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Uneven Diversification and Structural Robustness across Global Meat-Trade Networks

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Abstract: Strengthening the resilience of global agrifood systems to external shocks is a central challenge for food security. While international trade can buffer localized supply shortfalls, heavy reliance on major exporters can simultaneously propagate systemic disruptions across global meat markets. Growth in network connectivity does not necessarily translate into diversified sourcing, and resilience may vary markedly across livestock products. Here we reconstruct physical trade networks for bovine, swine, poultry and sheep–goat meat over 2002–2024. Traded quantity nearly doubled from 21.4 to 42.5 million tonnes, yet no product showed simultaneous diversification of global export supply and importer-level sourcing. Persistent structural shifts were detected in 13 of 16 product–indicator series, while event-aligned responses to animal-disease outbreaks and COVID-19 varied across products and network dimensions. In 2024, removing 10% of exporters at random preserved about 90% of import quantities, whereas targeted removal of the largest suppliers preserved only 6–13%, and robustness improved over time only for poultry. Safeguarding global meat supply may require commodity- and importer-specific diversification away from dominant trade corridors to mitigate immediate structural vulnerability.

Keywords: international food trade; trade network analysis; supplier diversification; structural robustness

1. Introduction

Strengthening the resilience of agrifood systems against external shocks and stress is critical for global food security [1,2]. International trade has become an integral component of the global food system, linking geographically concentrated production with spatially dispersed consumption [3]. Meat production is unevenly distributed across countries because of differences in land availability, feed resources, production costs, animal-health conditions, and processing capacity [4,5]. Trade can broaden access to meat products and help offset localized production shortfalls, but reliance on international markets can also transmit disruptions from major supplying countries through animal-disease outbreaks, export restrictions, and logistical interruptions [6–8]. Assessing the stability of the meat trade thus requires attention not only to aggregate trade volumes but also to how trade is distributed across exporters, importers, and bilateral relationships [9,10].

An expanding trade network does not inherently guarantee greater supply diversification. The number of participating countries and bilateral links may increase while most trade remains concentrated among a small group of high-volume exporters [11]. Global concentration and country-level dependence represent fundamentally distinct dimensions of trade structure. Exporter concentration describes how global supply is distributed across exporting countries, whereas importer concentration reflects how global demand is distributed across destination markets [12]. Supplier concentration instead captures the degree to which an individual importing country relies on specific foreign



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partners [13]. The three dimensions may follow different trajectories as trade expands, so broader participation in global trade may not translate into greater sourcing diversity for individual importers [14]. Lower global exporter concentration does not necessarily imply more diversified sourcing for individual importing economies.

Disaggregating meat trade by product allows the structural heterogeneity of global trade networks to be examined directly [15]. Bilateral trade networks represent economies as nodes and physical trade quantities as directed weighted links, and reveal major trade corridors, export centers, and import hubs. Community analysis complements the node-level view by identifying groups of economies bound together through relatively intensive trade and by tracking whether the groups persist, consolidate, or shift over time [16]. The perspective matters because comparable network structures cannot be assumed across meat products. Bovine, swine, poultry, and sheep–goat meat differ in production geography, biological cycles, market organization, and exposure to animal disease [17]. Aggregating the four products into a single network may obscure product-specific differences in export leadership, geographical reach, and importer-level supplier dependence [18].

While existing research on international food trade has systematically explored trade growth, network connectivity, centrality, and market concentration, several gaps remain [19]. Geographical corridors, community organization, and importer-level supplier dependence are often studied separately, making it difficult to relate network expansion to changes in sourcing diversity [20,21]. Many studies also focus on individual years or broad commodity aggregates, which may obscure long-term and product-specific variation. Global exporter and importer concentration likewise do not capture the supplier structure faced by individual importing economies [22]. A longer-term, product-resolved framework is needed to connect network growth, community reconfiguration, and importer-level sourcing concentration.

External disruptions compound the analytical complexity of meat-trade networks. Animal-disease outbreaks and system-wide events can produce persistent structural transitions, short-lived anomalies, or shifts in trading partners without any decline in aggregate trade quantities [23,24]. Selecting historical events only after unusual years have been detected invites post hoc attribution [25,26]. Persistent breaks and temporary deviations should instead be identified separately and compared with event windows defined independently of the detection results [27]. Temporal alignment may be consistent with plausible disruption mechanisms but does not establish causality, and direct comparisons across episodes remain limited by differences in duration, geographic footprint, and product exposure [28]. Standardized exporter-removal simulations provide a complementary stress test by quantifying retained imports under random disruptions and targeted losses of major suppliers [29].

Here we develop a product-resolved network framework for bovine, swine, poultry and sheep–goat meat, based on harmonized bilateral trade data for 2002–2024. Our primary contribution lies in integrating multiple dimensions of trade structure and robustness within a unified framework, while explicitly distinguishing global export concentration from importer-level sourcing concentration. We map major bilateral corridors, trace community reconfiguration, and compare exporter concentration, importer concentration, and importer-level supplier concentration. We then combine structural-break and anomaly diagnostics with independently defined event windows to examine event-aligned responses, and use exporter-removal simulations to quantify structural robustness under random disruption and the targeted loss of major suppliers. The framework connects long-term network expansion with sourcing diversification and structural robustness, and provides a consistent basis for identifying product-specific vulnerabilities and importer exposure in global meat trade.

2. Methods

2.1. Trade Data and Network Construction

The analysis comprised four stages: construction of annual product-specific trade networks, characterization of community structure and trade concentration, detection of persistent and short-term structural changes, and simulation of exporter disruptions and importer exposure. We used annual bilateral trade records from the BACI HS02 database [30,31], version V202601, covering 2002–2024. The analysis included four major meat categories. Bovine meat comprised HS codes 020110–020130 and 020210–020230. Swine meat comprised 020311, 020312, 020319, 020321, 020322, and 020329. Poultry meat comprised 020711–020714, 020724–020727, and 020732–020736. Sheep–goat meat comprised 020410, 020421–020423, 020430, 020441–020443 and 020450. The classification was designed to retain comparable meat products across categories while excluding separately identifiable offal wherever possible. Products classified under HS heading 0206 were excluded from all analyses. Poultry subheadings under HS heading 0207 that jointly report meat cuts and offal were retained because the two components cannot be separated under the HS02 classification.

Records with missing or non-positive trade quantities were excluded. Trade quantities, reported in tonnes, were aggregated by year, product, exporting economy, and importing economy. For each product p and year t , we

constructed a directed weighted network $G_{pt} = (V_{pt}, E_{pt})$, where V_{pt} denotes the set of active economies and E_{pt} denotes the set of directed bilateral trade links with positive quantities. Nodes represented economies, and a directed edge from exporter i to importer j represented a positive bilateral trade flow with weight Q_{ijpt} . An economy was considered active when it participated in at least one positive trade flow for the corresponding product and year. Total exports and imports were calculated as

$$X_{ipt} = \sum_j Q_{ijpt} \quad \text{and} \quad M_{ipt} = \sum_k Q_{kipt}$$

Here, X_{ipt} and M_{ipt} denote the total exports and total imports, respectively, of economy i for product p in year t , with the summation taken over all trading partners. Total trade strength was defined as the sum of exports and imports,

$$S_{ipt} = X_{ipt} + M_{ipt}$$

where S_{ipt} measures the overall trade participation of economy i through both exports and imports. The number of directed bilateral links was defined as the number of positive exporter–importer flows in each product–year network. All network indicators were calculated from the complete bilateral networks. The geographical mapping focused on the 2024 networks. National trade roles were characterized using the normalized trade balance,

$$R_{ipt} = \frac{X_{ipt} - M_{ipt}}{X_{ipt} + M_{ipt}}$$

The index ranges from -1 to 1 , with positive values indicating a stronger export orientation and negative values indicating a stronger import orientation. Economies with $R_{ipt} > 0.25$ were classified as export-oriented, those with $R_{ipt} < -0.25$ as import-oriented, and the remaining economies as mixed trade hubs. The node area was scaled to total trade strength, while curved directed arcs represented bilateral export flows and were scaled by trade quantity. To maintain visual clarity, each product map displayed the 40 largest bilateral trade flows in 2024, ranked by quantity. The top-40 threshold was applied only to visualization. All economy-level calculations and subsequent network analyses used the complete bilateral networks.

2.2. Community Detection and Trade Concentration

Trade communities were analyzed for 2002, 2013, and 2024. For each product and year, directed trade flows were converted into undirected bilateral weights by summing trade quantities in both directions, $W_{ijpt} = Q_{ijpt} + Q_{jipt}$. Communities were identified from the complete weighted networks using the Leiden modularity algorithm [32]. Twenty independent runs with different random seeds were conducted for each network, and the partition with the highest weighted modularity was retained. Modularity Q measures the extent to which trade is concentrated within communities relative to that expected from the network's strength distribution, with higher values indicating more clearly differentiated community structures [33].

Communities were matched between adjacent focal years within each product using Jaccard similarity and maximum-weight assignment. This procedure allowed community membership and colors to be tracked over time. Node coordinates were generated from a pooled network combining the three focal years and were fixed across years within each product. Community detection and all associated indicators were calculated from the complete networks, whereas edge filtering and community hulls were used only for visualization. We also calculated the share of total trade occurring within communities and the aggregate node strength of each community.

Trade concentration was evaluated from three complementary perspectives [6,10]. Exporter Herfindahl–Hirschman index (HHI) measured whether global exports were concentrated among a small number of exporting economies, while importer HHI measured the concentration of global import demand. Supplier concentration was calculated separately for each importing economy as

$$\text{HHI}_{jpt}^{\text{supplier}} = \sum_i \left(\frac{Q_{ijpt}}{\sum_i Q_{ijpt}} \right)^2$$

Product-level supplier concentration was obtained by averaging country-level values using import quantities as weights. This indicator represents the supplier concentration associated with an average tonne of imports. Its inverse was reported as the effective number of suppliers. Throughout the manuscript, a decline in exporter HHI is referred to as global export diversification, whereas a decline in supplier HHI is referred to as importer-level sourcing diversification. Importer HHI is treated separately as the concentration of global import demand. Long-term changes in exporter and supplier concentration were calculated as the differences between their 2024 and 2002 values.

2.3. Structural Diagnostics and Event-Aligned Responses

For each meat product, annual series were constructed for total trade quantity, the number of directed bilateral links, exporter HHI, and trade-weighted supplier HHI, yielding 16 series for 2002–2024. Trade quantity and link counts were log-transformed, whereas HHI values were analyzed on their original scales. Persistent structural changes were identified by comparing a linear trend model with a one-break piecewise-linear model. Each segment was required to contain at least five annual observations, and a break was retained when the one-break model reduced the Bayesian information criterion by at least two units. A maximum of one primary break was allowed per series. Break-year uncertainty was evaluated using 600 residual-bootstrap replicates. Short-term anomalies were identified using leave-one-year-out robust regression residuals. Observations with an absolute robust z-score of at least two were retained as anomalies after Benjamini–Hochberg correction at a false-discovery rate of 10%. Testing was restricted to 2003–2023 to reduce boundary effects.

Four event windows were defined independently before temporal matching: bovine spongiform encephalopathy in 2003–2005, highly pathogenic avian influenza in 2004–2006, African swine fever in 2018–2020, and COVID-19 in 2020–2021. Bovine, poultry, and swine meat were treated as directly exposed to the first three events, respectively, while COVID-19 was treated as a system-wide disruption. All product–event combinations were retained to assess possible cross-product responses. Event-aligned changes in trade quantity, bilateral links, and supplier HHI were estimated for the event year and the following two years relative to counterfactual values derived from up to five pre-event observations. A local linear trend was used with at least four pre-event observations and a pre-event mean with two or three observations. No response was estimated with fewer than two observations, so the BSE window was excluded from formal response estimation. Uncertainty was assessed using 1200 residual-bootstrap replicates. Quantity and link responses were reported as percentage deviations, while supplier-HHI responses were reported as absolute changes. Because event windows could overlap and no untreated control network was available, the estimates were interpreted as event-aligned associations rather than causal effects.

2.4. Simulated Exporter Disruptions and Importer Exposure

Structural robustness was evaluated using static exporter-removal simulations [14]. For each product, active exporters were removed under two scenarios: random removal and targeted removal from the largest to the smallest exporter according to baseline export quantity. For the 2024 networks, up to 30% of active exporters were removed. Random removal was repeated 500 times at each removal level to obtain mean retention curves and 95% simulation intervals. Network performance was measured as the proportion of baseline import quantity retained after removing a set of exporters D :

$$R_{pt}(D) = \frac{\sum_{i \notin D} \sum_j Q_{ijpt}}{\sum_i \sum_j Q_{ijpt}}$$

A higher retention value indicates greater short-term robustness under the existing trade structure. Long-term changes in targeted-disruption robustness were compared across 2002, 2013, and 2024 using the normalized area under the retention curve between 0% and 30% exporter removal. Importer exposure was assessed for the 2024 networks after removing approximately the largest 10% of active exporters for each product. For each importing economy, exposure was calculated as the proportion and absolute quantity of baseline imports lost. Economies ranking among the 50 largest importers for at least one product were included, and the 20 economies with the greatest affected import quantities were displayed. Cross-product loss shares were calculated by dividing total affected imports by total baseline imports across the four meat categories. The simulations represented immediate exposure under the observed bilateral trade structure. They did not allow remaining exporters to expand production or redirect trade and did not incorporate domestic production, inventories, prices, demand responses, or substitution among meat products. The resulting measures therefore describe structural robustness and trade-supply exposure rather than realized shortages or overall food-security vulnerability.

3. Results

3.1. Global Meat Trade Followed Distinct Product-Specific Corridors

Global trade in the four meat categories was highly uneven in 2024, with large shares of traded quantities channeled through a limited number of high-volume bilateral corridors (Figure 1). Poultry accounted for the largest traded quantity at 17.0 million tonnes (Mt), followed by swine meat at 12.2 Mt, bovine meat at 11.8 Mt, and sheep–goat meat at 1.5 Mt. Each product network connected at least 220 active economies, although the 40 largest bilateral flows accounted for 49.6% of poultry trade, 56.7% of swine trade, 61.6% of bovine trade, and 76.9% of

sheep–goat trade. Despite their broad geographical coverage, the four networks exhibited distinct spatial configurations. Bovine trade primarily connected exporters in South America and Oceania with major markets in East Asia and North America. Swine trade combined dense intra-European exchanges with large North American and trans-Pacific flows. Poultry trade reached the broadest range of destination markets, whereas sheep–goat trade remained strongly anchored in Oceania.

Bovine trade was dominated by Brazil, Australia, India, the United States, and Argentina, which together accounted for 56.8% of global exports. China was the leading destination market, receiving 22.8% of global bovine imports. The flow from Brazil to China was the largest bilateral corridor at 1.33 Mt, equivalent to 11.2% of global bovine trade. Other major corridors included exports from Argentina to China, Australia to the United States, and Canada to the United States (Figure 1A). Swine exports were distributed across North America, Europe, and South America. The United States ranked first, followed by Spain, Germany, Brazil, and Canada, with these five countries jointly supplying 62.9% of global exports. The United States–Mexico corridor was the largest bilateral flow at 1.12 Mt. Major European routes included exports from Germany to Italy and from Spain to China, while exporters in Europe and North America also supplied large East Asian markets, particularly Japan and the Republic of Korea (Figure 1B).

National trade roles overlapped only partly across product networks. China was the largest importer of bovine, poultry, and sheep–goat meat and the second-largest importer of swine meat, making it the most consistently important destination market across the four products. Changes in China's import demand also reoriented major trade corridors toward its principal suppliers, increasing the structural importance of several high-volume bilateral links. Export leadership was more product-specific. Brazil led bovine and poultry exports, the United States led swine exports and remained a major poultry supplier, and Australia occupied a central position in both bovine and sheep–goat trade. Several countries also assumed contrasting roles across products. The United States functioned as a mixed hub in bovine trade, an export-oriented supplier in swine and poultry trade, and an import-oriented market in sheep–goat trade. The Netherlands showed a similar degree of role differentiation, acting as a mixed hub in bovine and poultry trade but as a predominantly export-oriented node in swine trade. Overall, although the four networks shared several high-volume participants, the direction and geographical reach of their trade roles remained strongly product-specific.

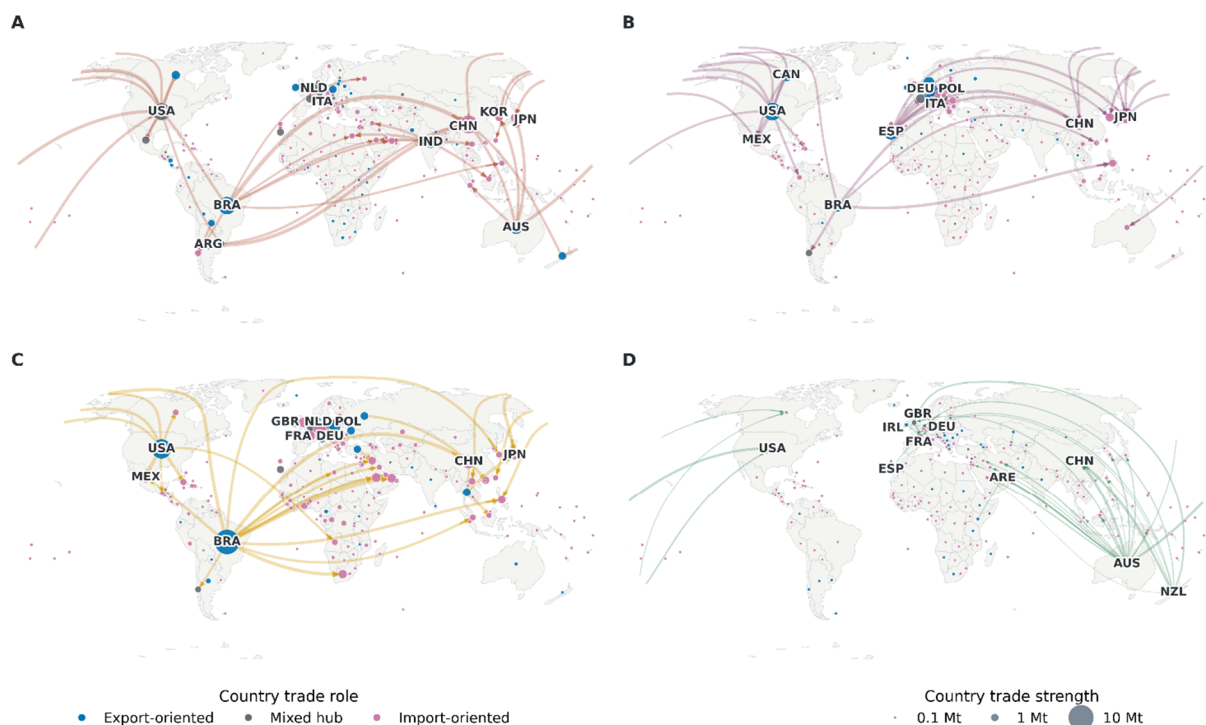


Figure 1. Product-specific geography and major bilateral corridors of global meat trade in 2024. (A–D), Bilateral trade flows for (A) bovine meat, (B) swine meat, (C) poultry meat, and (D) sheep–goat meat. Curved lines indicate directed trade flows from exporting to importing economies, with line width scaled to bilateral trade quantity. Node size represents the total trade quantity of each economy, calculated as the sum of imports and exports, while node color indicates whether an economy was export-oriented, import-oriented, or a mixed trade hub.

3.2. Meat-Trade Communities Underwent Uneven Product-Specific Reconfiguration

Community structure evolved along distinct product-specific trajectories between 2002 and 2024 (Figure 2A–L). Bovine trade retained six communities in 2002 and 2013 before consolidating into four by 2024, whereas weighted modularity (Q) remained broadly stable at 0.54, 0.57, and 0.54. Swine trade followed a non-monotonic path. The number of communities increased from five to seven and then declined to four, while Q fell from 0.43 to 0.37 before recovering to 0.41. Poultry showed a different pattern, with the number of communities increasing from four to six and then declining to four, while Q rising from 0.39 to 0.46 and 0.47, indicating stronger modular differentiation after 2002. Sheep–goat trade showed a gradual reduction in community number from nine to seven and then six, but remained the least modular network, with Q increasing only marginally from 0.31 to 0.34 over the study period. Community number, however, did not consistently track the degree of within-community concentration. The within-community share of bovine trade declined from 91.1% to 81.3% even as the number of communities decreased, whereas the corresponding share for swine increased from 74.2% to 81.1%. Poultry recorded a smaller increase from 74.9% to 77.5%. Sheep–goat trade followed a non-monotonic trajectory, declining from 78.9% to 59.6% before recovering to 68.6%.

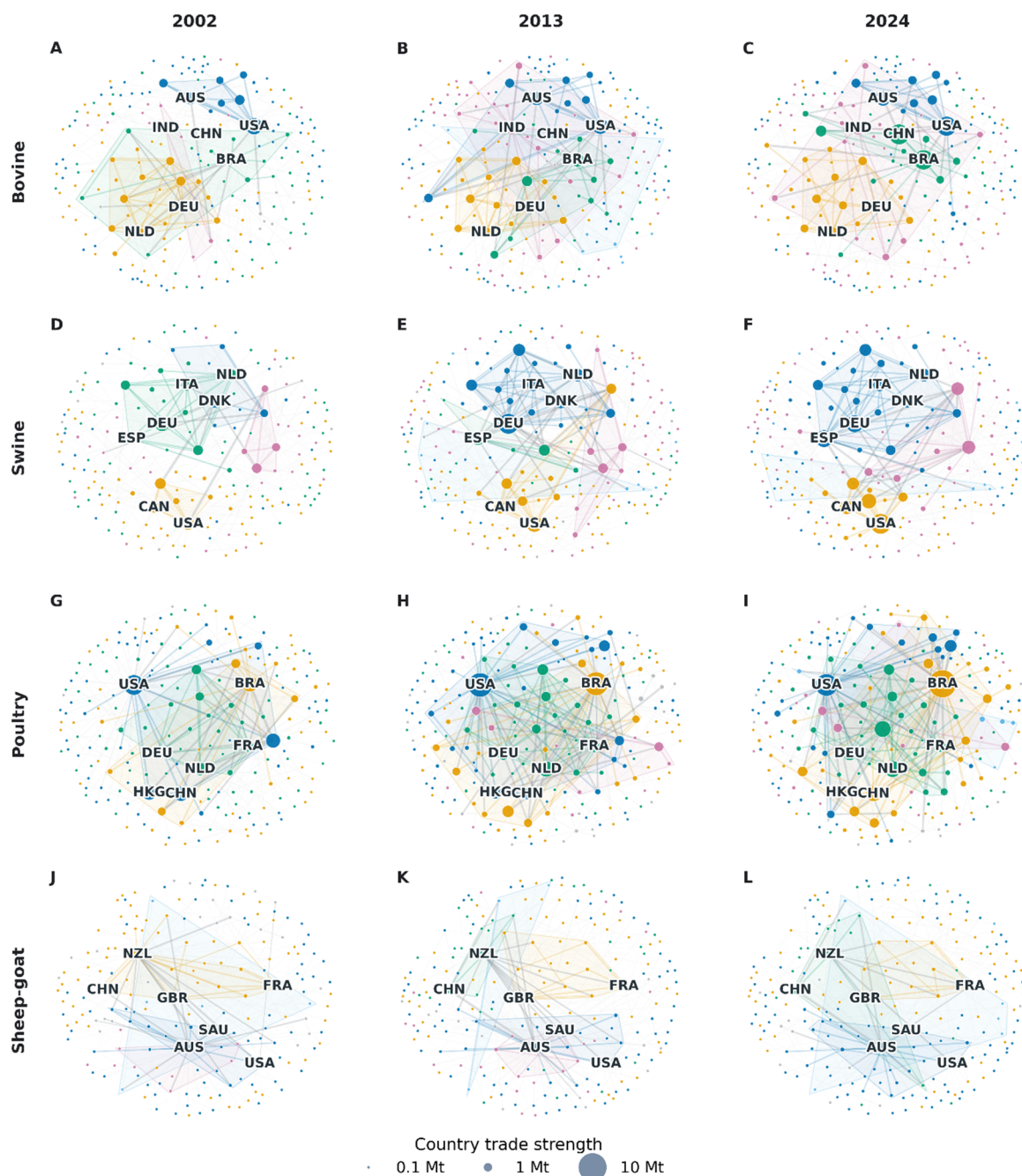


Figure 2. Product-specific reconfiguration of global meat-trade communities, 2002–2024. (A–L) Community structures of the global (A–C) bovine, (D–F) swine, (G–I) poultry, and (J–L) sheep–goat trade networks in 2002,

2013, and 2024. Node size represents total trade strength, edge width represents bilateral trade quantity, and node color indicates community membership. Community colors are matched across years within each product but are not comparable across products.

Community membership and the composition of dominant trade cores also evolved differently across products. Bovine trade retained recognizable groupings centered on the United States and Australia, continental Europe, South American exporters, and India-linked markets. By 2024, several smaller groups had consolidated into four larger communities. Between 2013 and 2024, the communities centered on the United States and Australia and on continental Europe retained Jaccard membership overlaps of 0.75 and 0.63, respectively, indicating that their core membership remained relatively stable despite changes among peripheral economies. Swine trade underwent more extensive recombination. European economies were distributed across several communities in 2002 and 2013, but Germany, Spain, the Netherlands, Italy, and Denmark belonged to the same major community by 2024. A North American community centered on the United States, Mexico, and Canada remained separate from a grouping linking Brazil and China. Poultry maintained six communities after 2013, including major groupings centered on Brazil and Asian–Middle Eastern markets, the United States and Mexico, and European exporters led by Poland and the Netherlands. Sheep–goat trade displayed a different relationship between the number and economic importance of communities. Although nine communities were detected in 2002, the two largest already accounted for 96.1% of aggregate country trade strength. By 2024, three major groupings centered on Australia, New Zealand, and China, and European traders accounted for 97.5% of trade strength. The sheep–goat network therefore remained dominated by a small number of economically important communities despite changes in the total number detected.

Changes in the rankings and community affiliations of high-strength economies further illustrated the product-specific reconfiguration of meat trade networks. In bovine trade, China rose from 37th in total trade strength in 2002 to first in 2024, while Brazil moved from eighth to second and the United States fell from first to third. China also shifted from the community centered on the United States and Australia in 2013 to the Brazil–Argentina grouping in 2024. In swine trade, the United States rose from third to first and Spain from twelfth to third, while Germany moved from first to second. China shifted from a community containing the United States, Canada, and Japan in 2013 to a Brazil-centered grouping in 2024. In the poultry trade, Brazil overtook the United States as the largest node, Poland emerged as the third-largest node, and China moved from a United States-centered community to a Brazil-centered grouping. In the sheep–goat trade, Australia overtook New Zealand in 2013 and remained the largest node in 2024, while China rose from tenth to third and joined a community centered on its trade relationship with New Zealand. Across the four products, established export centers generally persisted, but the growing prominence and changing community affiliations of major importing economies, particularly China, substantially reshaped the organization of global meat trade.

3.3. Trade-Network Expansion Did Not Yield Uniform Diversification across Meat Products

Exporter concentration, measured using the HHI, followed divergent trajectories across the four products (Figure 3A). Sheep–goat trade remained the most export-concentrated network throughout 2002–2024. Its exporter HHI declined from 0.293 in 2002 to 0.220 in 2011, before rising to 0.295 in 2024. Poultry ranked second in exporter concentration and followed a similarly non-monotonic trajectory. Its HHI increased from 0.152 in 2002 to 0.195 in 2008, fell to 0.120 in 2018, and recovered to 0.142 by 2024. Bovine exporter HHI declined to 0.065 in 2011 before increasing to 0.089 in 2024, slightly above its 2002 level of 0.085. Swine exporter concentration varied within a narrower range but increased overall from 0.089 to 0.102, reaching its highest levels in 2023–2024. Early diversification in bovine, poultry and sheep–goat exports was therefore partly or fully reversed by the end of the study period.

Import-demand concentration and importer-level supplier concentration followed different trajectories (Figure 3B,C). Importer HHI, which captures whether global import demand was distributed across many markets or concentrated in a small number of large importers, declined from 0.066 to 0.024 for poultry and from 0.080 to 0.049 for swine. Swine nevertheless showed a temporary increase to 0.129 in 2020. Bovine importer HHI followed a U-shaped trajectory, falling from 0.069 in 2002 to 0.039 in 2013 before increasing to 0.082 in 2024. Sheep–goat importer HHI also increased overall from 0.064 to 0.092, although it reached a temporary peak of 0.141 in 2021. Trade-weighted supplier HHI captured a different dimension by measuring the concentration of suppliers associated with the average tonne of imports. It remained highest for sheep–goat meat, increasing slightly from 0.481 to 0.487, and also rose for poultry from 0.376 to 0.406. Swine supplier HHI changed only modestly from 0.321 to 0.327, whereas bovine supplier HHI declined from 0.341 to 0.304. The bovine decline corresponded to an increase in the effective number of suppliers from 2.93 to 3.29, while the corresponding value for poultry

decreased from 2.66 to 2.46. Import demand for poultry therefore became more geographically dispersed, even as individual importing economies relied on a narrower set of suppliers. Bovine trade showed the opposite configuration, with import demand becoming more concentrated globally while importer-level sourcing became more diversified.

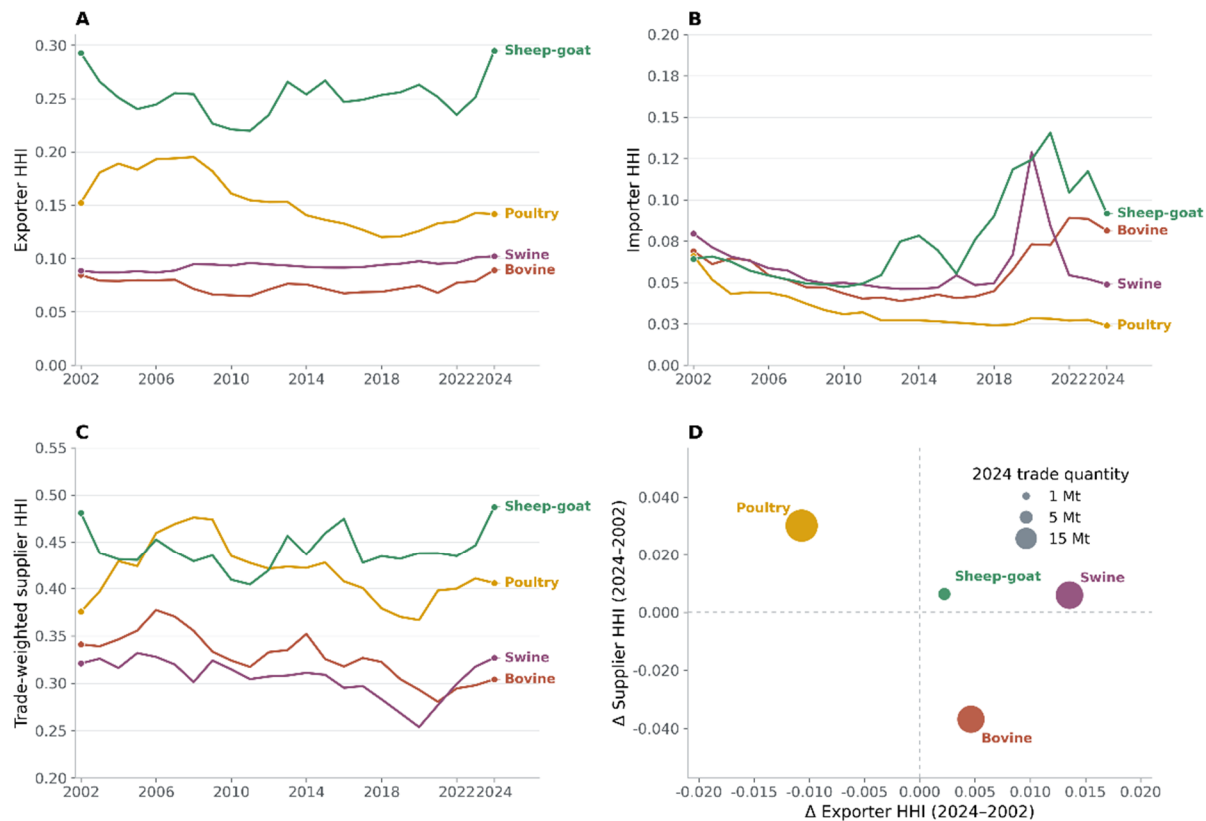


Figure 3. Divergent trajectories of trade concentration and supplier diversification across meat products, 2002–2024. (A) Exporter concentration is measured using the exporter HHI. (B) Concentration of global import demand measured using importer HHI. (C) Trade-weighted importer-level supplier concentration. (D) Changes in exporter HHI and supplier HHI between 2002 and 2024.

Endpoint comparisons reinforced the divergence between exporter concentration and importer-level supplier concentration (Figure 3D). Swine showed increases in both dimensions, with exporter HHI rising by 0.0136 and supplier HHI by 0.0059 between 2002 and 2024. Sheep–goat trade followed the same directional pattern, although the increases were smaller at 0.0022 and 0.0063, respectively. Bovine trade combined a modest increase in exporter HHI of 0.0046 with a larger decline in supplier HHI of 0.0368. Poultry displayed the opposite configuration, with exporter HHI declining by 0.0107 while supplier HHI increased by 0.0302. No product therefore experienced simultaneous declines in both global exporter concentration and importer-level supplier concentration. This lack of joint diversification occurred despite increases of 67–111% in traded quantity and 61–88% in the number of directed bilateral links across the four products. Greater trade volumes, denser bilateral connectivity and community reconfiguration therefore did not consistently translate into lower concentration. However, the long-term series also contained temporary peaks and sharp reversals that endpoint comparisons could not distinguish from persistent structural transitions. We therefore separated structural breaks from anomalous years and assessed their temporal alignment with predeclared external-event windows (Figure 4).

3.4. Structural Transitions and Event-Aligned Responses Were Product- and Indicator-Specific

One-break diagnostics selected structural transitions in 13 of the 16 product–indicator series, although most were only broadly localized in time (Figure 4A). No break was detected in bovine trade quantity, while transitions in bilateral links, exporter HHI, and supplier HHI were centered on 2015, 2009, and 2008, respectively. All four swine series contained selected breaks. The clearest signal occurred in supplier HHI in 2019, whereas the quantity and link transitions were localized less precisely around 2020 and 2016. Poultry exporter and supplier HHI shifted concurrently around 2010, while quantity and links showed broader transitions centered on 2011 and 2015. Sheep–

goat trade showed no selected break in quantity or supplier HHI, although transitions in links and exporter HHI were centered on 2009 and 2012. Nine of the 13 selected breaks had wide bootstrap intervals and were therefore interpreted as broadly localized structural transitions rather than changes attributable to a single year. Short-term anomalies were less frequent. Among 41 observations with $|z| \geq 2$, 13 occurred in the boundary years 2002 or 2024 and were treated as exploratory. After false-discovery-rate adjustment, seven interior anomalies remained. Four occurred in poultry quantity in 2004, 2006, 2014, and 2015, while the other three involved sheep–goat concentration in 2008, 2011, and 2016. Bovine and swine changes were therefore expressed mainly as persistent structural transitions rather than isolated annual deviations.

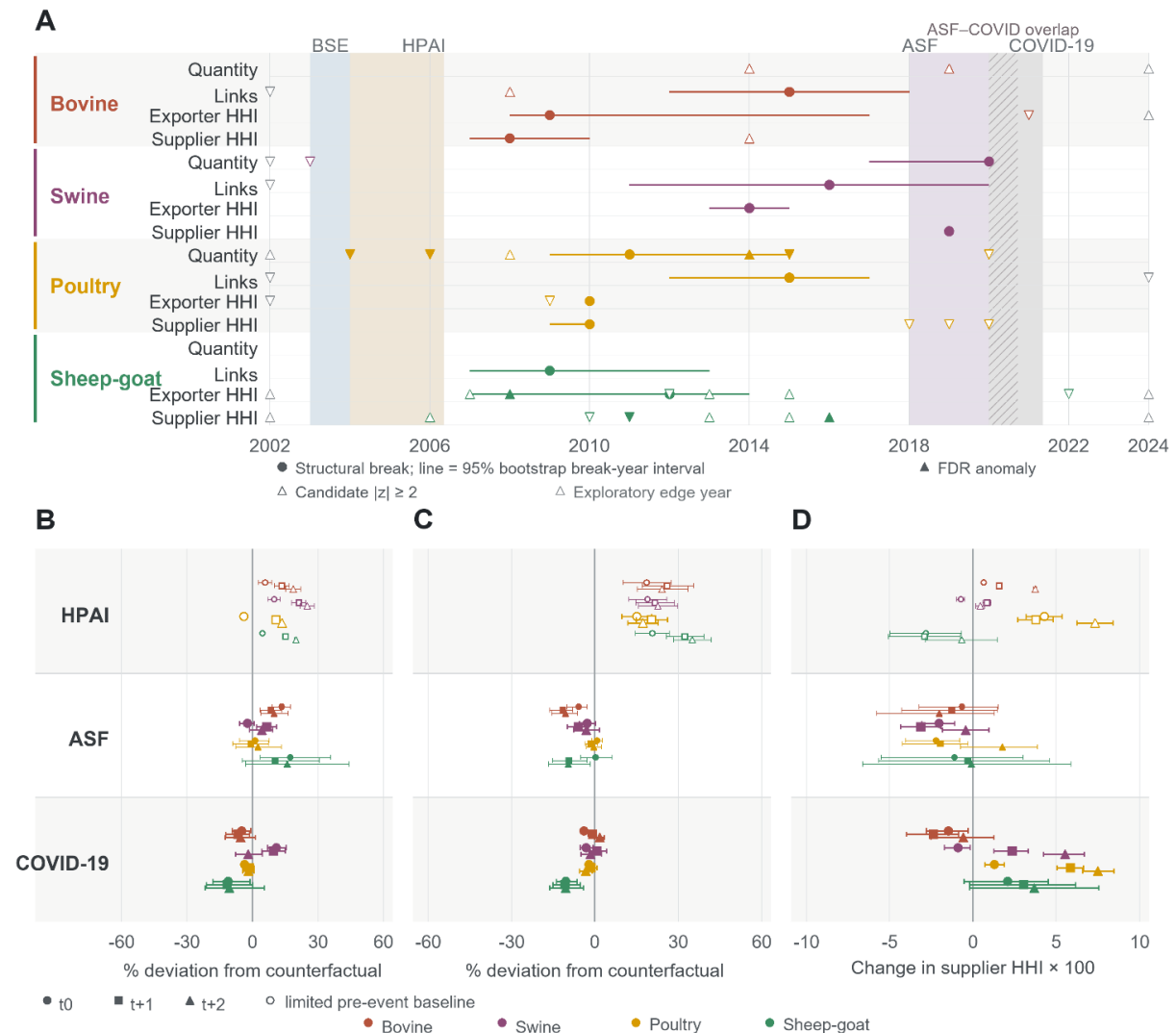


Figure 4. Structural transitions, anomalous years and event-aligned responses in global meat trade, 2002–2024.

(A) Detected structural transitions and anomalous years for trade quantity, bilateral trade links, exporter HHI, and trade-weighted supplier HHI across the four meat products. (B–D) Deviations from locally estimated counterfactual baselines in (B) trade quantity, (C) bilateral trade links, and (D) importer-level supplier HHI during predeclared external-event windows. BSE responses are not shown in panels (B–D) because the 2004 anchor year provided only one pre-event observation, which was insufficient for counterfactual estimation.

Because these analyses lack an untreated control and some event windows overlap, the estimated responses are interpreted as temporal associations rather than causal effects. The clearest event-aligned signal occurred in the poultry trade during the predeclared highly pathogenic avian influenza (HPAI) window. Poultry quantity showed a strong negative anomaly in 2004 ($z = -7.75$, FDR-adjusted $q < 0.001$), consistent with direct exposure of the sector to the outbreak (Figure 4B–D). Relative to the event-response counterfactual, poultry trade quantity was 4.0% lower in the event year, but increased to 10.7% and 13.5% above the counterfactual one and two years later. Bilateral links were already 15.0% above the counterfactual in 2004 and remained 17.2–20.3% higher during the following two years. Supplier HHI also increased by 0.04 in the event year and by 0.07 after two years,

indicating that the recovery in trade quantity coincided with greater supplier concentration. The estimates were based on only two pre-event observations and were therefore treated as limited-baseline results. Moreover, the anomaly and event-response analyses used different reference models, so their estimated deviations are not directly comparable. Responses aligned with the bovine spongiform encephalopathy window were not estimated because the 2004 anchor year provided only one pre-event observation.

Event-aligned deviations during the African swine fever (ASF) and COVID-19 windows further showed that trade scale, connectivity, and supplier concentration did not move in parallel. For the direct ASF–swine pair, trade quantity was 2.4% below the counterfactual in the event year, although the confidence interval included zero, and increased to 6.5% above the counterfactual one year later (95% CI, 1.9–11.1%). Bilateral links, however, were 6.0% lower after one year (95% CI, −10.0 to −2.3%), while supplier HHI declined by 0.02 in the event year and by 0.03 one year later. The 2019 transition in swine supplier HHI therefore coincided with greater supplier diversification rather than the predeclared expectation of increased concentration. Attribution remained uncertain because the ASF and COVID-19 windows overlapped in 2020. During the COVID-19 anchor year, bilateral links were below their counterfactuals for all four products, with deviations ranging from −2.2% for poultry to −10.5% for sheep–goat meat. Quantity responses were more heterogeneous. Bovine, poultry, and sheep–goat quantities were lower by 4.9%, 3.6%, and 11.1%, respectively, whereas swine quantity was 11.0% higher. Supplier HHI declined initially for bovine and swine, increased for poultry, and remained imprecisely estimated for sheep–goat meat. The event-aligned results therefore indicated product- and indicator-specific network reorganization rather than a common contraction across meat-trade networks.

3.5. Simulated Exporter Disruptions Revealed Uneven Product Robustness and Concentrated Importer Exposure

The 2024 meat-trade networks were substantially more sensitive to targeted than to random exporter disruptions (Figure 5A–D). Across 500 random simulations, removing approximately 5%, 10%, and 20% of active exporters left an average of 93.2–95.1%, 89.3–90.5%, and 79.1–81.2% of baseline import quantity intact, respectively. When exporters were instead removed from largest to smallest, retention fell to 11.9–31.9% after approximately 5% had been removed and to 6.1–12.8% at the 10% threshold. The gap between random and targeted removal reached 77–83 percentage points at approximately 10% removal. Although the removed countries represented only 10.0–10.6% of active exporters, they supplied 87.2–93.9% of baseline trade quantity. Retention declined further to only 1.2–3.5% when approximately 20% of exporters were removed. Sheep–goat trade was the most sensitive at low removal levels, while bovine trade retained the largest share. Nevertheless, all four networks lost most of their existing import quantity following the removal of a small proportion of major exporters. These simulations quantify immediate structural exposure under the observed bilateral trade network rather than predicted shortages or realized food-security losses.

Long-term changes in robustness to targeted exporter removal were also uneven across products (Figure 5E). The normalized area under the largest-exporter-first retention curve declined for bovine trade from 0.169 in 2002 to 0.160 in 2013 and 0.154 in 2024. Swine showed a larger deterioration, with AUC falling from 0.190 to 0.136 and then remaining nearly unchanged at 0.135. Poultry followed a different trajectory. Its AUC declined from 0.126 in 2002 to 0.118 in 2013, before increasing to 0.134 in 2024 and exceeding its initial level. Sheep–goat trade remained the least robust throughout the three years, with AUC values of 0.087, 0.081 and 0.084. Poultry was therefore the only product whose targeted-disruption robustness was higher in 2024 than in 2002. This improvement was not shared by the other networks, despite increases in the number of active exporters from 125 to 150 for bovine, 96 to 123 for swine, 114 to 153 for poultry, and 95 to 123 for sheep–goat meat. Growth in the number of participating exporters did not consistently create greater functional redundancy against the loss of the largest suppliers.

Importer-level exposure was concentrated among a limited number of major markets (Figure 5F). Under the removal of approximately the largest 10% of exporters, China recorded the largest absolute exposure, with 4.76 Mt of affected imports and a trade-weighted loss share of 93.5% across the four products. Mexico and Japan combined similarly high proportional losses with large affected quantities, reaching 97.8% of 2.46 Mt and 99.3% of 2.17 Mt, respectively. The United States had 2.05 Mt of affected imports and an overall loss share of 92.7%, although its exposure varied sharply by product. Losses exceeded 95% for bovine, swine, and sheep–goat meat but reached only 1.0% for poultry. Several East and Southeast Asian markets were exposed across all four products, with product-specific losses of 97.0–99.8% in Japan, 93.5–99.7% in the Republic of Korea and 92.8–98.9% in the Philippines. High exposure also extended to major importers in Europe, the Middle East, and North America. The simulated losses represent immediate trade-supply exposure under the existing 2024 bilateral trade structure rather than realized food

shortages. The analysis did not allow trade rerouting or production expansion and did not incorporate domestic production, stocks, consumption, prices, purchasing power, or substitution among meat products.

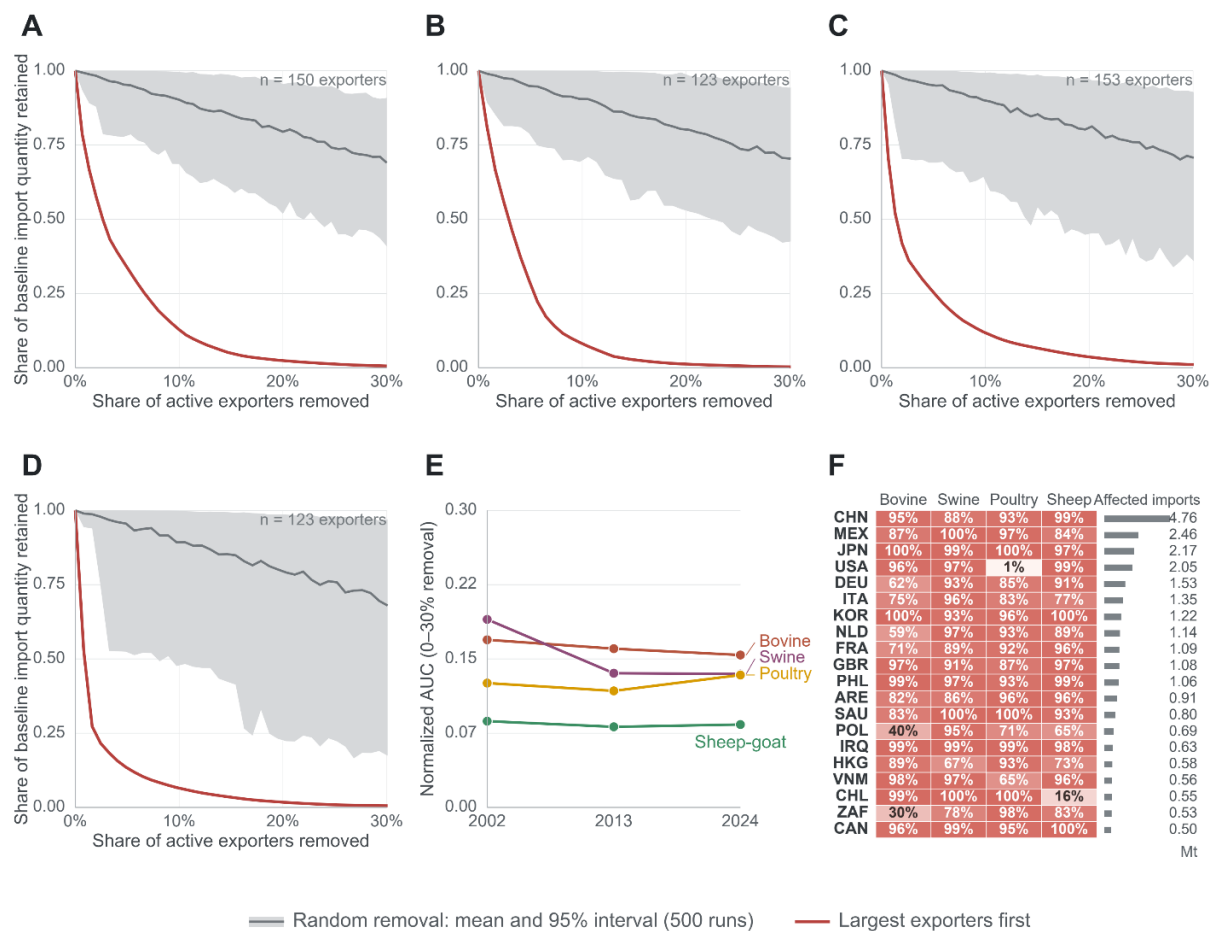


Figure 5. Structural robustness and importer exposure under simulated exporter disruptions. (A) Bovine meat, (B) swine meat, (C) poultry meat, and (D) sheep–goat meat. Panels (A–D) show the shares of baseline import quantity retained in the 2024 trade networks following random exporter removal and targeted removal of the largest exporters. (E) Changes in targeted-disruption robustness, measured by the normalized area under the retention curve, in 2002, 2013, and 2024. (F) Product-specific import losses among major importing economies following the removal of approximately the largest 10% of exporters.

4. Conclusions

Global meat trade expanded substantially between 2002 and 2024, but greater connectivity did not produce uniform diversification or structural robustness. The four product networks followed distinct geographical, community, and concentration trajectories. Bovine importers gained broader supplier access despite slightly greater exporter concentration, whereas poultry exports became less concentrated globally while importer-level sourcing became more concentrated. Swine and sheep–goat trade became more concentrated across both dimensions. Historical disruptions were likewise associated with product-specific changes in trade quantity, connectivity, and supplier concentration rather than a common contraction.

Simulated exporter disruptions revealed the consequences of concentrated trade for network performance. Removing about 10% of exporters at random retained roughly 90% of baseline import quantities, whereas removing the largest exporters reduced retained trade to only 6–13%. Targeted-disruption robustness improved over time only for poultry, and several major importing economies remained highly exposed to dominant suppliers and bilateral corridors. The number of trading partners and links alone is an incomplete measure of trade resilience. Trade-resilience strategies should distinguish among expanding supplier portfolios, reducing the volume share of dominant suppliers, and improving the substitutability and replacement capacity of alternative suppliers. In practice, importing economies could identify secondary suppliers with established trade links and meaningful export capacity and gradually rebalance import shares toward these alternatives to reduce dependence on dominant suppliers. As the simulations capture immediate losses under observed bilateral trade structures, the estimates

represent structural trade exposure rather than realized shortages or broader food-security outcomes. Future work could integrate domestic production, inventories, prices, consumption, and cross-meat substitution to capture national buffering capacity and adaptive responses beyond observed trade links. Linking these data with the present network framework would allow importer exposure to be evaluated against broader supply conditions and provide a more comprehensive assessment of national food-security risk.

Author Contributions

K.S.: conceived the study, developed the methodology, curated the data, conducted the analyses, prepared the visualizations, and drafted the manuscript; F.X.: contributed to the study design and methodology, supervised the research, validated the results, and revised the manuscript. Both authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable. This study analysed country-level agricultural and meat trade statistics obtained from the publicly available BACI database and did not involve human participants, animal subjects, or personally identifiable information.

Informed Consent Statement

Not applicable.

Data Availability Statement

The code used in this study is available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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