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Conflicts and Climate Change: The Evolving Structure of the International Agricultural Trade Network

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Conflicts and Climate Change: The Evolving Structure of the

International Agricultural Trade Network

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Over the past decade, global agricultural trade has been disrupted by a series of major events – climate change, the COVID-19 pandemic, and armed conflicts – collectively referred to as the "Three C's." These shocks have shifted the focus of trade from efficiency toward resilience, national security, and geopolitics. Using a network-based approach, this study examines how trade relationships in food supply chains have changed at the country, community, and global levels. Descriptive network analysis of key commodities like pork and wheat reveals signs of deglobalization, including shifts in trade influence, the rise of friendshoring, and declining connectivity across the network. To explore the drivers behind these changes, the study employs Exponential Random Graph Models (ERGMs), which offer advantages over traditional gravity models by capturing complex interdependencies and community structures within trade networks. Results show that the Three C's significantly reduce the likelihood of forming new trade relationships, particularly in recent years. While traditional factors like GDP and distance still matter, their influence appears to be weakening. This suggests that global food trade is entering a new phase shaped more by strategic considerations than by market efficiency—raising important implications for food security and international cooperation in an increasingly fragmented world.

Keywords: conflicts, sanctions, climate change, agricultural trade, network graphs and exponential random graph model.

JEL Codes: F14, C45, Q17

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1.Introduction

Over the past decade, the global economy has faced a series of major, interconnected events that have deeply disrupted the cross-border exchange of goods and services. Once shaped by growing integration—improving economic efficiency and raising living standards through multilateral cooperation—the global supply chain has come under intense pressure. These strains include a major trade conflict between the U.S. and China (2017–18), a global health crisis (COVID-19), and armed conflicts such as that between Russia and Ukraine war and in the Middle East. Consequently, trade decisions are no longer guided purely by efficiency or comparative advantage. Instead, national security, strategic interests, and geopolitics are playing larger roles in shaping trade relationships (Staiger, 2021). This shift is particularly visible in how climate change, COVID-19, and armed conflict—referred to as the "Three C's" (Hendricks et al., 2022)—have sparked critical discussions about the fragility and future of global supply chains among stakeholders and policymakers alike.

Recent studies have explored how climate shocks and the pandemic affected production and logistics (Arora, 2019; Pu and Zhong, 2020). At the same time, armed conflicts, especially the ongoing war in Ukraine, have raised tough questions about the direction of globalization and the stability of international cooperation (Aiyar et al., 2023; Crozet and Hintz, 2020). These shocks have added to earlier trade disputes, such as the U.S.–China conflict (Staiger, 2021), pushing countries to rethink their supply chains to focus more on resilience and flexibility. In response, policy measures like the USMCA (2021), the CHIPS and Science Act (2022), and the European Chips Act (2023) have been introduced to reduce risks arising from the Three C's. Simultaneously, new research is looking into how growing geopolitical divisions are affecting international trade. The new stream includes studies on trade bloc formation (Jacks and Novy, 2020), the effects of technology separation between countries (Cerdeiro et al., 2021), and how these political divides challenge traditional systems of cooperation (Aiyar et al., 2023). For instance, Campos et al. (2023) suggest that global trade could shrink significantly if these political divisions continue. However, the impact of Three C's on agricultural trade has not received much attention—despite food security being a top priority for all nations. The broader shift away from globalization may have serious consequences for how food is produced, accessed and shared around the world.

This study adds to the emerging deglobalization literature by assessing how the Three C's are shaping global food supply chains. Using a network-based approach, we explore how trade relationships have shifted at national, regional and global levels. While past studies have mostly looked at each of the Three C's in isolation—or in pairs (e.g., Porfirio et al., 2018; Ahn and Steinbach, 2022; Arita et al., 2022; Khojasteh et al., 2022; Góes and Bekkers, 2023; Larch, Luckstead and Yotov, 2024)—our work brings these pieces together to understand their combined effects. We do this by using network graphs and models where countries are treated as points (nodes), and the trade between them are considered links (edges). As detailed below, this setup gives us new ways to track changes in trade flows and to uncover key patterns of influence and connectivity of countries over time.

We begin by looking at how individual countries behave within the trade network for any chosen commodity. Measures like in-degree (number of import sources), out-degree (number of export destinations), and betweenness (conduit for other countries' trade) centrality show how much influence a country has in importing, exporting, or bridging others in that trade network. We also use a measure called Laplacian energy to capture how critical a country is to the network, e.g., does a network lose its stability if a country is removed? To understand how trade is organized globally, we look at clusters of countries that trade more heavily among themselves. These "communities" are identified using a method that groups together tightly connected countries (Gui et al., 2014; Clauset et al., 2004). That is, countries within the same group trade more with each other than with those outside the group. At the global level, we use network-wide measures—like clustering coefficients and reciprocity—examine overall connectivity and stability of the trade network. A time series of these measures – centrality, communities and clustering – offer insights on the evolving structure of international agricultural trade networks.

Our descriptive analysis shows clear signs that food supply chains are moving away from global integration—a trend similar to what has already been observed in manufacturing and other sectors (Khadka et al., 2025). To illustrate, we look closely at two major commodities: pork (worth $36.9 billion in global trade) and wheat (worth $61.8 billion of global trade). Between 2011 and 2022, both commodities experienced significant shifts in their trade networks. Additional results for trade of other agricultural commodities—worth a combined $1.8 trillion—are included in the Appendix. For pork and wheat, we observe realignments in trade influence: China, for instance, has become more central, while Russia and the U.S. have become less critical to these networks. At the same time, the number of trade communities has increased, pointing to a trend of "friendshoring," where countries prefer trading with politically aligned or non-sanctioning partners. The decline in clustering coefficients for both commodities signals that the trade networks have become more fragmented.

Given these patterns, we next turn to explaining the forces behind changing influences, increased number of communities and fragmentation in agricultural trade networks. For this purpose, we use a statistical method called Exponential Random Graph Models (ERGMs) to analyze how and why countries form or break trade connections. These models allow us to account for each country's characteristics (e.g., economic size) and their relationships with others. We chose this method over more common trade models—like the gravity model—because network models better capture the web of dependencies in real-world trade (Anderson and van Wincoop, 2003; Yotov et al., 2016; Herman, 2022). There are several advantages in choosing network modeling over traditional econometric methods used in the trade literature such as the gravity model. First, network models capture the interdependencies inherent in trade relationships, while most regression models assume trade between countries to be independent, conditional on the covariates, thereby ignoring the implied interdependencies that exist in practice (De Nicola et al., 2023). The second is the ability to measure connectivity, and by extension, the stability of such trade networks, unlike econometric approaches (Khadka et al. 2025). Finally, gravity approaches are susceptible to a variety of specification and estimation issues (Krisztin and Fischer, 2015; Jeong et al. 2024).[2]

While traditional models are strong in explaining trade volumes between country pairs, network-based approaches are especially useful for uncovering the structure, dynamics, and resilience of the overall trade system—insights that are essential for understanding the current phase of deglobalization. ERGMs have been increasingly used in recent trade research. For example, De Nicola et al. (2023) used ERGMs to study arms trade patterns, and Smith et al. (2019) used a similar method to explore the global trade of medical equipment at the firm level.

[2]The difference in our approach is best illustrated by the Laplacian centrality measure, which assesses the systemic importance of a country by the impact of its removal from the network structure, efficiency, and resilience, considering the interconnectedness of its trading partners. This is in contrast to the potential biases introduced when removing a country from the estimation of a gravity model. Likewise, global metrics that describe the overall stability and resilience of food supply chains, such as the clustering coefficient, are inherent to network analysis but are absent in the gravity model framework. These metrics provide valuable insights into the structural properties of the supply chain based on the density of existing trade relationships compared to all possible connections.

ERGMs have also been used to study power structures in trade networks (Smith and Sarabi, 2022), the impact of R&D spending (Liu et al., 2022), and how trade relationships expand or contract (Herman, 2022). In this study, we apply ERGMs to agricultural trade data from 2002 to 2022, with a focus on how armed conflict, sanctions, and climate change—along with core trade drivers like GDP and distance—affect global food trade. This method also allows us to test how well the model can replicate real-world trade patterns, strengthening the reliability of our findings (Herman, 2022).

As with the descriptive analysis, we focus on pork and wheat in the main text, while results for 12 other key agricultural goods are presented in the Appendix. Across all commodities, we find that the Three C's have introduced serious disruptions into agricultural trade networks—especially in recent years. Conflicts and sanctions tend to lower the chances that countries will trade at all (the extensive margin), while higher greenhouse gas emissions are also linked to fewer new trade relationships. These findings support the earlier network-based observations in Khadka et al. (2025), which showed a weakening of global connectivity in food trade. While traditional economic factors like GDP and distance still play a role, their influence seems to be fading, suggesting that geopolitical and environmental issues are becoming more important drivers of trade decisions.

The remainder of this paper is structured as follows: section 2 outlines the data sources and methodological framework employed in our analysis. Following this, we present and discuss the key results from both our descriptive network analysis and ERGM estimations in section 3. Finally, section 4 provides policy implications while section 5 summarizes our main findings and offers insights into future research and policy.

2. Data and Methods

2.1 Data

To analyze the dynamics of international agricultural trade, this study utilizes trade data on pork and wheat. Data for pork were acquired from IHS Markit (S&P Global Market Intelligence), while data on wheat were sourced from UN-Comtrade.[3] Both datasets provide bilateral trade

[3] In the full dataset of 13 commodities, wheat and rice data are obtained from UN-Comtrade while data on the rest are retrieved from IHS Markit based on a subscription. See Chen et al. (2022) for a discussion on issues with UN-Comtrade data.

values at the Harmonized System (HS) 4-digit level. While the broader analysis encompasses eleven additional commodities,[4] this study focuses on pork and wheat to illustrate the key findings. Pork, with a global trade value of approximately $36.9 billion in 2022, represents the most traded meat commodity and a significant source of protein in Asia and Europe, underscoring its economic and dietary importance. Similarly, wheat, valued at around $61.8 billion in global trade, stands as one of the most traded grain and a staple food in numerous regions worldwide. These commodities are particularly relevant to our analysis of the 'Three C's' due to the significant involvement of countries engaged in trade and armed conflicts (e.g., Russia and China in pork trade, and Russia and the Middle East in wheat trade) in their production and exchange, thereby highlighting the divergence in food supply chains in response to these global challenges. To mitigate potential issues arising from data reporting and recording errors, we have restricted our analysis to trade relationships with an annual value exceeding $100,000.

Beyond the primary trade data, our analysis incorporates several additional datasets to represent traditional drivers of trade, as well as the influences of conflicts, sanctions, and climate change. Table 1 provides a comprehensive overview of these data sources and their respective variables.

Traditional Drivers of Trade: To account for conventional determinants of international trade, we include measures of population and GDP per capita, sourced from the World Bank's World Development Indicators (WDI, 2025). Data on geographical factors, specifically bilateral distance and border contiguity between countries, were obtained from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII), as described in Mayer and Zignago (2011). These variables are standard in the international trade literature and serve as baseline controls in our analysis.

Sanctions: Information on international sanctions was sourced from the Global Sanctions Database (GSDB) (Syropoulos et al., 2023). This comprehensive database provides yearly data on sanctions imposed across six categories: arms, military, trade (imports and exports), financial, travel, and other. The GSDB also includes details on the objectives and reported success rates of

[4] Fresh/chilled beef, frozen beef, pork, chicken, sheep/goat, rice, wheat, corn, soybean, soybean oil, palm oil, sunflower oil, rapeseed oil, and peanut oil.

these sanctions, allowing us to capture the multifaceted impact of such economic measures on trade relationships.

Conflict: To measure the impact of armed conflicts, we utilized data from the Uppsala Conflict Data Program (UCDP) (Davies et al., 2023). The UCDP provides dyadic-level information on armed conflicts resulting in more than 25 fatalities between two opposing actors, where at least one party is the government of a state. This dataset enables us to identify countries involved in both internal (within-state) and external (inter-state) conflicts. While there might be some overlap between conflict and sanctions data, it is crucial to distinguish between the two. As highlighted by Eberhard-Ruiz (2024) and De Groot et al. (2022), armed conflicts directly involve physical disruptions to trade and associated fatalities, whereas sanctions, as noted by McCormack and Pascoe (2015), can be imposed as a preventative measure in response to the threat of conflict or for other geopolitical objectives. Our analysis considers both dimensions to provide a more complete understanding of geopolitical fragmentation.

Climate Change: Climate-related data were obtained from NASA's Goddard Institute for Space Studies (GISS; Lenssen et al., 2019). The GISS dataset offers a wide array of climate change indicators. For this study, we selected greenhouse gas emissions (specifically methane) as a key proxy for climate change. This choice is motivated by the direct relevance of methane emissions to agricultural production and trade (Dellink et al., 2017; Shindell, 2016), as agriculture is a significant contributor to methane emissions, and these emissions can also be indicative of broader environmental changes impacting agricultural output and trade patterns.

2.2 Network Analysis

This study models international agricultural trade as a network, consistent with prior research in this area (Karakoc et al., 2022; Herman, 2022; Antonietti et al., 2020; Li et al., 2020; Rossi et al., 2018; Pathak et al., 2009), as well as other works cited in the introduction. A network is fundamentally composed of nodes, which represent individual entities, interconnected by edges, which represent the relationships between these entities. In a directed network, the relationship between two nodes is directional, meaning a connection from node A to node B is distinct from a connection from node B to node A. Conversely, an undirected network treats these two connections as the same. Furthermore, networks can be weighted, where each edge is assigned a numerical value reflecting the strength or intensity of the relationship between the connected nodes. In contrast, an unweighted network treats all connections as having equal significance.

For each commodity analyzed in this study, we construct an annual, directed, and weighted network. In these networks, individual countries serve as the nodes, and the edges represent the trade relationship between them for that specific commodity, with the weight of the edge corresponding to the value of the trade flow. Figure 1 provides a visual example of such a directed network.

2.2.1 Centrality Measures

Beyond simply examining the magnitude of trade flows, network analysis offers a more nuanced understanding of a country's role and significance within the export market. This importance can be quantified through various centrality measures, which provide insights into the nature of a country's connections across multiple dimensions within the trade network. Centrality measures have been widely applied in diverse research contexts. For example, Bramoullé et al. (2014) utilize them to investigate how interactions within a network can amplify the effects of individual agents' actions. Similarly, Firgo et al. (2016) employ centrality measures to explore the relationship between a country's influence within a network and its retail gasoline prices. In this study, we employ the following centrality measures to assess shifts in the importance of countries within the global food trade network.

Degree Centrality: This measure quantifies the number of direct connections a node has with other nodes in the network. In mathematical terms, the degree of a node is calculated as the sum of the connections it has. In a directed international trade network, out-degree centrality specifically measures the number of countries to which a given country exports, while in-degree centrality measures the number of countries from which a country imports. To facilitate comparison across networks of different sizes, the degree centrality values for each node in a network with n nodes can be normalized by dividing by the maximum possible degree in a simple directed network, which is $n-1$.

Betweenness Centrality: This measure assesses the frequency with which a particular node lies on the shortest path between all pairs of other nodes in the network. Mathematically, the betweenness centrality of a node is calculated by considering all pairs of nodes in the network and determining the proportion of shortest paths between them that pass through the node in question. A country exhibiting high betweenness centrality is likely to play a significant role as an intermediary, facilitating trade flows between other countries. In this study, these values are normalized by $(n-1)^2$ for directed networks (where n is the number of nodes), allowing for comparison of this measure across different networks.

Laplacian Centrality: This measure evaluates the importance of a node by assessing the impact of its removal on the overall stability and efficiency of the network. Specifically, it quantifies the reduction in the network's Laplacian Energy – a measure of the network's interconnectedness – that occurs when a particular node is removed. The Laplacian centrality of a node is calculated as the difference between the Laplacian Energy of the original network and the Laplacian Energy of the network without that node. Consequently, a country with a high Laplacian centrality is deemed to have a more substantial impact on the network's structure and stability, suggesting it plays a critical role in maintaining overall network cohesion.

2.2.2 Community Identification

A natural extension of employing network-based approaches is the identification of community structure, which involves partitioning the network into clusters of nodes that exhibit a high degree of connectivity among themselves. Within the context of international trade, each identified community represents a group of countries that engage in particularly close trading relationships. A widely used method for identifying these communities involves optimizing a metric known as modularity, which quantifies the strength of the division of the network into communities. Modularity is calculated by assessing the density of edges within communities compared to the density of edges between communities. Specifically, it compares the number of actual connections within a group of nodes to the number of connections that would be expected by chance, given the overall structure of the network.

For directed graphs, the Clauset-Newman-Moore greedy modularity maximization algorithm (Clauset et al., 2004; Gui et al., 2014; Monken et al., 2021) is employed in this study. This algorithm is an efficient method for finding communities by iteratively merging nodes or communities in a way that maximizes the modularity score. The algorithm begins by assigning each node to its own community. It then proceeds by iteratively joining pairs of communities together, selecting the merge that results in the largest increase (or smallest decrease) in the overall modularity of the network. This process continues until no further improvement in modularity can be achieved. In our application, the values of the trade relationships are incorporated as weights on the edges of the directed network, and community detection is performed on this weighted and directed structure. For algorithmic optimization purposes, nodes with fewer than two trading partners are excluded from the network prior to community detection. These network analyses are conducted for each year between 1995 and 2022. However, for clarity in presentation, the results pertaining to the average number of communities are presented as five-year averages. All network-based analyses in this study are implemented using the NetworkX package in the Python programming language. Khadka et al. (2025) provide a further discussion of two alternative community detection measures: Louvain's algorithm (Dugué and Perez, 2022) and asynchronous label propagation (Raghavan et al., 2007).

2.2.3 Average Clustering Coefficient (c)

The average clustering coefficient of a network quantifies the propensity of nodes within the network to form clusters or triangles, indicating the extent to which a country's trading partners are also trading with each other (Henriet et al., 2012). For a weighted directed network, the clustering coefficient for each node is calculated as the geometric mean of the normalized weights of the edges forming the closed triplets (directed triangles) connected to that node. This calculation considers the number of directed triangles centered on the node, the sum of its in-degree and out-degree, and the normalized weights of the incoming and outgoing edges involved in these triangles. The average clustering coefficient for the entire network is then computed as the average of the clustering coefficients of all individual nodes in the network. A network with a high average clustering coefficient suggests a greater prevalence of interconnected trading among a country and its immediate trading partners, which typically contributes to higher overall network stability and resilience. Conversely, a low average clustering coefficient implies a more fragile network where trading relationships are less clustered, and disruptions to key bilateral linkages could potentially have cascading effects, destabilizing larger portions of the network.

2.2.4 Exponential Random Graph Methods (ERGMs)

This study employs Exponential Random Graph Models (ERGMs), following the methodological framework detailed by Lusher et al. (2013), to analyze the structural determinants of international agricultural trade. Consistent with the network representation described previously and illustrated in Figure 1, countries engaged in trade are modeled as nodes, and the trade relationships between them constitute the edges of the network. Country-specific variables, such as population size and Gross Domestic Product (GDP), are incorporated into the analysis as attributes of the nodes, while inter-country variables, including the presence of sanctions, involvement in armed conflicts, and geographical distance, are included as attributes of the edges. As discussed in the introduction, the application of ERGM offers several advantages over traditional gravity models, particularly in its ability to account for the inherent interdependencies within trade networks, to model complex network structural attributes including stability, and to address certain specification and estimation challenges (Anderson and van Wincoop, 2003; Krisztin and Fischer, 2015; Yotov et al., 2016; Herman, 2022; De Nicola et al., 2023; Jeong et al. 2024; Khadka et al. 2025).

ERGMs are a class of statistical models that treat the observed network as a single realization from a probability distribution of possible networks. The fundamental principle underlying ERGMs is the idea that the probability of observing a particular network configuration is determined by a combination of local network structures and node or edge attributes. In its simplest form, one can consider a scenario where each potential trade relationship (an edge between two countries) is assumed to occur with an identical probability. Under this assumption, the probability of observing a specific network configuration would be the product of the probabilities of each individual potential relationship being either present or absent (Erdős and Rényi, 1959; Gilbert, 1959). However, this basic specification is inadequate for capturing the complexities of real-world trade relationships, which are influenced by a multitude of factors as outlined in the data section.

To account for these complexities, ERGMs allow the probability of a trade relationship between any two countries to be conditional on a set of explanatory variables. Specifically, a matrix of covariates is introduced, enabling the probability of each potential edge to be unique and dependent on the characteristics of the trading partners and their relationship. The logarithm of the odds of a trade relationship existing between two countries can be modeled as a linear function of these covariates, with the coefficients of this function estimated using maximum likelihood methods (De Nicola et al., 2023). This framework leads to a model where the probability of observing a particular trade network configuration is a function of the exponential of a weighted sum of these covariates, normalized by a term that ensures the probabilities of all possible network configurations sum to one.

Each ERGM can be formally characterized as belonging to the exponential family of distributions. The probability of observing a particular network is expressed as an exponential function of a vector of parameters and a corresponding vector of sufficient statistics that summarize the structural features of the observed network. This formulation also includes a baseline measure and a normalizing constant that depends on the model parameters (Wasserman and Pattison, 1996). The values of the parameters in the ERGM are estimated using Markov Chain Monte Carlo (MCMC) simulation techniques. The goal of this estimation process is to find the parameter values that make the observed trade network the most probable outcome among all possible network configurations. The estimated parameters thus reveal the strength and direction of the association between each included attribute or structural feature and the formation of trade relationships in the network (Herman, 2022). The estimation typically begins with an initial set of parameter values, which are then iteratively updated using algorithms such as the Metropolis-Hastings algorithm (Robert et al., 2015) to explore the space of possible networks and converge on the parameter estimates that best fit the observed data. Following the MCMC estimation, the ensemble of simulated networks is compared to the observed network using various diagnostic tests to assess the goodness of fit of the model. If the model fit is deemed inadequate based on these diagnostics, the estimation process is repeated with adjustments to the model specification or estimation parameters.

The specific ERGM specification employed in this study models the presence of a trade relationship as a function of several factors, including the baseline propensity for trade (edges term), the tendency for transitive relationships (Geometrically-Weighted Edgewise Shared Partnerships – GWESP), the attributes of the trading partners (population, difference in GDP, greenhouse gas emissions), geopolitical factors (conflict within and between countries, sanctions), and geographical or cultural factors (common language, border contiguity).

A key distinction within ERGMs lies between dyad-independent and dyad-dependent terms. Dyad-independent terms model the likelihood of a trade relationship forming between two countries based solely on their individual attributes or the characteristics of their direct relationship, without considering the broader network structure. Conversely, dyad-dependent terms capture the influence of the network structure itself on the formation of individual trade relationships. In this analysis, we primarily employ the Geometrically-Weighted Edgewise Shared Partnerships (GWESP) term to capture this network dependence, focusing on the tendency for countries that share common trading partners to also trade with each other. While other dyad-dependent specifications exist, such as k-stars, Geometrically-Weighted Dyadwise Shared Partnerships (GWDSP), and Geometrically-Weighted Degrees (GWDEGREE), their inclusion in this analysis was limited due to computational constraints.

The estimated parameters from the ERGM can be transformed to obtain the log-odds of a trade relationship forming, and subsequently, the conditional probabilities of such a relationship. These probabilities offer insights into the relative importance of each variable in determining the likelihood of trade flows, providing a perspective somewhat analogous to the coefficients obtained from gravity models. Furthermore, ERGMs allow for the analysis of homophily, which refers to the tendency of nodes with similar attributes to form connections more frequently. This enables us to investigate whether, for example, countries with similar GDP levels are more likely to trade with each other, or if countries facing similar geopolitical challenges exhibit distinct trading patterns.

A significant advantage of ERGMs is their capacity to examine the structural properties of networks, an aspect often not directly addressed by traditional econometric methods in international trade. Given the inherent network structure of international trade, applying ERGM allows us to uncover shifts in patterns of cooperation and interconnectedness among countries. Specifically, the GWESP term serves as a valuable metric for evaluating the level of embeddedness within the network by estimating the likelihood of observing mutual trade partners between countries. A significantly positive coefficient for GWESP indicates a higher prevalence of transitive relationships (triangles) in the network than would be expected by chance, suggesting that countries sharing trade partners are more likely to form a trading relationship themselves. This phenomenon of "triadic closure" has important implications for the efficiency and resilience of global trade flows. High interconnectivity can, for instance, provide alternative trade channels that can mitigate the impact of disruptions in specific bilateral relationships.

All ERGM analyses in this study were conducted using the ergm package (version 4.6.0) within the R programming language (version 4.1.2). Due to the limitations of the package in handling missing data, the analysis was restricted to the top 45 largest economies based on GDP (a list of these countries is provided in the Appendix). Individual trade networks were constructed for each commodity and for each year between 2002 and 2022, and ERGM models were fitted to each of these networks. The best-fitting model for each case was identified through a process of assessing model diagnostics and evaluating the goodness of fit. This involved using the estimated ERGM parameters to generate multiple simulated networks and then comparing key structural properties of these simulated networks (such as network density, degree distribution, and edgewise shared partners) to those observed in the actual trade data. The Appendix provides a detailed account of the model validation measures employed in this study.

3. Results

3.1 Centrality Changes

Beyond traditional analyses that focus on fluctuations in trade volumes, examining centrality measures offers a valuable alternative lens through which to understand the evolving relative importance of countries within the global agricultural supply chain. Figure 2 visually represents the changes in four key centrality measures for the United States, Russia, and China between 2010 and 2022. These three countries are of particular interest as the former two are significant exporters of agricultural commodities, while the latter is a major global importer. The shaded region in the figure highlights the period impacted by the COVID-19 pandemic (2020-2022). The top panel of Figure 2 focuses on pork, while the bottom panel examines wheat. The corresponding results for the remaining eleven commodities included in this study can be found in the Appendix.

The trends depicted in Figure 2 reveal considerable year-to-year variation in the centrality measures for both pork and wheat, as well as for the other commodities analyzed (Appendix Figure A.1). Focusing first on in-degree centrality, which reflects the number of countries from which a nation imports, Russia experienced a notable decrease in its pork import partners starting around 2014. This decline coincides with the period following the annexation of Crimea and the subsequent imposition of international sanctions. Conversely, China exhibited a steady increase in the number of countries from which it imports pork, reaching a peak in 2018. This peak likely reflects the impact of the African Swine Fever (ASF) outbreak, which significantly constrained China's domestic pork supply. The United States, a major global exporter of pork, showed a consistent downward trend in its out-degree centrality, which measures the number of countries to which it exports pork, decreasing from 0.470 in 2010 to 0.330 in 2022. Interestingly, both Russia and the United States experienced a marked decline in betweenness centrality for pork, although the underlying drivers appear different. Russia's decline appears to be associated with its reduced number of import sources, while the United States' decline is linked to a decrease in its export destinations.

Similar patterns emerge in the wheat market. China has also expanded the number of countries from which it imports wheat over the period examined. On the export side, Russia was consistently successful in establishing new markets for its wheat exports in the years leading up to the pandemic. In contrast, the United States has shown a consistent trend towards engaging with fewer export partners for wheat, with its out-degree centrality decreasing from 0.477 in 2010 to 0.327 in 2022. This trend is also mirrored in the betweenness centrality of the United States for wheat, with the exception of a temporary increase observed during the pandemic years.

The Laplacian centrality of a country, which reflects its influence on the overall supply chain by measuring the change in the network's Laplacian energy upon its removal, reveals interesting dynamics (rightmost panels of Figure 2). The data suggest a declining influence of the United States in the global food supply network since the latter half of the 2010s, with the COVID-19 pandemic period representing a temporary deviation from this trend. This decline is particularly pronounced in the wheat market, although a decrease in Laplacian centrality is also observed in the pork market following a peak in 2017. Conversely, China's Laplacian influence has shown a steady increase in both the pork and wheat markets throughout our sample.

However, the changes observed in the influence of the United States and China are less dramatic than the significant decline in Russia's influence, which coincides with the period of reciprocal sanctions following the Crimean invasion in early 2014. As detailed by Bown (2023), the European Union (EU) and the United States independently implemented successive rounds of economic sanctions against Russia following the Crimean annexation. In response, Russia imposed its own import bans on the countries that had sanctioned it, effectively transforming what began as an import sanction into a broader trade sanction, as discussed by Joshi (2024). It is important to reiterate that while this study observes these correlations, this particular section does not delve into establishing causal relationships between sanctions and trade patterns. Nevertheless, these reciprocal actions provide valuable context for understanding the effects of sanctions, especially when considered alongside the findings on community structure changes presented in the subsequent section.

Finally, the analysis highlights an important distinction. The trade disruptions linked to sanctions and conflicts represent IDIOSYNCRATIC SHOCKS affecting specific countries, while COVID-19 acted as a SYSTEMIC GLOBAL SHOCK. The next section builds on this distinction by examining how these shocks also altered the broader community structure of global agricultural trade.

3.2 Community Detection

Examining the evolution of community structure within the global agricultural trade network provides another critical perspective on the shifts occurring in the food supply chain. The number of distinct trading communities is influenced by two primary, often opposing, forces. On one hand, economic optimization, driven by principles of comparative advantage operating on a global scale, tends to foster larger, more integrated communities as countries specialize and trade efficiently. Conversely, concerns regarding the resilience and robustness of supply chains, particularly in the face of geopolitical tensions, pandemics, and climate-related disruptions (the 'Three C's'), can incentivize the formation of smaller, more localized trading blocs, leading to an increase in the number of communities and greater fragmentation.

Table 2 presents the average number of communities identified for pork and wheat using the Clauset-Newman-Moore modularity optimization algorithm across different time periods: a five-year average for 2010-2014, another for 2015-2019, and a specific average for the post-pandemic period of 2020-2022. Results for the eleven additional commodities analyzed in this study are available in Appendix B. The observed increase in the average number of communities in recent years strongly suggests a growing fragmentation of the global food supply chain into smaller, more tightly knit groups of trading partners. This trend towards fragmentation likely results in reduced overall efficiency compared to a hypothetical network configuration driven solely by traditional economic factors like comparative advantage.

Analyzing the temporal evolution of network structure reveals a dynamic interplay between forces of convergence and divergence. The initial period of 2010-2014, when the global economy was in a phase of recovery following the 2008 financial crisis, generally exhibited a smaller number of trading communities for both pork and wheat, suggesting a degree of convergence. However, the subsequent period, beginning around 2015, witnessed an acceleration of de-globalization, coinciding with significant geopolitical events such as the 2014 Crimean invasion, the political uncertainties surrounding the 2016 US presidential election and the UK's Brexit referendum, and the escalation of US-China trade disputes starting in 2018-2019. The increase in the five-year average number of communities from 2010-2014 to 2015-2019 for both pork (7.6 to 8.4) and wheat (7.8 to 8.4) provides quantitative evidence of this growing divergence in the global food supply chain. This trend aligns with existing literature highlighting the contractionary effects of conflicts, trade disputes, sanctions, and the COVID-19 pandemic on international trade, often driven by heightened economic uncertainty (Bonadio et al., 2021; Frank, 2018; Glick and Taylor, 2010; Khadka et al., 2023). Sensitivity analyses using alternative community detection algorithms, presented in Khadka et al. (2025), corroborate these findings.

Figure 3 further illustrates the annual fluctuations in the number of communities for pork and wheat. Up until approximately 2015, the trade patterns in both commodities displayed a tendency towards fewer communities, indicating a period of convergence following the disruptions of the 2008 Global Financial Crisis. However, the period from 2015 to 2019 marked a return of uncertainty and a corresponding increase in the number of trading communities. The onset of the systemic COVID-19 pandemic in 2020 appears to have triggered some degree of regrouping in trade patterns, a phenomenon that will be discussed further in conjunction with clustering effects.

A closer examination of the identified communities provides insights into the impact of sanctions and the emergence of friendshoring within global food trade networks. For instance, in 2013, Russia's primary sources of pork imports were Brazil, Germany, Denmark, Canada, and Poland. However, following the 2014 Crimean invasion and the subsequent reciprocal sanctions, Russia's trade strategy underwent a significant transformation. By 2015, Brazil became an even more dominant pork supplier to Russia, while other major partners were replaced by countries like Chile, Ukraine, Serbia, and China, each with significantly lower import values. This increased reliance on Brazil and the shift away from Western European partners exemplifies how sanctions can lead to friendshoring, where trade is redirected towards countries perceived as friendly or non-sanctioning. Furthermore, Russia significantly increased its domestic pork production from 2.8 million metric tons in 2013 to 4.5 million metric tons in 2022. This surge in domestic production, coupled with the shift from being a net importer to a net exporter of pork within a decade, is reflected in the network structure. In 2022, the Russian pork trading community had shrunk to include only itself and Belarus, following its exit from a larger community comprising Brazil, Argentina, and China in 2020. These shifts in community membership corroborate the previously observed declines in Russia's in-degree and Laplacian centralities in the pork network, likely driven by the imposition of sanctions and the subsequent adoption of friendshoring strategies.

Similarly, the community structure for wheat experienced substantial changes in the last decade. As a major exporter, Russia saw its wheat trading community expand from 14 members in 2010 to 20 members in 2019, primarily consisting of countries importing wheat from Russia. A particularly notable change occurred with Turkey. In 2013, the United States was Turkey's second-largest wheat supplier. However, in 2014, Turkey significantly increased its wheat imports from Russia. This trend intensified following the imposition of US sanctions on Turkey in 2018, leading to a complete cessation of Turkish wheat imports from the United States while Russian wheat exports to Turkey remained consistently high. These developments further illustrate the simultaneous effects of sanctions, which create incentives for supply chain realignments, and trade diversions facilitated by friendshoring.

The observed surge in the number of communities after 2015, driven by economic uncertainties stemming from the 'Three C's', carries significant implications for global food security. This increased fragmentation can lead to several adverse economic outcomes, including higher trade costs, reduced efficiency in resource allocation, diminished economic opportunities, impediments to global poverty reduction efforts, and ultimately, lower overall living standards, with potentially disproportionate impacts on developing economies (Aiyar et al., 2023). The changes in community structure also suggest that sanctions, regardless of their intended effectiveness in other sectors, can inadvertently contribute to further divergence within food supply chains. These findings align with existing literature suggesting the relative ineffectiveness of sanctions due to the availability of alternative mechanisms for circumventing trade bans or embargoes (Felbermayr et al., 2020).

It is important to note the differential impact of systemic versus idiosyncratic shocks on the network structure. While idiosyncratic events, such as Russia's military action in 2014, appear to create divisive forces leading to fragmentation, systemic shocks like the COVID-19 pandemic seem to have initially prompted some degree of network stabilization or regrouping. This distinction will be further explored after examining the clustering effects in the subsequent section.

3.3 Global Changes

Beyond examining changes at the country and aggregate levels, analyzing global-level properties of the international agricultural trade network also reveals an emerging pattern of divergence. This subsection presents one such measure, the average clustering coefficient, to evaluate the overall connectivity between countries in the network. Khadka et al. (2025) provide an alternative global network metric for all analyzed commodities. Figure 4 displays the temporal changes in the average clustering coefficient for pork and wheat. The average clustering coefficient provides an indication of the density of observed linkages in the supply chain relative to the total number of possible linkages, reflecting the overall interconnectedness of the network.

In both the pork and wheat markets, a noticeable drop in the average clustering coefficient occurs following the 2014 Crimean invasion and the subsequent imposition of sanctions. This effect is particularly pronounced in the wheat trade, where Russia plays a dominant role as an exporter. This decline in clustering, in addition to signifying increasing levels of divergence, further highlights the potential indirect effects of sanctions, such as trade diversion, in global markets. In both the pork and wheat cases, where alternative trading partners were readily available for both importers and exporters, the clustering within the network decreased considerably. The impact of the COVID-19 pandemic is also clearly evident in the trends of the average clustering coefficient for both wheat and pork supply chains, with a sharp decline observed at the onset of the pandemic in 2020. This reflects the significant disruption caused by the near-total collapse of both the demand and supply sides of the global economy. While an upward trend appears to be emerging in both commodities as the global economy gradually returns to normalcy, the clustering coefficient levels have not yet shown signs of recovering to their previous peaks observed during the 2010-2014 period, suggesting a potentially lasting impact on the overall interconnectedness of these supply chains.

3.4. Idiosyncratic vs. Systemic Shocks

A comparative analysis across all thirteen agricultural commodities examined in this study, utilizing the array of network measures including centrality, community structure, and clustering coefficients (and their respective alternative metrics detailed in Khadka et al. (2025)), reveals a clear distinction in the impact of different types of global shocks. Specifically, the evidence strongly suggests that idiosyncratic shocks tend to induce a divergence within the international agricultural trade network. Conversely, the COVID-19 pandemic, particularly in its later phases (2021 and 2022), generally fostered a tendency towards convergence and increased interconnectedness.

This differential impact is particularly evident when examining centrality measures. Idiosyncratic shocks, such as the Crimean crisis and the outbreak of African Swine Fever (ASF), appear to redistribute influence within the network, with certain countries gaining prominence often at the expense of others. In contrast, the onset of the systemic COVID-19 pandemic witnessed a broader recovery of centrality and influence across a larger proportion of network participants. This suggests that while localized crises can create winners and losers in terms of trade influence, a global systemic shock like a pandemic may, in its later stages, prompt a re-engagement and strengthening of ties for a wider range of actors.

The analysis of community structure further supports this dichotomy. The period between 2014 and 2019, characterized by several idiosyncratic shocks, saw a marked increase in the number of distinct trading sub-chains (communities), indicative of a fragmentation of the global agricultural trade landscape. However, during the COVID-19 pandemic, this trend of increasing community numbers either stagnated or slowed down, suggesting a potential resistance to further fragmentation or even a degree of consolidation in trading relationships.

Similarly, the trends in clustering coefficients, a measure of overall network interconnectedness, reveal contrasting patterns. Following the idiosyncratic shocks that occurred during the study period, the clustering coefficients generally exhibited a downward trajectory, suggesting a decrease in the density of local trading relationships and increased network fragility. Conversely, the COVID-19 pandemic period typically saw an inflection point in these trends, with clustering coefficients generally moving upwards, indicating a strengthening of local connections and potentially greater network resilience in the face of a global crisis.

These findings resonate with observations in the financial literature, which has documented a similar phenomenon during systemic crises such as the 2008 Global Financial Crisis and the COVID-19 pandemic. Research in that domain suggests that such widespread crises can trigger market-driven dynamics that lead to increased connectedness and interdependence among countries (Dermirer et al., 2018). Our analysis of the international agricultural trade network provides further evidence of this contrasting response to different types of global shocks, highlighting the complex and evolving nature of international trade relationships in the face of both localized disruptions and global systemic events.

3.5 ERGM Results

With descriptive statistics of agricultural trade networks pointing to fragmentation associated with the “Three C’s”, we turn our attention to causal modeling with the ERGM framework. The underlying drivers of international pork trade relationships, as revealed by our Exponential Random Graph Models (ERGMs) estimated over five-year intervals from 2002 to 2022, offer compelling insights into the structural forces at play (Table 3).

Focusing on a key ERGM coefficient, a consistent and statistically significant positive estimate for the Geometrically-Weighted Edgewise Shared Partnerships (GWESP) term across all periods underscores a robust tendency for triadic closure within the pork trade network. This finding suggests that countries are significantly more inclined to forge bilateral trade links when they already share a common trading partner, indicating a form of network embeddedness. However, the gradual decline in the magnitude of this coefficient over time, decreasing by 17.93 percent from 2002 to 2022, hints at a subtle shift where the likelihood of such transitive relationships forming has slightly decreased, even after accounting for other influential factors. This could potentially be linked to the increasing fragmentation observed in our community detection analysis, where new trading relationships might be forming outside of established triadic structures.

As expected, traditional variables typically included in gravity models – GDP, population, distance, common language and shared borders – exhibit anticipated effects but with mixed trends. For example, the GDP coefficient in table 3 becomes smaller and turns statistically not significant between 2002 and 2022. In contrast, sharing a border or having a common language indicate a substantially higher probability of trade between countries, reinforcing the well-established role of such ties in facilitating international exchange.

Interestingly, the coefficient associated with greenhouse gas emissions is consistently negative and statistically significant across most of the examined years. This finding suggests that higher levels of greenhouse gas emissions are associated with a reduced likelihood of bilateral pork trade. While the precise mechanisms behind this effect warrant further investigation, one plausible explanation aligns with the understanding that agricultural production is a significant contributor to such emissions. As countries potentially prioritize domestic pork production to meet local demand, as was the case with Russia discussed earlier, this could lead to increased emissions and a corresponding decrease in international trade volumes. Alternatively, the climate change induced by these emissions may introduce greater volatility and uncertainty in agricultural production and distribution networks, thereby discouraging the formation of new or the maintenance of existing trade relationships (Dellink et al., 2017). The documented negative impacts of methane emissions (a key greenhouse gas) on crop yields (Shindell, 2016) further support this interpretation, as disruptions in feed production could indirectly affect pork trade.

In line with expectations and the observed trends in centrality and community structure, our ERGM results demonstrate that conflict acts as a significant deterrent to the formation of international pork trade relationships. Our analysis distinguishes between the impact of domestic conflicts (within a country) and international conflicts (between countries). Notably, the conditional probability of engaging in pork trade was lowest for countries experiencing domestic conflict in 2022, and similarly low for countries involved in armed conflict with each other. These findings, supported by data from the Uppsala Conflict Data Program highlighting the involvement of several populous nations in conflicts in 2022, underscore the disruptive influence of both internal and external strife on international trade, echoing the theme of idiosyncratic shocks leading to divergence.

The impact of sanctions on international trade, a subject of considerable debate in the existing literature, is also clearly evident in our ERGM results. Our analysis consistently reveals that the imposition of sanctions significantly diminishes the likelihood of establishing pork trade relationships. This negative effect appears to have intensified in recent years, raising concerns about the broader implications of sanctions on global food supply chains. The case of Russia provides a compelling illustration. Prior to the Crimean invasion and subsequent sanctions (and Russian counter-sanctions), Russia maintained significant pork import relationships with Brazil, Germany, and other European nations. However, following these geopolitical events, Russia strategically shifted its import dependence towards Brazil while simultaneously investing heavily in expanding its domestic pork production capacity. This case study highlights the potential of sanctions to trigger significant realignments in established trade patterns and foster friendshoring, a trend also observed in our community detection analysis.

The results for international wheat trade, presented in Table 4, reveal a set of underlying factors shaping trade relationships that echo some of the patterns observed in the pork market, albeit with notable distinctions. The Geometrically-Weighted Edgewise Shared Partnerships (GWESP) term, which captures the tendency for triadic closure, remains positive and statistically significant across all examined years. This indicates that, similar to pork, countries involved in wheat trade are more likely to establish new trade links with partners who share existing trade connections. However, the magnitude of these coefficients is smaller for wheat compared to pork, suggesting a less pronounced clustering tendency in the global wheat trade network. Furthermore, the GWESP coefficient for wheat experienced a substantial decrease of over 37% between 2002 and 2022, signaling a weakening of this clustering effect over time. This trend could be indicative of a shift towards more diverse or less embedded trading relationships in the wheat sector, potentially contributing to the increased number of communities observed in our earlier analysis.

Notably, and consistent with the pork results, many coefficients associated with traditional gravity model variables in the wheat model lack statistical significance or have diminished in magnitude since 2002, suggesting a potentially evolving role of these factors in shaping wheat trade.

Mirroring the findings for pork, both domestic and international conflicts exert a negative influence on the likelihood of wheat trade. However, the magnitude of these detrimental effects has more than doubled between 2012 and 2022, underscoring the increasing disruptive power of conflict on wheat supply chains. The impact of international conflicts was particularly pronounced around 2017. Given the significant role of Russia and Ukraine as major global wheat exporters (collectively accounting for a substantial share of global exports), we anticipate that the downstream consequences of the ongoing conflict in the region will further amplify these negative effects as more recent data become available, aligning with the theme of idiosyncratic geopolitical shocks causing significant trade divergence.

Sanctions also consistently reduce the probability of wheat trade, with their impact intensifying over the study period. While the effect of sanctions was statistically weak in the earlier years (2012 and 2017), it has significantly strengthened by 2022, becoming highly statistically significant. This growing impact of sanctions, likely to be further evidenced in post-Russia-Ukraine conflict data, highlights the increasing role of geopolitical factors in reshaping global wheat trade patterns. Consistent with our pork findings, negative coefficients associated with greenhouse gas emissions suggest that climate change is also contributing to disruptions in international wheat trade.

In summary, the ERGM results for wheat, in conjunction with those for pork and the broader set of agricultural commodities (detailed in the Appendix), reinforce the conclusion that factors beyond traditional economic drivers, namely conflicts, sanctions, and climate change, are playing an increasingly significant role in distorting the landscape of international agricultural trade. Figures 5 and 6 present the trend of estimates for the features under study, scaled for better comparison among them and ease of visualization. Figure 2 highlights the growing impact of conflicts, sanctions, and climate change on pork trade formation in recent years, with a notable inflection point around 2016.[5] Fitted trends indicate that this pattern is likely to persist. Interestingly, the trendline for GWESP runs in the opposite direction with the same inflection point. Together, the evidence suggests that the stresses put on trade due to these factors are incentivizing countries to solidify their trading blocs. The effects of features under study on wheat trade exhibit similarities to those observed in pork trade but are more pronounced. Notably, the adverse impacts of domestic conflicts and sanctions have intensified significantly since 2017. Likewise, the effects of international conflicts on wheat trade have been particularly severe around 2014, coinciding with Russia's annexation of Crimea. This event directly affected two of the largest wheat exporters, Russia and Ukraine, which collectively accounted for $7.7 billion in exports. Subsequent shocks to these producers have further amplified disruptions, propagating downstream effects throughout the trade network, as evident in the data. Additionally, the trend in the GWESP term suggests an increasingly fragmented global trade network. Collectively, these patterns signal a more disconnected network.

4. Policy Implications

The above research using network-based methods provides fresh evidence of deglobalization in global agricultural trade. Unlike the conventional gravity model, this approach applies a structural and theoretically consistent framework to capture the evolving dynamics of international trade networks. The results show a notable decline in global integration, demonstrated by falling clustering coefficients and the rise of smaller, more insular trade communities—often described as "friendshoring" (Khadka et al., 2025). This shift has been accelerated by the "Three C's"—conflicts, climate change, and COVID-19—each of which has disrupted established supply chains and weakened the comparative-advantage foundations that traditionally underpinned globalization. The consequences are immediate and far-reaching: both the availability of food and access to essential nutrients are increasingly determined by geopolitical alignments and mutual alliances, rather than solely by market forces.

[5] Additional charts including the effects of traditional drivers are available on request.

Agricultural trade reform has historically been contentious, as illustrated by the Uruguay Round Agreement on Agriculture in 1994 and the stalled Doha Round negotiations that remain unresolved after more than two decades. Today, rising uncertainty surrounding the criteria for "friendly" trade partners adds new complexity to this already difficult landscape. This trend toward deglobalization carries implications well beyond trade negotiations. It influences investment patterns, reshapes innovation strategies, and complicates poverty alleviation efforts, particularly in the agriculture and food sectors where global market interdependence has long played a stabilizing role. Countries excluded from new clusters or lacking strong alliances face heightened vulnerability, while those within influential trade blocs stand to gain disproportionate benefits.

Causal analysis in the above network based research reinforces the importance of non-traditional factors such as conflicts, sanctions, and climate shocks in shaping trade outcomes. These forces now rival conventional drivers of trade and exert structural impacts on global networks. Conflicts and sanctions that restrict major exporters can amplify food price volatility, exacerbate supply shortages, and undermine confidence in global markets. Climate-related disruptions—whether through droughts, floods, or extreme weather events—intensify the fragility of supply chains and highlight the urgency of diversifying trade routes and investment in resilient infrastructure. COVID-19 further underscored the long-term risks of overdependence on a narrow set of suppliers, as many countries adopted policies of self-reliance and selective partnership, leaving lasting imprints on trade connectivity.

For policymakers, these findings signal the need for a recalibrated approach to agricultural trade policy. Strategies should prioritize the diversification of trade partners to reduce exposure to geopolitical and climate-related shocks, while also evaluating the unintended consequences of sanctions that may disrupt global supply chains. At the same time, integrating climate resilience into trade policy is increasingly critical, requiring investment in sustainable logistics, adaptive production systems, and cooperative mechanisms for crisis management. Strengthening multilateral institutions remains essential to coordinate responses, stabilize markets, and provide platforms for addressing systemic shocks collectively rather than through fragmented national approaches. Special attention must also be given to developing countries, which are disproportionately affected by volatility in global markets and face acute risks of food and nutrition insecurity if excluded from emerging trade blocs.

Ultimately, the evidence points to an urgent need for stronger international cooperation at the intersection of trade, climate, and conflict policy. Coordinated emissions reductions, more effective institutions for conflict resolution, and the deliberate integration of resilience strategies into trade agreements are essential to safeguard both global and national interests. Without such measures, the erosion of global connectivity risks undermining decades of progress in agricultural development and poverty alleviation. Conversely, deliberate alignment of climate policy, conflict mitigation, and trade reform offers a path to a more stable and equitable global food system. For governments, multilateral bodies, and development partners, the central message is clear: the future of agricultural trade and food security will depend as much on political and environmental choices as on economic efficiency, and proactive policy action is required now to ensure resilience in the face of growing systemic shocks.

5. Conclusions

In recent years, a discernible shift away from decades of consistent globalization and trade integration towards increasing economic fragmentation has become evident. This trend, propelled by pivotal events such as the 2014 Crimean invasion and subsequent conflicts, US-China trade tensions, and Brexit, alongside growing uncertainties stemming from the COVID-19 pandemic and climate change, has prompted a significant re-evaluation of the benefits and future trajectory of globalization. While realignments in the sectors such as energy and manufacturing have been discussed at length in the literature, the food and agriculture sectors have received comparatively less attention in this context. The evidence presented in this study, analyzed across country, group, and global levels, reveals the emergence of a more fragile and disjointed agricultural supply chain. This evolving landscape is characterized by a tendency for countries to coalesce into smaller groupings based on geographical proximity and potentially shared ideological perspectives, rather than adhering to a globally integrated system driven primarily by comparative advantage and efficiency-based trade dynamics.

Notably, the influence of major historical exporters such as Russia and the United States appears to be waning within this shifting landscape. The observed increase in the number of trading communities and strongly connected components further substantiates the growing divergence within global agricultural supply chains. Similarly, global network measures, such as changes in the clustering behavior, point towards a decline in the overall stability of the supply chain. Furthermore, our analysis highlights the potential indirect effects of economic sanctions, which, while not always directly targeting the food sector, can induce significant distortions in food supply chains, often preceding notable shifts in the influence and composition of individual countries within the global food network.

Employing Exponential Random Graph Models (ERGMs), this study aims to integrate causal analysis to examine the impact of key determinants – namely conflicts, sanctions, and climate change – on the formation of international agricultural trade relationships. The findings underscore the significant role of these factors in reducing the probability of trade between countries, particularly in recent years, thereby contributing to the observed fragmentation and potentially exacerbating trade imbalances. This highlights the utility of network analysis, which, unlike traditional econometric approaches focusing on aggregate trade flows, allows for a more detailed exploration of the intricate interconnections between countries and the underlying structural factors driving trade dynamics.

As the global economy grapples with the imperative of building resilient supply chains, policymakers must recognize the profound impact of external shocks on international trade and overall economic stability. Policy adjustments in areas such as trade partnerships and the diversification of trade routes can play a crucial role in mitigating the adverse consequences of conflicts and climate-related disruptions. Moreover, the insights from this research can inform assessments of the unintended consequences of economic sanctions, particularly when imposed on significant players in global agricultural markets, potentially leading to supply chain bottlenecks and price volatility.

The findings of this study underscore the critical need for enhanced international cooperation in addressing the intertwined challenges of conflicts and climate change, given their far-reaching implications for global trade and food security. Concerted efforts to reduce greenhouse gas emissions and strengthen multilateral organizations could contribute to stabilizing trade networks and ensuring more equitable access to agricultural goods. Furthermore, integrating the potential effects of climate-related policies and conflict resolution into global trade negotiations could bolster the resilience of economies, especially for developing nations that are particularly vulnerable to such shocks. In this context, continued advancements in data collection and modeling techniques will be indispensable for governments and international organizations in formulating informed, forward-looking trade policies that foster both economic growth and global sustainability.

While this study provides compelling evidence of the ongoing fragmentation and the role of key drivers, future research could fruitfully explore the causal relationships behind the observed changes in network structure more formally, potentially through the application of supervised network graphs. Such endeavors could provide a sharper focus on the specific impacts of sanctions and climate change on food supply networks, further enriching contemporary discussions about sustainability and the evolving future of globalization in the critical domain of food and agriculture.

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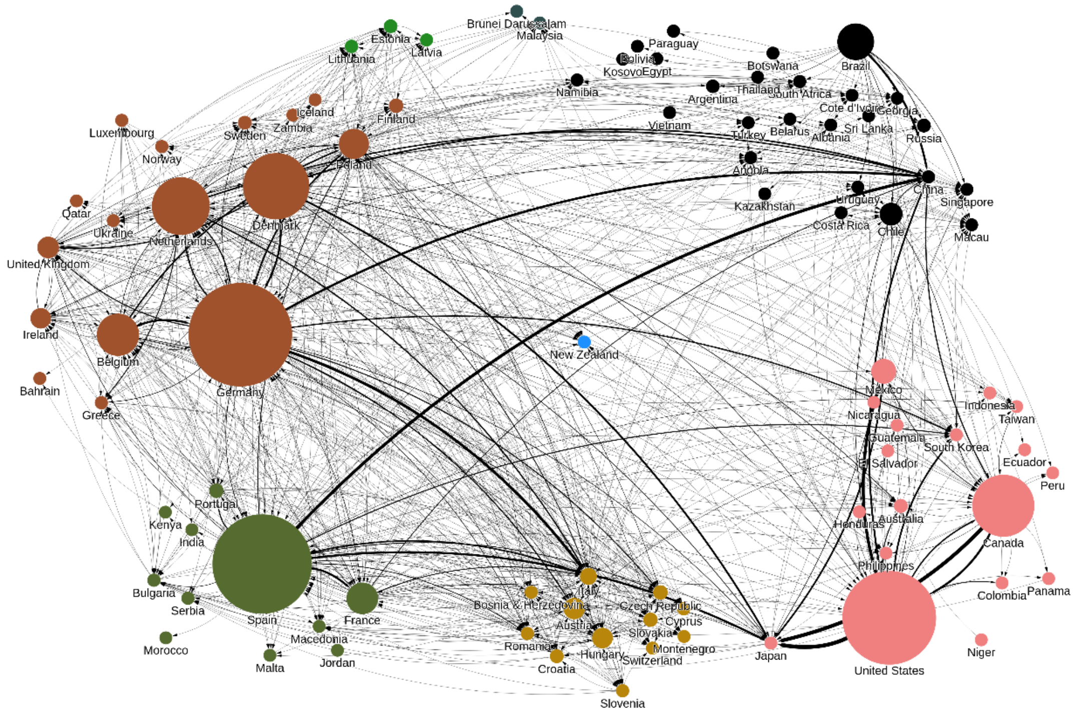

Figure 1. Sample directed network for Pork in 2020.

Note: Nodes are sized according to totals exports by a country and edges according to bilateral trade value. Colours of the nodes represent communities detected in the data.

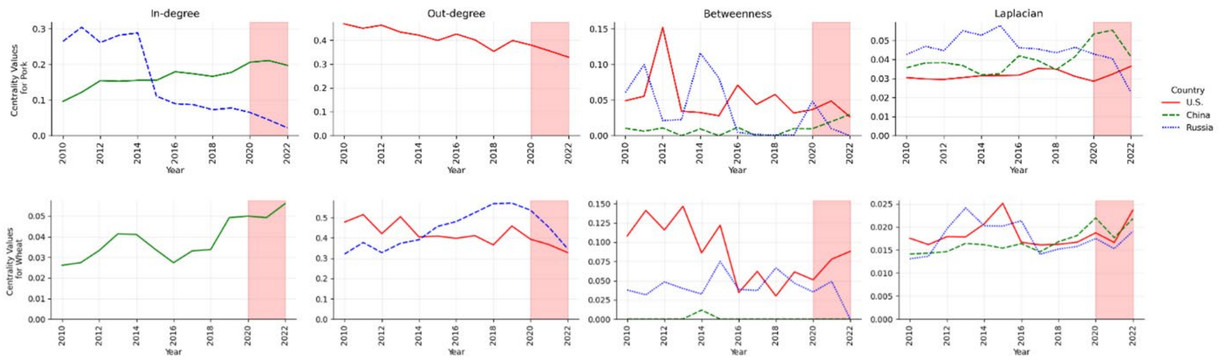

Figure 2. Centrality changes in Pork (top panel) and Wheat (bottom panel) by year for the United States, Russia, and China.

Note: Higher values imply larger influence on the agricultural trade network. For in- and out-degree centralities, countries are selected according to their relevance in the import/export markets.

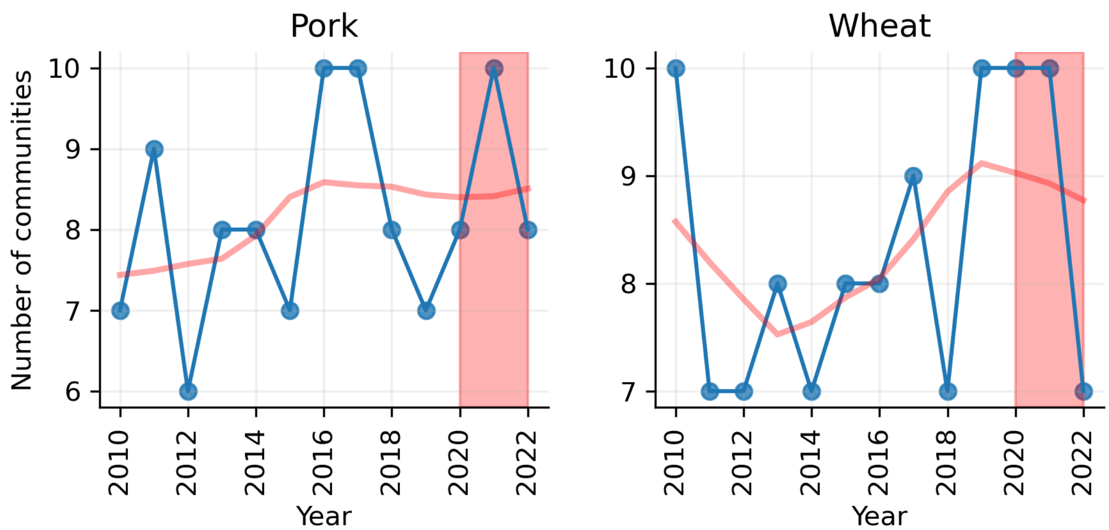

Figure 3. Number of identified communities by year.

Note: Each community (i.e., densely interconnected groups of countries) is identified by maximizing the modularity metric. A larger number of communities implies a more fragmented network. The red line provides the trend fitted via locally weighted smoothing (LOWESS).

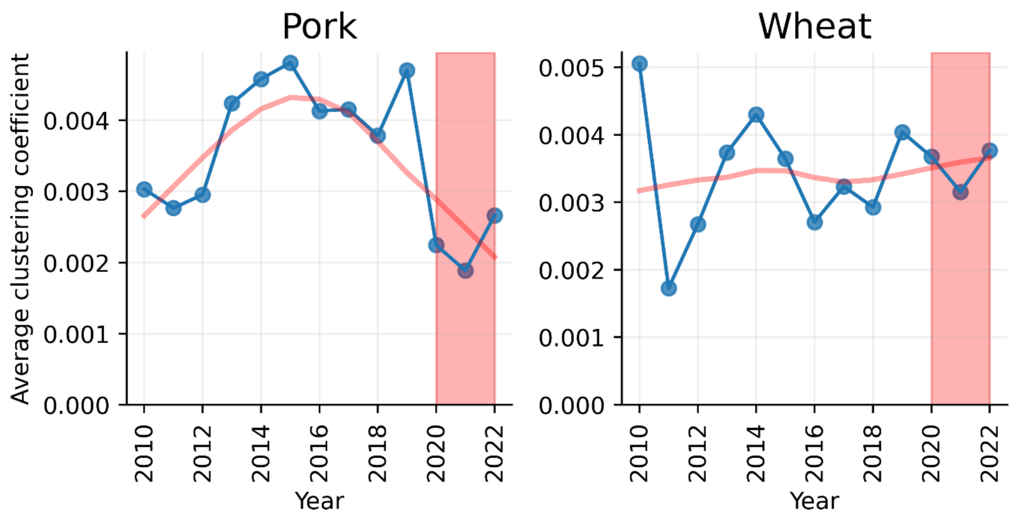

Figure 4. Global clustering by year.

Note: Clustering represents the overall degree of connectivity in the network and has significant implications for the ability of the network to adapt to shocks. Thus, a network with a higher clustering coefficient would suggest that it is more stable than another with a lower value. The red line provides the trend fitted via locally weighted smoothing (LOWESS).

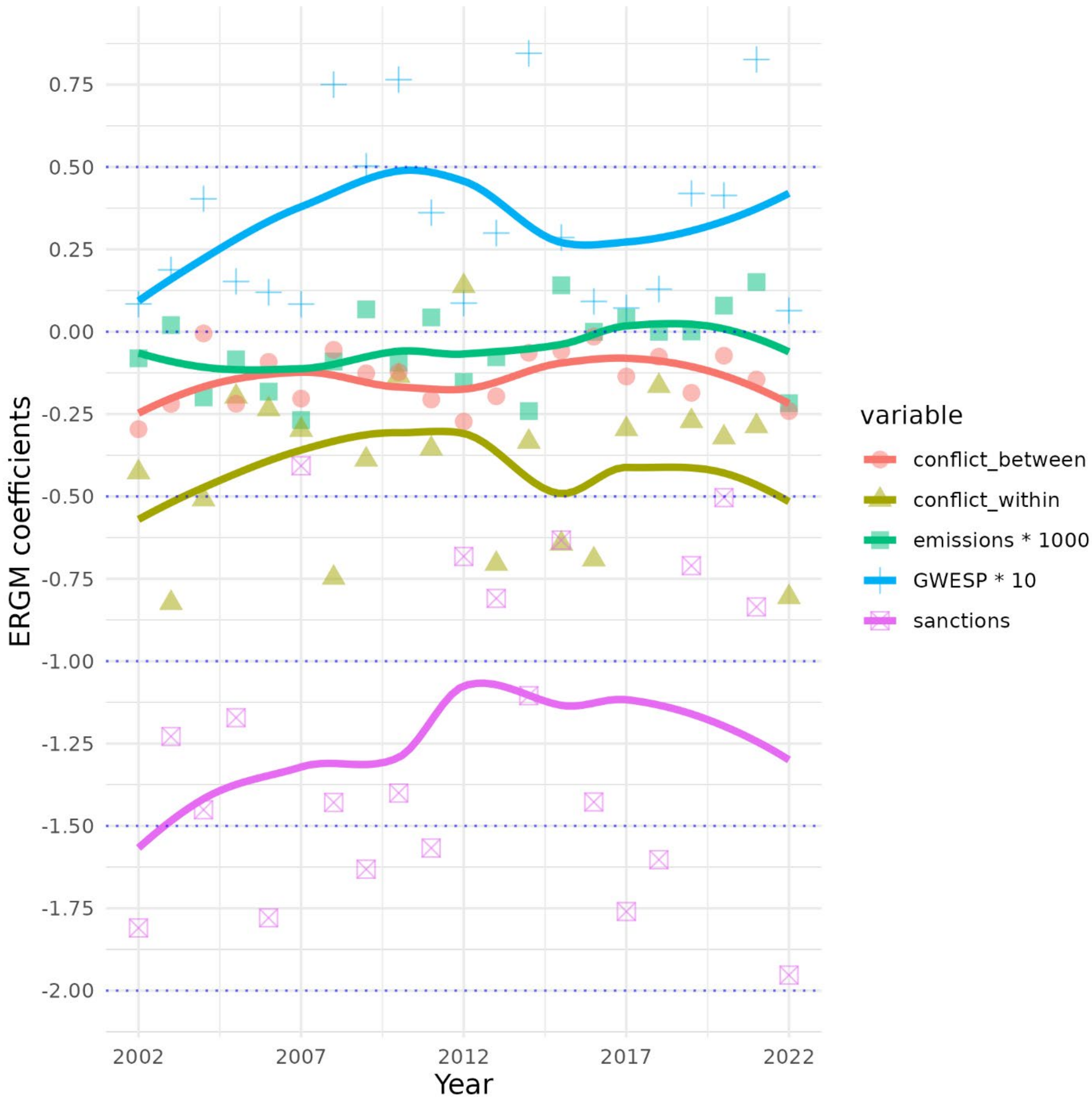

Figure 5. Effects of Conflicts, Sanctions and Climate Change on the Pork Trade Network

Note: Each series, plotting labelled coefficients estimated at five-year intervals between 2002 and 2022, is depicted with a trendline of the same color fitted via locally weighted smoothing (LOESS). For ease of visualization, the coefficients on GWESP and emissions are scaled by factors of 10 and 1000, respectively.

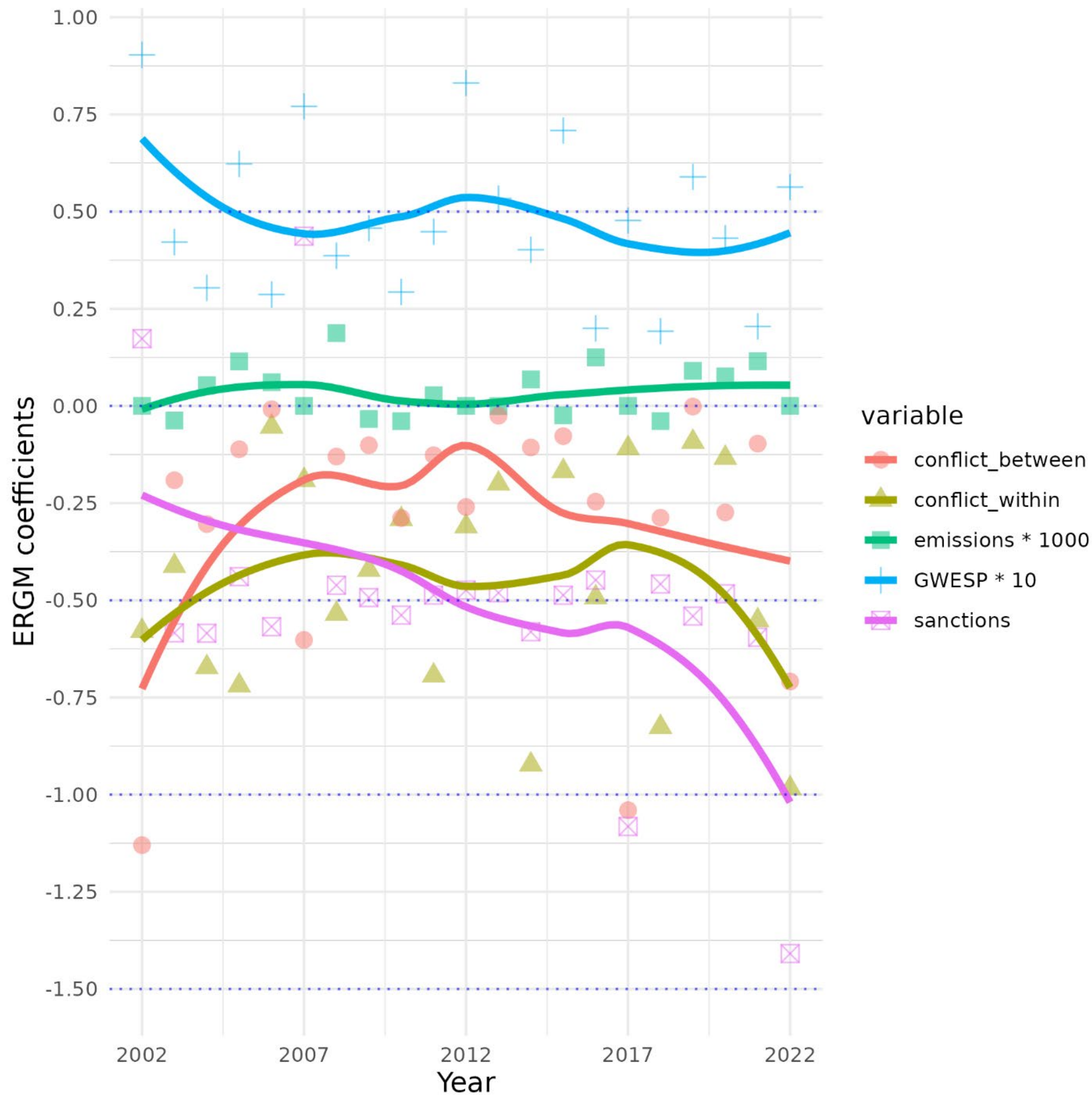

Figure 6. Effects of Conflicts, Sanctions and Climate Change on the Wheat Trade Network

Note: Each series, plotting labelled coefficients estimated at five-year intervals between 2002 and 2022, is depicted with a trendline of the same color fitted via locally weighted smoothing (LOESS). For ease of visualization, the coefficients on GWESP and emissions are scaled by factors of 10 and 1000, respectively.

Table 1. Data sources

Data	Source	Description
Drivers of trade	World Bank, Center for Prospective and International Information Studies (CEPII) , Mayer and Zignago (2011)	traditional drivers of trade (pop^n, GDP, contiguity …)
Sanctions	Global Sanctions Database (GDSB), Syropoulos et al. (2023)	trade and other sanctions imposed by countries on others
Climate variables	NASA GISS, Lensenn et. al (2019)	greenhouse emissions
Conflicts	Upsala Conflict Data Program (UCDP), Davies et al. (2023)	armed conflicts between countries resulting in more than 25 deaths

Table 2: Average number of communities

	Number of communities		
Commodity	2010-2014	2015-2019	2020-2022
Pork	7.6	8.4	8.67
Wheat	7.8	8.4	9.00

Note: Table 2 shows the average number of communities identified in the two selected commodities at five-year intervals between 2011 and 2019, with the 2020-2022 period added for comparison with the post-pandemic supply chain. In this context, a community refers to a group of interconnected nodes such that countries are densely connected within a community and sparsely connected across communities.

Table 3: ERGM results for Pork (HS-0203)

	2002	2007	2012	2017	2022
Edges	-1.647*** (0.258)	-1.874*** (0.375)	-1.382*** (0.229)	-1.769*** (0.462)	-1.499*** (0.231)
GWESP	0.0841*** (0.0002)	0.0836*** (0.0003)	0.0868*** (0.0003)	0.0717*** (0.0005)	0.0641*** (0.0004)
Population	6.04e-04*** (6.31e-05)	9.29e-05*** (2.63e-05)	5.59e-05 (4.41e-05)	6.69e-05*** (2.19e-05)	9.31e-04*** (6.92e-05)
GDP	9.18e-04*** (2.04e-04)	2.66e-04 (4.66e-04)	3.27e-04** (1.41e-04)	7.78e-04*** (3.22e-04)	1.96e-04 (4.69e-04)
Emissions	-8.08e-05 (7.82e-05)	-2.68e-04*** (5.58e-05)	-1.53e-04* (8.70e-05)	4.24e-05 (9.35e-05)	-2.17e-04*** (6.61e-05)
Conflict-within	-0.427*** (0.010)	-0.298** (0.144)	0.138 (0.088)	-0.296*** (0.083)	-0.806*** (0.100)
Conflict-between	-0.296* (0.152)	-0.203 (0.155)	-0.273*** (0.053)	-0.136 (0.135)	-0.241*** (0.061)
Sanctions	-1.810*** (0.449)	-0.407 (0.353)	-0.682*** (0.110)	-1.76*** (0.409)	-1.953*** (0.429)
Common Language	0.789*** (0.053)	0.427*** (0.099)	0.391*** (0.0769)	0.804*** (0.105)	0.919*** (0.097)
Shared Borders	0.179*** (0.056)	0.537*** (0.037)	0.070 (0.068)	0.792*** (0.024)	0.183*** (0.041)
AIC	1463	1390	1613	1517	1689

Values in the parenthesis provide standard errors for the coefficient estimates from the best-fitting ERGM model. A positive coefficient implies positive impact on the probability of trade formation between any two countries.

*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$

Table 4: ERGM results for Wheat (HS-1001)

	2002	2007	2012	2017	2022
Edges	-1.168*** (0.222)	-2.632*** (0.570)	-2.776*** (0.418)	-1.353*** (0.444)	-1.295*** (0.379)
GWESP	0.0903*** (0.0004)	0.0771*** (0.0004)	0.0831*** (0.0006)	0.0477*** (0.0005)	0.0563*** (0.0004)
Population	3.81e-06*** (1.45e-06)	1.12e-06 (4.78e-06)	5.32e-06*** (1.87e-06)	4.65e-06* (2.77e-06)	3.47e-07 (4.71e-06)
ΔGDP	2.71e-06 (4.40e-06)	7.12e-06*** (1.42e-07)	4.01e-06*** (6.10e-07)	7.59e-06*** (2.02e-06)	3.76e-06 (6.85e-06)
Emissions	-4.59e-09 (7.21e-09)	-6.96e-09*** (1.71e-09)	-6.63e-09 (9.10e-09)	-2.96e-08*** (9.77e-09)	-1.95e-08*** (6.86e-09)
Conflict-within	-0.579*** (0.074)	-0.191 (0.194)	-0.310* (0.184)	-0.109 (0.103)	-0.984*** (0.075)
Conflict-between	-1.130 (0.742)	-0.602*** (0.135)	-0.260*** (0.081)	-1.040* (0.565)	-0.709*** (0.231)
Sanctions	0.173 (0.142)	0.437 (0.492)	-0.474 (0.503)	-1.082* (0.565)	-1.409*** (0.231)
Common Language	0.715*** (0.025)	0.695*** (0.079)	0.126*** (0.016)	0.198*** (0.063)	0.226*** (0.042)
Shared Borders	0.519** (0.394)	0.488 (0.406)	0.622*** (0.185)	0.279 (0.381)	0.783*** (0.247)
AIC	1292	1552	1579	1425	1541

Values in the parenthesis provide standard errors for the coefficient estimates from the best-fitting ERGM model. A positive coefficient implies positive impact on the probability of trade formation between any two countries.

*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$