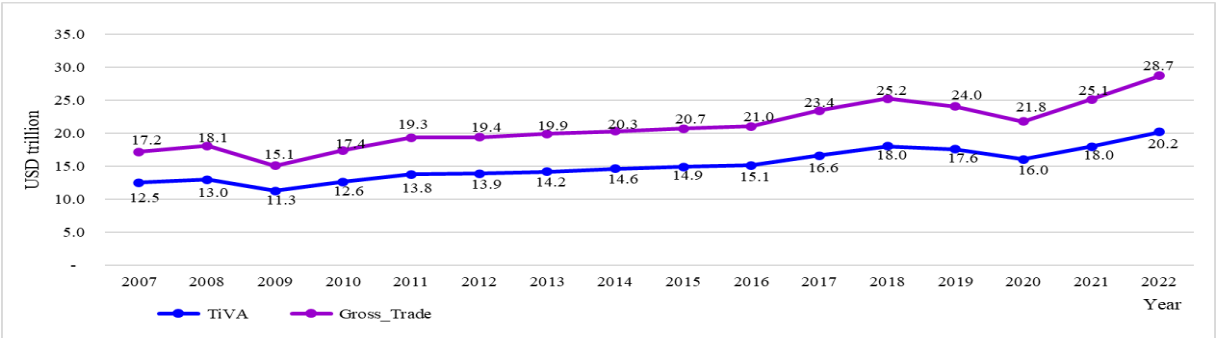


FIGURE 2. Time series of global TiVA and gross trade flow

The descriptive analysis uses six standard indicators to examine the structure of the global TiVA network from 2008 to 2020 (Table 2). In-degree results identify Germany as the most diversified importer throughout the study period, followed by the United Kingdom and the United States before the crisis, while China entered the top three from 2018 onwards. Out-degree patterns also place Germany first in 2008-2009, but China became the leading exporter from 2018 onwards, reflecting its rise as a central supplier of value-added inputs. Network strength confirms deepening global integration, with the United States remaining the world's largest importer by strength, though China's import demand has grown sharply since 2018. Export strength mirrors this shift, with the United States dominant before the GFC and China taking the lead from 2018 onwards, consistent with the expansion of East Asian production networks centred on China (Miroudot 2020).

TABLE 2. Top 5 countries by various network indicators for 2008, 2009, 2018, 2019, and 2020.

Indicator	Year	Rank				
		1	2	3	4	5
In-degree	2008	DEU	GBR	USA	ITA	FRA
	2009	DEU	GBR	USA	ITA	FRA
	2018	DEU	USA	CHN	GBR	FRA
	2019	DEU	USA	CHN	GBR	FRA
	2020	DEU	CHN	USA	GBR	FRA
Out-degree	2008	DEU	CHN	ITA	USA	GBR
	2009	DEU	CHN	ITA	USA	GBR
	2018	CHN	DEU	USA	ITA	GBR
	2019	CHN	DEU	USA	ITA	FRA
	2020	CHN	DEU	USA	FRA	ITA
In-strength	2008	USA	DEU	CHN	GBR	FRA
	2009	USA	DEU	CHN	GBR	FRA
	2018	USA	CHN	DEU	GBR	FRA
	2019	USA	CHN	DEU	GBR	FRA
	2020	USA	CHN	DEU	GBR	JPN
Out-strength	2008	USA	DEU	CHN	JPN	GBR
	2009	USA	CHN	DEU	JPN	GBR
	2018	CHN	USA	DEU	JPN	GBR
	2019	CHN	USA	DEU	JPN	FRA
	2020	CHN	USA	DEU	JPN	GBR
Eigenvector Centrality	2008	USA	CAN	DEU	CHN	GBR
	2009	USA	CAN	DEU	CHN	GBR
	2018	USA	CHN	DEU	CAN	JPN
	2019	USA	CHN	DEU	CAN	JPN
	2020	USA	CHN	DEU	JPN	CAN
Closeness Centrality	2008	DEU	USA	CHN	CAN	JPN
	2009	DEU	USA	CHN	CAN	MEX
	2018	USA	CHN	DEU	CAN	JPN
	2019	USA	CHN	DEU	CAN	JPN
	2020	CHN	USA	DEU	CAN	JPN
Core country	2008	CHN, DEU, JPN and USA				
	2009	CHN, DEU, JPN and USA				
	2018	CHN, DEU, JPN and USA				
	2019	CHN, DEU, JPN and USA				
	2020	CHN, DEU, JPN and USA				

Note: Countries are identified by their ISO3 codes: USA (United States of America), CHN (China), DEU (Germany), JPN (Japan), CAN (Canada), GBR (United Kingdom), ITA (Italy), and FRA (France). Most countries appear repeatedly among the top ranks across all years and indicators, underscoring their dominant and persistent positions in the network.

Eigenvector centrality consistently assigns the greatest systemic influence to the United States, indicating its strong ties with other well-connected partners. Canada held the second position before 2010, but China has occupied this place since 2018, signaling its growing importance within the network's central trade clusters. Closeness centrality ranks the United States and Germany highest across all periods, underscoring their key roles in maintaining network accessibility and facilitating the rapid transmission of trade flows or shocks. China's post-crisis surge in centrality further highlights its growing strategic importance in global production linkages. Japan remains consistently central but appears more sensitive to external shocks, reflecting vulnerabilities typical of highly export-dependent economies. Overall, these indicators show that global interconnectedness has intensified while remaining concentrated around a small set of structurally important countries. China, Germany, Japan, and the United States form the persistent structural core under the applied core-periphery procedure. However, this does not imply

that other countries are unimportant. The United Kingdom, France, and Canada also ranked highly across selected centrality measures, indicating strong network positions in terms of partner diversity, trade intensity, influence, and accessibility. Importantly, centrality rankings measure the importance of individual nodes, whereas the core-periphery classification identifies membership of a dense and mutually connected core group.

Comparative visual analysis across the crisis periods (Figure 3) reveals distinct structural adjustments in the global TiVA network. Node size represents network strength, edge thickness reflects bilateral TiVA flows, and node colour indicates income group (blue: high income; purple: upper middle; green: lower middle). In 2009, thinner edges along major trade routes illustrate the contraction of trade during the GFC. Comparing the 2018 baseline with the 2019 network during the US-China Trade War reveals more pronounced structural changes. Specifically, thinner edges between the United States and China indicate bilateral disruption, whereas thicker edges among other high- and upper-middle-income countries suggest trade diversion and network adaptation. By 2020, during the COVID-19 pandemic, these substitution patterns had intensified, with new linkages emerging while others weakened or disappeared, reflecting a broader reconfiguration of global trade under simultaneous supply- and demand-side shocks.

Overall, the descriptive network analysis shows that the United States and China function as the primary hubs, with dense connections extending across peripheral countries. This structure is important because core countries are more likely to serve as key transmission nodes for supply- and demand-side shocks.

TRADE NETWORK SHOCK PROPAGATION (TNSP) ANALYSIS

The TNSP results should be interpreted as scenario-based simulations rather than empirically calibrated estimates of realised crisis losses. Simulations are reported for k=2, 4, …, 20 in Tables 3 and 4. The maps focus on k=10, which corresponds to a 50% trade reduction under the assumed infection threshold of 5%, and are used only to visualise a mid-range scenario. The same k values are applied to supply-side and demand-side shocks to ensure a standardised comparison, rather than implying empirical equivalence between the two shock types. Because the model uses deterministic binary infection rules, the mapped arrows should be interpreted as potential propagation pathways under the model assumptions rather than observed cascades involving partial losses, recovery, substitution, or price adjustment.

SUPPLY-SIDE SHOCK

The supply-side TNSP simulations trace how export reductions from China and the United States propagate through the 49-node TiVA network. Table 3 shows that in the 2008 baseline, very small shocks (k=2) remain localised, only the United States triggers spillovers, infecting two partners (avalanche ratio 4.2 %). At k=4, China reaches four direct partners and one indirect node, while the United States affects four countries. Contagion becomes nonlinear at k=6, when China disables 26 countries (11 directly and 15 indirectly), whereas the United States infects only 11, reflecting greater redundancy among its suppliers. By k=10, both origin countries disable 36 countries (75 %), and by k=12, the system approaches total collapse, leaving at most two nodes uninfected. These patterns indicate that in 2008, only high-intensity shocks ($k \geq 12$) could destabilise the network.

The 2018 baseline displays a compressed transition from stability to systemic failure, reflecting a denser and more centralised trade structure. At k=2, China and the United States cause only three and one infections, respectively, but at k=4, China's avalanche reaches nine countries (compared with three for the United States). By k=6, China again triggers 26 infections (17 direct, 9 indirect), while the United States reaches 13 (10 direct, 3 indirect). Systemic failure occurs earlier, at which k=10, both countries infect all 49 countries in the network. This shift shows that by 2018, moderate-intensity shocks within the simulated (k)-scale were sufficient to generate multi-tier cascading failures when originating from major supplier hubs.

The integrated results highlight two structural features. First, the global TiVA network has become substantially more sensitive to upstream disruptions. The sharper propagation at moderate k-values in 2018 reflects increased centralisation around China and the United States. A disruption at either hub cuts off inputs to many direct partners, and those partners then transmit the shock further, accelerating the cascade. This mechanism aligns with Grassia et al. (2022), who show that directed shock flows in food-trade networks can rapidly transmit disruptions to import-dependent countries, and with Zhang & Zhou (2022), who find that concentrated supplier structures elevate systemic risk.

Second, indirect transmission has become far more important. In 2008, most disruptions were confined to first-order partners. However, by 2018, higher-order propagation had become pervasive. A Chinese supply shock disrupts production not only among China's direct importers, but also among their subsequent trading partners. This expanded reach is consistent with Kang et al. (2024), who emphasise that stronger global trade ties intensify contagion even as they provide potential diversification channels. Overall, the growing role of indirect links and the earlier onset of system-wide failure suggest that global production has crossed a critical connectivity threshold. The same structures that enable efficiency now amplify vulnerability to supply disruptions originating from core countries.

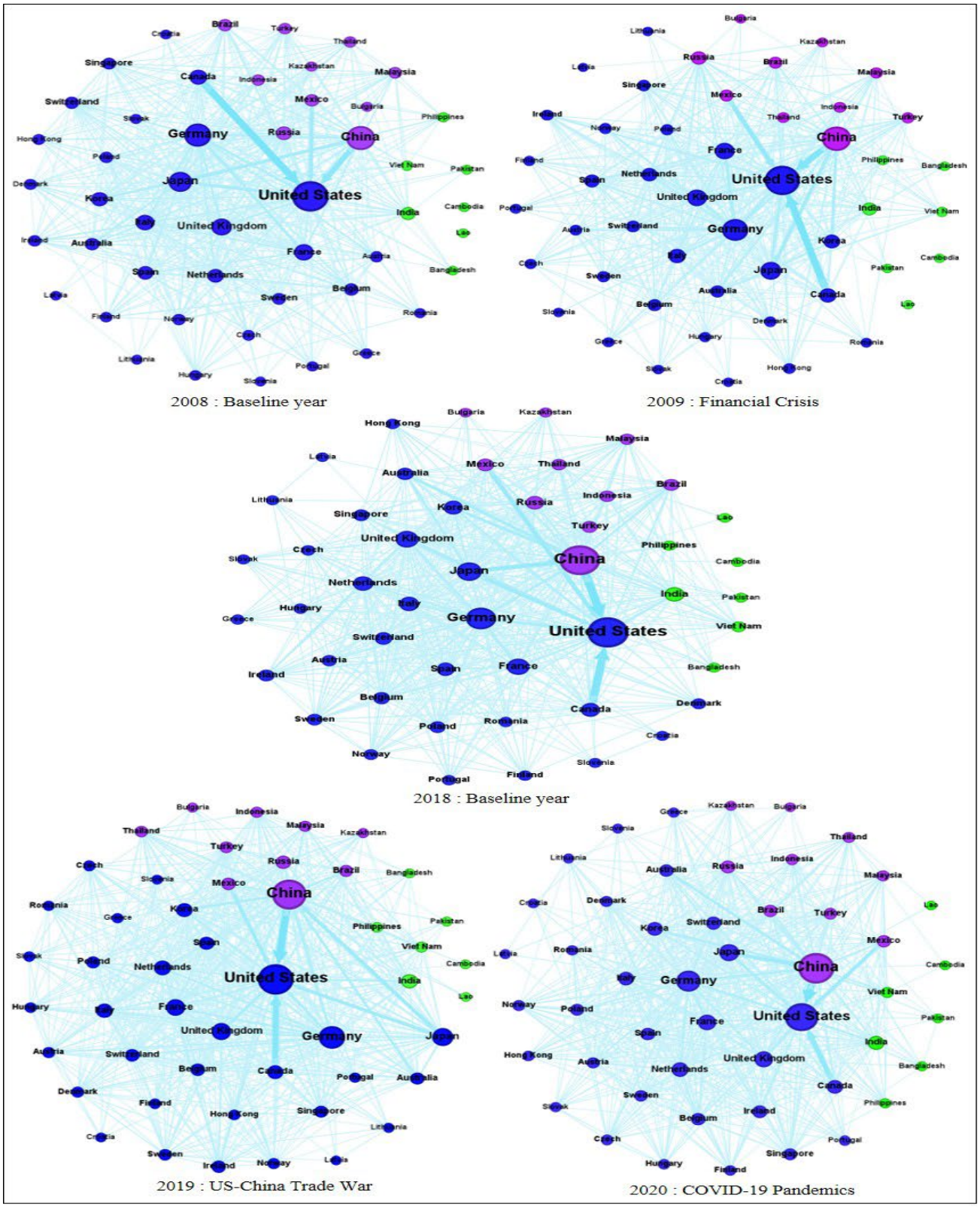


FIGURE 3. Global value-added trade network in 2008, 2009, 2018, 2019, and 2020.

Note: The weight of the edge indicates the TiVA flows, arrows indicate the direction of trade, the node's colour represents country income level, and the nod size is equal to the total TiVA.

TABLE 3. Supply shock propagation round in core countries for 2008 and 2018

k		2008		2018	
		China	USA	China	USA
k=2	AR	0.0%	4.2%	6.3%	2.1%
	AS	0	2	3	1
	T1	0	2	3	1
k=4	AR	10.4%	8.3%	18.8%	6.3%
	AS	5	4	9	3
	T1	4	4	9	3
	T2	1			
k=6	AR	54.2%	22.9%	54.2%	27.1%
	AS	26	11	26	13
	T1	11	10	17	10
	T2	15	1	9	2
	T3				1
k=8	AR	62.5%	62.5%	60.4%	60.4%
	AS	30	30	29	29
	T1	16	13	20	14
	T2	14	6	9	10
	T3		11		5
k=10	AR	75.0%	75.0%	93.8%	93.8%
	AS	36	36	45	45
	T1	19	18	25	22
	T2	14	6	15	16
	T3	3	11	5	7
	T4		1		
k=12	AR	95.8%	95.8%	100.0%	100.0%
	AS	46	46	48	48
	T1	22	24	27	26
	T2	18	22	21	22
	T3	6			
k=14	AR	95.8%	95.8%	100.0%	100.0%
	AS	46	46	48	48
	T1	26	28	32	29
	T2	20	18	16	19
k=16	AR	95.8%	95.8%	100.0%	100.0%
	AS	46	46	48	48
	T1	33	29	35	31
	T2	13	17	13	17
k=18	AR	95.8%	95.8%	100.0%	100.0%
	AS	46	46	48	48
	T1	36	32	37	33
	T2	10	14	11	15
k=20	AR	95.8%	95.8%	100.0%	100.0%
	AS	46	46	48	48
	T1	39	33	38	35
	T2	7	13	10	13

Note: k is shock propagation coefficient, AR is Avalanche Ratio, AS is Avalanche Scale, and T is the number of steps of transmission

Figure 4 maps the spatial spread of a 50% export reduction (k=10) from China and the United States. In 2008, China's contagion was mainly regional, with first-round infections (T1=19) concentrated in developing Asia and a few regional hubs, before later rounds reached Europe. This reflects China's position within Asia-centred manufacturing supply chains. The United States exhibited a broader but slower pattern, with 18 first-round infections (T1=18) distributed across the Americas, Asia, Europe, and Oceania. Although both countries ultimately infected 36 partners, the United States cascade unfolded across more rounds, indicating a more diffuse transmission pathway.

By 2018, propagation intensified markedly. China's first-round infections increased to 25 and spanned all regions, signaling its emergence as a global supplier of key intermediate inputs. Subsequent rounds brought near-global contagion within three steps. The United States similarly generated a larger and more diverse first-round cluster (T1=22), including high- and middle-income countries, with total infections rising to 49. The sharper rise in direct infections and shorter cascade lengths reflect a tightly integrated production structure and heightened dependence on both hubs. The TNSP results for the 2008 and 2018 supply-side shocks are shown in Appendix A.

Overall, the shift from 2008 to 2018 reflects a transition from regional segmentation to global synchronisation. China's cascade follows a bottom-up pathway through developing Asia, while the United States' contagion spreads multidirectionally

across income groups. Higher avalanche ratios and shorter propagation chains confirm that increased connectivity has reduced resilience, echoing concerns that hyper-integration amplifies systemic risk (Inoue & Todo 2021). The growing prevalence of indirect infections further underscores the importance of upstream dependencies. For a policy perspective, shocks originating in China or the United States now propagate quickly across regions, leaving limited scope for substitution. Consistent with Clemente et al. (2023), resilience requires monitoring not only direct suppliers but also deeper upstream networks, with diversification and redundancy remain essential for mitigating concentrated supplier risk.

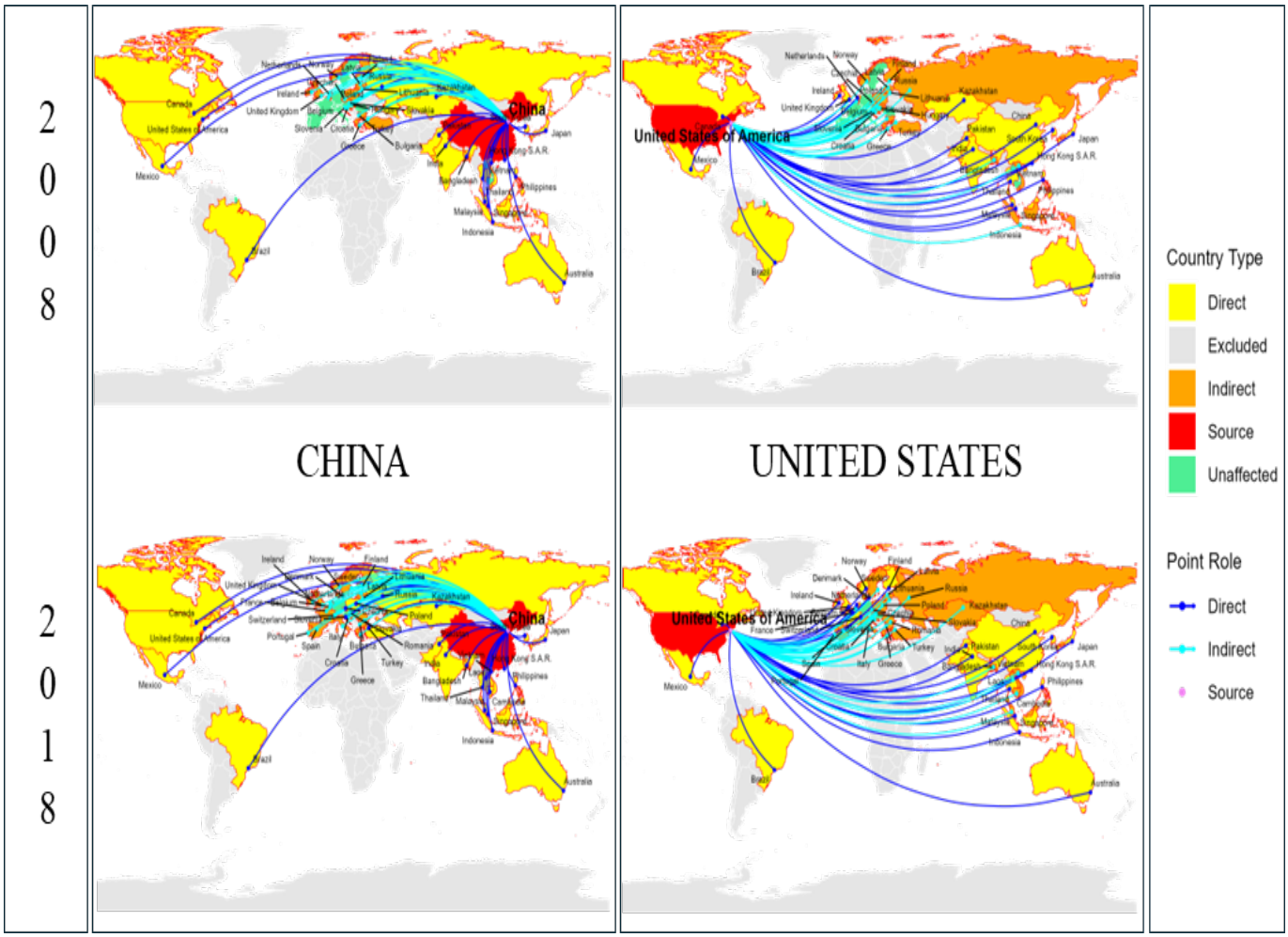


FIGURE 4: Global propagation patterns under a 50% supply shock (k=10) for each core country (China, USA), comparing 2008 and 2018.

Note: The shock origin (source) is marked in red; directly affected countries (T1) are in yellow; indirectly affected countries (T2 onward) are in magenta; unaffected countries are in green; and countries excluded from the study are in grey. Arrows indicate major shock transmission pathways along trade linkages.

DEMAND-SIDE SHOCK

The demand-shock experiment evaluates how a contraction in final demand from each core economy propagates through the same 49-node value-added network. Table 4 shows that under the 2008 baseline, the system absorbed small shocks with minimal disruption. At k=2, China produced no infections, while the United States generated only limited spillovers, similar to the supply-side scenario. Propagation emerges at k=6, where a 30% demand reduction causes the United States to infect 18 exporters (14 directly, 4 indirectly), compared with China's nine. At k=10, the United States becomes the dominant amplifier, triggering 36 infections over five rounds, while China reaches only 13. Increasing the shock to k=12 widens the gap, with the United States reaching 45 infections, whereas China still infects only 13. Full contagion occurs only at k=18, when both core nodes infect all 49 exporters. These results confirm that under the 2008 network structure, demand retrenchment in the United States posed the most acute systemic risk, reflecting its central role as the world's primary consumer market (Benguria & Taylor 2020), whereas a comparable contraction in China required near-total withdrawal to generate similar effects.

By 2018, the escalation pattern becomes far more compressed, consistent with deeper global interdependence. At k=2, the network remains largely stable except for two infections originating from the United States. By k=4, China infects seven exporters and the United States infects eight. At k=6, the United States jumps to 25 infections, while China reaches 16. At k=8, both produce similar contagion levels (29 infections). At k=10, China and the United States each infect nearly all suppliers, with avalanche ratios of 97.9%. This symmetry marks a structural shift, in which China's demand shock now propagates almost identically to that of the United States'.

The decade-long evolution reflects broader changes in global consumption patterns. Emerging markets, particularly China, have become central drivers of world demand (Zahedi et al. 2022), meaning that demand-side shocks originating in China can now produce global contractions comparable to those triggered by the United States. This finding is consistent with IMF assessments and recent analyses showing that shocks to large consumer markets have outsized multiplier effects throughout GVCs (Fontagné & Santoni 2022). Whereas the 2009 GFC was essentially a demand shock emanating from advanced economies (Benguria & Taylor 2020), by 2018, the global economy had developed two equally systemic demand hubs.

TABLE 4. Demand shock propagation round in core countries for 2008 and 2018

Shock propagation coefficient, k		2008		2018	
		China	USA	China	USA
k=2	AR	0.0%	8.3%	0.0%	4.2%
	AS	0	4	0	2
	T1	0	4	0	2
k=4	AR	4.2%	8.3%	14.6%	16.7%
	AS	2	4	7	8
	T1	2	4	7	8
k=6	AR	18.8%	37.5%	33.3%	52.1%
	AS	9	18	16	25
	T1	5	14	13	13
	T2	4	4	3	9
	T3				3
k=8	AR	25.0%	45.8%	60.4%	60.4%
	AS	12	22	29	29
	T1	8	16	16	18
	T2	4	6	10	8
	T3			2	3
	T4			1	
k=10	AR	27.1%	75.0%	97.9%	97.9%
	AS	13	36	47	47
	T1	12	20	18	25
	T2	1	6	13	21
	T3		2	16	1
	T4		4		
	T5		4		
k=12	AR	27.1%	93.8%	97.9%	97.9%
	AS	13	45	47	47
	T1	13	24	21	27
	T2		21	25	19
	T3			1	1
k=14	AR	29.2%	93.8%	97.9%	97.9%
	AS	14	45	47	47
	T1	14	25	25	30
	T2		20	22	17
k=16	AR	35.4%	93.8%	97.9%	97.9%
	AS	17	45	47	47
	T1	14	28	27	33
	T2	1	17	20	14
	T3	2			
k=18	AR	93.8%	93.8%	97.9%	97.9%
	AS	45	45	47	47
	T1	17	32	29	35
	T2	28	13	18	12
k=20	AR	93.8%	93.8%	97.9%	97.9%
	AS	45	45	47	47
	T1	17	33	32	37
	T2	28	12	15	10

Note: AR is Avalanche Ratio, AS is Avalanche Scale, and T is the number of steps of transmission

Figure 5 visualises the k=10 demand-shock scenario as an illustrative mid-range simulation. In 2008, China's panel shows only a small cluster of first-round infections with almost no secondary spread, whereas the United States displays much wider transmission. By 2018, however, both China and the United States panels are almost fully saturated. The red core is encircled by dense rings of yellow and magenta nodes, leaving only a few peripheral countries uninfected. These colour patterns confirm that, at an identical propagation coefficient, demand shocks originating in China or the United States can now reach nearly the entire supplier base. The TNSP results for the 2008 and 2018 demand-side shocks are shown in Appendix B.

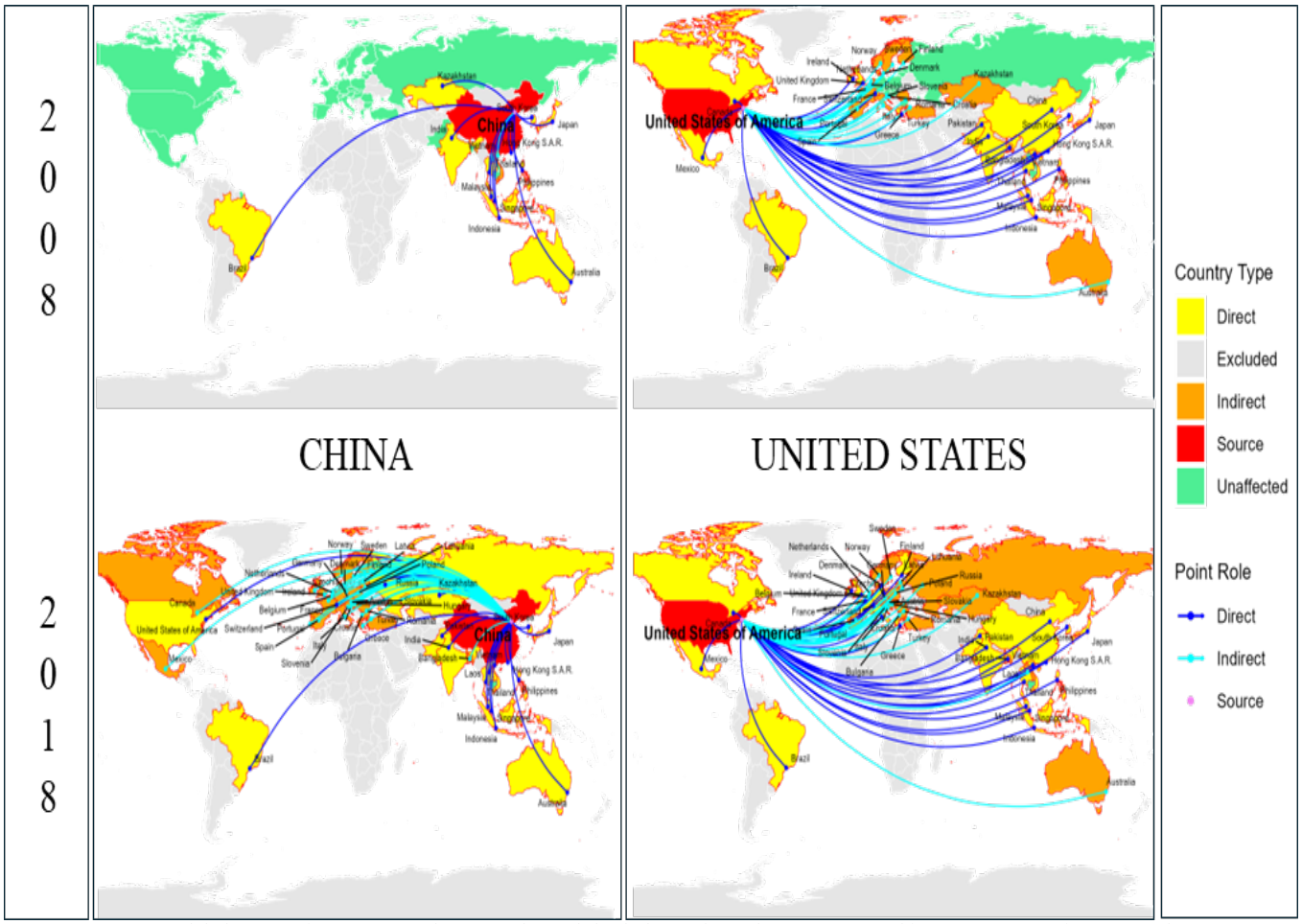


FIGURE 5. Global propagation patterns under a 50% demand shock (k=10) for each core country (China, USA), comparing 2008 and 2018.

Note: The shock origin (source) is marked in red; directly affected countries (T1) are in yellow; indirectly affected countries (T2 onward) are in magenta; unaffected countries are in green; and countries excluded from the study are in grey. Arrows indicate major shock transmission pathways along trade linkages.

OVERALL TNSP

The TNSP simulations should be interpreted as baseline vulnerability assessments rather than direct simulations of realised crisis years. The 2008 network assesses how shocks could have propagated through the global TiVA structure immediately before the 2009 GFC, while the 2018 network assesses the pre-escalation structure before the wider effects of the 2019 US-China trade. The 2019 and 2020 networks are not included as additional TNSP simulation years.

The 2008 baseline results are consistent with the demand-driven nature of the 2009 GFC. In the demand-shock simulation, the United States generated larger avalanches than China at moderate k-values, reflecting its position as the dominant final-demand hub before the crisis. This pattern is consistent with evidence that the global trade collapse during the GFC was closely linked to falling demand and credit tightening in advanced economies (Benguria & Taylor 2020). In contrast, China's demand-side propagation remained more limited under the 2008 baseline, suggesting that its role as a global demand centre had not yet reached the systemic scale observed by 2018.

The 2018 baseline results show a more fragile and synchronised network structure. Under both supply- and demand-side shocks, China and the United States generated larger avalanche ratios than in 2008, especially at moderate to high k-values. These results do not directly simulate the 2019 trade war; rather, they indicate that the pre-2019 TiVA network had already become highly exposed to disruptions originating from either hub. This interpretation is consistent with studies showing that US-China tariff measures reshaped trade costs, supply-chain allocation, and regional spillovers (Boylan et al. 2021; Fajgelbaum & Khandelwal 2022).

CONCLUSION

This study examined potential shock propagation in the global TiVA network by combining descriptive network analysis with TNSP simulations using ADB TiVA data covering 2008-2020. The findings show that the global value-added trade network remained structurally concentrated around China and the United States, which occupy key positions as supplier and demand hubs. The TNSP results suggest that shocks originating from these hubs can propagate widely under the model's threshold-based assumptions, with the 2018 baseline network showing greater vulnerability than the 2008 baseline.

Academically, the study contributes to empirical trade network research by extending the TNSP framework to bilateral TiVA data and comparing supply- and demand-side shock propagation across the 2008 and 2018 baseline networks. From a policy perspective, the findings provide evidence to inform risk management rather than direct policy validation. At the multilateral level, the evidence supports maintaining broad and diversified market access, as open, multi-directional trade networks tend to cushion shortages. Organisations such as the WTO or APEC could use these results to identify critical supplier-buyer pairs and to guide supply-chain cooperation initiatives. At the national level, mapping vulnerability profiles can help governments prioritise diversification, reduce reliance on a small number of dominant suppliers, or build strategic buffer stocks in sectors most likely to trigger global spillovers. By quantifying each country's systemic shock footprint, the study offers practical guidance for strengthening the resilience of global trade networks.

Several limitations should be acknowledged. To maintain analytical tractability, the TNSP model relies on deterministic threshold rules, whereby partners become infected once supply or demand falls below a fixed threshold. In reality, inventory adjustments, price responses, and substitution create more complex and partly stochastic dynamics. These constraints provide promising avenues for future research. In particular, extending the model to incorporate multi-sector dynamics rather than aggregated bilateral flows would enable researchers to examine how shocks to critical intermediate industries propagate differently from those affecting final-demand sectors.

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APPENDIX

APPENDIX A: TNSP simulation result for supply-side shocks in 2008 and 2018 (k=10)

Year	Initial Country	Round	Avalanche Scale	Infected Country
2008	China	1	19	Bangladesh, Pakistan, Philippines, Kazakhstan, Viet Nam, Thailand, Indonesia, Brazil, Singapore, Malaysia, Mexico, Hong Kong, India, Australia, Canada, Russia, Korea, Japan, United States
2008	China	2	14	Latvia, Croatia, Bulgaria, Slovak, Lithuania, Czech, Hungary, Greece, Finland, Poland, Turkey, Netherlands, Ireland, United Kingdom
2008	China	3	3	Slovenia, Belgium, Norway
2008	United States	1	18	Pakistan, Kazakhstan, Philippines, Thailand, Malaysia, Hong Kong, India, Australia, Brazil, Singapore, Netherlands, Korea, Ireland, United Kingdom, China, Japan, Mexico, Canada
2008	United States	2	6	Bangladesh, Indonesia, Belgium, Viet Nam, Norway, Russia
2008	United States	3	11	Latvia, Croatia, Bulgaria, Slovak, Lithuania, Czech, Hungary, Greece, Finland, Poland, Turkey
2008	United States	4	1	Slovenia
2018	China	1	25	United States, Japan, Korea, Mexico, India, Australia, Viet Nam, Canada, Russia, Hong Kong, Indonesia, Malaysia, Thailand, Brazil, Singapore, Poland, Turkey, Philippines, Pakistan, Czech, Bangladesh, Kazakhstan, Cambodia, Slovenia, Lao
2018	China	2	15	United Kingdom, France, Netherlands, Ireland, Switzerland, Denmark, Norway, Finland, Greece, Romania, Slovak, Lithuania, Bulgaria, Latvia, Croatia
2018	China	3	5	Belgium, Italy, Spain, Portugal, Sweden
2018	United States	1	22	China, Canada, Mexico, Japan, Korea, United Kingdom, India, France, Netherlands, Brazil, Ireland, Singapore, Australia, Switzerland, Thailand, Hong Kong, Indonesia, Denmark, Norway, Philippines, Pakistan, Finland
2018	United States	2	16	Viet Nam, Russia, Malaysia, Poland, Turkey, Czech, Bangladesh, Kazakhstan, Cambodia, Slovenia, Lao, Belgium, Italy, Spain, Portugal, Sweden
2018	United States	3	7	Greece, Romania, Slovak, Lithuania, Bulgaria, Latvia, Croatia

APPENDIX B: TNSP simulation result for demand-side shocks in 2008 and 2018 (k=10)

Year	Initial Country	Round	Avalanche Scale	Infected Country
2008	China	1	12	Philippines, Hong Kong, Kazakhstan, Thailand, Singapore, Malaysia, Indonesia, India, Brazil, Australia, Korea, Japan
2008	China	2	1	Viet Nam
2008	United States	1	20	Greece, Bangladesh, Pakistan, Hong Kong, Viet Nam, Philippines, Thailand, Indonesia, Ireland, Singapore, India, Switzerland, Malaysia, Brazil, Korea, United Kingdom, Japan, Mexico, China, Canada
2008	United States	2	6	Australia, Portugal, Denmark, Spain, Norway, Kazakhstan
2008	United States	3	2	Sweden, France
2008	United States	4	4	Finland, Romania, Belgium, Italy
2008	United States	5	4	Netherlands, Slovenia, Croatia, Turkey
2018	China	1	18	Japan, United States, Australia, Korea, Brazil, Russia, Indonesia, Malaysia, India, Switzerland, Thailand, Singapore, Hong Kong, Viet Nam, Kazakhstan, Philippines, Lao, Pakistan
2018	China	2	13	Canada, Mexico, Germany, United Kingdom, France, Italy, Ireland, Denmark, Finland, Bangladesh, Greece, Lithuania, Latvia
2018	China	3	16	Netherlands, Poland, Austria, Spain, Czech, Turkey, Belgium, Sweden, Hungary, Slovak, Romania, Portugal, Slovenia, Bulgaria, Croatia, Norway
2018	United States	1	25	China, Canada, Mexico, Japan, Germany, United Kingdom, India, France, Korea, Brazil, Italy, Switzerland, Ireland, Singapore, Malaysia, Indonesia, Viet Nam, Thailand, Denmark, Philippines, Finland, Bangladesh, Hong Kong, Pakistan, Greece
2018	United States	2	21	Australia, Russia, Kazakhstan, Lao, Netherlands, Poland, Austria, Spain, Czech, Turkey, Belgium, Sweden, Hungary, Slovak, Romania, Portugal, Slovenia, Bulgaria, Lithuania, Croatia, Norway
2018	United States	3	1	Latvia