



A social network analysis approach to estimate export disruption spread in the US during the Covid-19 pandemic: how policy response and industry ties relate

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Received: 11 November 2022 / Revised: 14 April 2023 / Accepted: 24 April 2023 /
Published online: 3 June 2023

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Abstract

We examine how the Covid-19 pandemic led to the propagation of export disruptions on a state-by-state basis using a social network analysis model. We measure the impact of import disruptions, Covid-related hospitalizations, subsequent policy responses, and structural network effects on economic outcomes. In addition to examining contemporaneous effects, we include lagged policy response variables to determine their effect on disruption recovery trends. Findings suggest that disruptions cluster along shared industry connections. The results are consistent with previous work that shows that non-pharmaceutical policy interventions had limited contemporaneous and medium-term effects on trade flows.

Keywords Covid-19 · Supply chains · Social network analysis · Disruptions · Trade · Policy response

JEL Classification C1 · F1 · R1

1 Introduction

The Covid-19 pandemic caused both significant demand and supply shocks in international trade. It is reasonable to presume that the latter may have resulted both from policy interventions intended to slow the spread of the pandemic by, among other things, temporarily halting or slowing production as well as from labor shortages caused by the spread of the pandemic itself. Likewise, the former may be partly

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attributable to increased demand for some goods and decreased demand for others. Moreover, shifts in consumption patterns, such as where goods are consumed, resulted in distribution challenges, especially along the agricultural supply chain. Taken together, the shock to global supply chains caused by the pandemic presents an opportunity to understand how global shocks, pandemic related or otherwise, cause supply-chain disruptions that affect an economy.

The emergence of the pandemic, its subsequent impact on supply chains, and the downstream effects on national and international trade generated an abundance of scholarly research.¹ A report issued by the Organization for Economic Cooperation and Development (OECD) estimated that, for member countries, the value of exported services declined by 16.7% and the value of goods exported declined by 8.2%, largely due to supply chain disruptions (OECD, 2022). The report concluded that private enterprises could increase supply chain resilience by shortening the distance between final products and consumers or by managing their own supply chains rather than depending on second- or third-party logistics. The impacts of supply chain disruptions on trade varied disproportionately across, and occasionally within, sectors. For example, beef and pork exports were more vulnerable to disruptions than grains and oilseeds, while the poultry sector remained comparatively strong (Mallory, 2021). Multinational corporations witnessed relatively mild reductions in export volume, whereas exports from suppliers of intermediate goods were more likely to contract (Benguria, 2021). Small businesses were hit especially hard. In a representative survey of small businesses, Bartik et al. (2020) found that 43% temporarily shut down due to interrupted demand and employee absenteeism.

The effects of pre-existing trade relations and supply chain disruptions caused by the pandemic had differential impacts on trade relations. Barbero et al. (2021) used a gravity model to estimate the impacts of the pandemic on the bilateral trade flows of 68 countries. Their study concluded that the trade volume of exporting countries that had regional trade agreements (RTA) decreased more precipitously than that of bilateral trading partners who were not RTA members. Other studies that focused on multilateral trading partners attribute diminished demand and labor supply shortages (Kejzar & Velic, 2022), obstructed access to global value chains (Espitia et al., 2022), supply shocks (Baldwin & Tomiura, 2020), and stringent social distancing policies (Hayakawa & Imai, 2022) as proximate causes of reductions in export trade volume. Rose and Walmsley (2021) used a Computable General Equilibrium (CGE) model of trade to analyze the spatial transmission of the economic impacts caused by the pandemic. They concluded that the effects of Covid-19 on a country's economy depended on the volume and scope of pre-existing linkages between countries and on whether the traded goods were essential (e.g. agriculture, utilities, and critical manufacturing). Arguably, all of these proximate causes worked together in complex ways to reduce trade after pandemic-induced supply chain disruptions. Gaun et al. (2020) and Pichler and Farmer (2022) used adaptive economic input–output models to quantify the upstream and downstream effects the pandemic

¹ A Google search on the key words “covid-19” and “effects on trade” generated 212 thousand search results (January 17, 2023).

had on supply chains. Pichler and Farmer showed that the initial size of shocks as well as sparseness or density of the network structure affect the speed with which these shocks propagate through a network.

This research uses social network analysis (SNA) methods to model the trade networks that connect states in the United States (US) to the rest of the world. The objective is to quantify the trade shocks and supply chain disruptions resulting from the pandemic. More specifically, the analysis captures how shared commodity export disruptions were propagated through trade networks. Like Rose and Walmsley (2021) and Guan et al. (2020), we postulate that high levels of interconnectiveness in global trade, both domestically and internationally, make it more likely that trade shocks and supply chain disruptions will propagate along industry-level trade networks. However, the methodological procedure is a departure from previous empirical approaches commonly used in the trade creation-disruption literature, including multiregional input-output, partial equilibrium models, CGE models, or econometric models, and gravity models in particular. Direct modeling of network endogeneity, along with concomitant trade shocks and supply chain disruptions as we propose here, allows us to demonstrate not only the structure of trade networks themselves, but also how disruptions propagate along them and the duration of these shocks.

2 Social network analysis background and theory

SNA originates from the development of a general systems theory by Katz and Kahn (1966). SNA emphasizes the interdependence and interrelationships between actors that constitute a network. SNA has since evolved into an analytic tool to map interactions among actors in a social structure, and as a method for identifying and analyzing the structure, capacity, and the intensity of interactions between agents and the implications of these linkages for a system's dynamics and evolution (Barrat et al., 2004; Butts, 2008; Wasserman & Faust, 1994). Wichmann and Kaufmann (2016) extended SNA methods and procedures to understanding the social-dynamic drivers that affect the management of supply chain logistics. De Andrade and Chaves Rêgo (2018) and Lovrić et al. (2018) extended SNA methods to analyze trade flow networks. Schmutzler (1999), Ter Wal and Boshma (2009), and McNerney et al. (2013) used SNA to estimate inter-organizational network structures in economic and regional contexts.

Previous empirical studies find that the magnitude and scope of the effects of global supply chain disruptions on trade flows depend on pre-existing inter-industry transactions, business structured and management, and their physical location (Arto et al., 2015; Mackenzie et al., 2012). For industries that export most of their products downstream to consumers, or industries that depend on imports for intermediate goods, disruptions at the border or at a port eventually translate into output reductions, increased variable costs, and lower profits. These supply chain ripple effects might compel firms to modify business strategies, which might include seeking alternative markets, diversifying product lines, or purchasing advanced technology, even though these come with higher costs (Tecece, 2018). However, according

to Teece et al. (1994), in the short-term, such changes are likely incremental since industries can only allocate limited resources over competing uses, and short-term trajectories of firm output are largely determined by what firms are currently producing.

Exports and firm productivity are closely related for both developing and industrialized countries (Marin, 1992). Fluctuations in trade flows affect regional economic activities through supply and demand linkages among production sectors, transportation and logistics, and buyers and sellers of intermediate and final goods and services in local and global markets (Carroll & Blair, 2008). These linkages are dynamic and complex, and often exhibit substantial agent heterogeneity (Hidalgo & Hausmann, 2008; Hidalgo et al., 2007). Understanding the causal relations among economic actors requires innovative approaches to determine how networks effect agent decision-making (Cristelli et al., 2015; Pietronero et al., 2019). The micro- and meso-scale supply- and demand-side networks developed by these previous studies are applied here to analyze the impact of Covid-19 on trade-flow patterns and its distribution in all 50 of the United States.

Prior to the Covid-19 pandemic, most discussions on supply chain disruption focused on natural disasters, breakdowns in geopolitical relationships, financial crises, changes in technology, cyber-attacks, and transportation failures as the primary threats to supply chain stability. The literature divides these causes into quadrants based on controllability and on whether shocks, which are internal or external to the firm experiencing the disruption (Agrawal & Pingle, 2020). Agriculture and food-stuffs figure prominently in the literature due to their vulnerability to external disruptions (Barman et al., 2021; Karwasra et al., 2021; Reardon et al., 2020; Norwood & Peel, 2021), but the pandemic has shown that most, if not all, industrial supply chains are vulnerable to global disruptive events (Sharma et al., 2021). These disruptions coincide with a general trend among firms to underestimate supply chain exposure to risk, often leaving them unprepared to respond to disruptions as they occur (Zsidisin et al., 2000). Moreover, while the literature indicates that both the costs associated with such disruptions and their frequency has increased globally, the underlying assumption has long remained that disruptions tend to be rooted locally (Sharma et al., 2021). That disruptions tend to have local origins means that conventional mitigation strategies may leave firms unprepared or ill-equipped to deal with a global disruption (Tang, 2006). An important exception is Taleb (2014)'s work. Taleb assessed the vulnerability of global supply chains supporting Just-In-Time manufacturing and concluded that fail-safes and backup systems were needed to mitigate the impact of network disruptions. This research uses methods developed in the SNA literature to examine network vulnerabilities for all industries, while controlling for interactions between global and local levels, to fill the aforementioned gap in our understanding of supply chain resilience.

Several metrics are commonly used to quantify supply chain resilience. Euromonitor International, for example, publishes a supply chain sensitivity index that relies on existing measures of sustainability, supply chain complexity, geographic dependence, and transportation networks (Liuima, 2020). Sharma et al. (2021)'s comprehensive assessment of supply chain sensitivity found that dependence on critical part suppliers, supplier location, supply chain lead times, and misaligned incentives were

the most important determinants of supply chain resilience. These indices identify critical aspects of supply chain vulnerability, but they do not fully account for the manner in which supply chain risk compounds as disruption spreads along industry connections.

Depending largely on qualitative case studies to map out how disruptions propagate through industry-based supply chain triads consisting of suppliers, manufacturers, and consumers, Scheibe and Blackhurst (2018) provided the theoretical groundwork for compounding risk. Earlier, Cerina et al. (2015) mapped industrial linkages on a global scale using the World Input–Output Database (WIOD). Cerina et al.'s research found that asymmetric industry linkages could amplify the effects of local disruptions along a supply chain. This study extends the existing theoretical framework of SNA with a quantitative analysis of the world's largest national market and its connections across the globe. We contend that, much like Barrot and Sauvagnat (2016)'s work, which showed how idiosyncratic firm-level shocks spread through production networks, that trade disruptions spread through ties between geographic units along network structures created by industry connections. We hypothesize that industry ties between US states will be an important lead to network clustering in the export disruption network between US states. Put differently, when US states share export disruptions for the same commodity, they are more likely to experience shared disruptions in other commodities as well.

Due to the rarity of global pandemics of this severity, limited research exists on effects of policy measures intended to mitigate against them. The last comparable global pandemic, in terms of both severity and scale, was the 1918 influenza pandemic. Policy assessments of that pandemic conclude that public health interventions, such as economic support and lockdowns, did not cause adverse economic consequences and were positively correlated with faster recovery (Correia et al., 2020). The emerging literature assessing the efficacy of lockdowns for Covid-19 suggests that stay-at-home orders did not affect trade, whereas workplace closures affected trade negatively (Hayakawa & Mukunoki, 2021). This suggests a limited impact for policy measures targeting adverse economic impacts on trade flows. The study by Hayakawa and Mukunoki focused on country-level variation that was attributable to stay-at-home orders and workplace closures. We build on Hayakawa and Mukunoki's work by examining the domestic propagation of disruptions, while including potential policy confounders such as economic support as well as network confounders such as cluster effects. Our study thus represents a methodological innovation building on prior work that examined the effects of the pandemic on global supply chains by employing SNA to peer into the manner in which supply disruptions travel along industry networks and measuring the impact of Covid-19 policy on those disruptions and their spread.

3 Data

Monthly US state-level commodity import and export data were collected by the US Census using the U.S. Customs' Automated Commercial System (U.S. Census Bureau, 2022). The study period spans from December 2018 to November 2021.

This window permits us to investigate several important aspects of trade disruption. First, these data include a baseline for disruptions prior to the pandemic. Second, the study period allows us to investigate longer trends and potential lagged effects of policy interventions. Import and export data are reported in total unadjusted value, in US Dollars. All 50 states are included in the analysis.

3.1 Dependent variable

We first assembled a bipartite network to construct the dependent variable used in the models. A bipartite network is made of two different types of units where two nodes of different types share an edge. In this application, we use states as the first node and exports at the four-digit level commodity code of the Harmonized System (HS-4) as the second node. The edges in the bipartite graph are the dependent variable, and measure export disruptions by comparing the export value of the current month to a 3 month window centered on the same month of the previous year. If the value of the current month was less than 75% of the minimum value in the window for the previous year, it was coded as a ‘1’ for a disruption, otherwise as ‘0’ for no disruption. Beginning in 2021, we look at the window for two years prior so that disruptions were based on values prior to the Covid-19 pandemic. We then collapse the bipartite graph into a monopartite graph. The monopartite graph only has one type of node that shares edges with other similar nodes. In this network of US states, the sum of the 1/0 edges are counts of the number of shared disruptions a state had with other states at the same HS-4 commodity level. We collapse the data primarily for methodological reasons², but since our objective is to measure the spread of trade disruption across industry transactions, this step does not forgo information relevant to our purposes. Given that 75% is an arbitrary definition for disruption, we include a sensitivity check of the same process using a 50% minimum value threshold to define “disruption”. We did not include time-pooled models, in part because we are primarily interested in variation across time and because different periods during the pandemic are not comparable to other periods in the pandemic due to learning and subsequent firm-level adjustments.

3.2 Covariates

In addition to using US Census data to construct the export disruption dependent variable, we also use import data to control for import disruptions of inputs for exporting industries. The variable is constructed as a weighted count using the 2014 World Input–Output Database (WIOD) (Timmer et al., 2015). Import disruptions were first constructed in the same manner as export disruptions and then assigned weights for each HS-4 commodity. The weights were assigned using concordance

² It is common in the network analysis literature to collapse bipartite graphs due to failed convergence in bipartite inferential models and for additional model features not available in bipartite models. Past work has shown that collapsing into a monopartite project still preserves important information about the network (Saracco et al., 2017).

tables to convert HS-4 codes to match International Standard of Industrial Classification codes. Next, the commodity's input value was calculated as a percentage of the total output value for an industry. Since the weights are percentages based on values reported in the WIOD and applied to counts of disruption, and not to trade values, no transformation was necessary to match real US dollar values. Last, the bipartite networks were collapsed to match the monopartite network. Disruptions for each commodity were calculated at the state level, while the weights were calculated at the country level with a maximum of one (since disruptions cannot exceed 100%) and then multiplied by the state level disruption binary value before adding all disruptions together. This step was performed to capture input unavailability in a country and to measure industry input disruption more broadly because it is common for states to buy inputs for commodities across state lines.

To measure the impact of Covid-19 on edge effects, we include hospital bed utilization. Hospital bed utilization is a monthly average of the percentage of inpatient beds occupied by Covid-19 patients. Hospitalization was chosen instead of case count due to it being less volatile. This is because hospitalizations are less impacted by changes in test rates and reporting due to holidays and test eligibility and availability throughout the pandemic. Hospitalizations are also a better proxy for workforce disruptions and medical system strain because symptom severity changed overtime due to strand and population immunity shifts.

We include an Economic Support Index (ESI) and a Containment Index (CI) to measure the impact of Covid-19 related policies. Data were accessed from the official US Department of Health and Human Service's website for Covid-19 related data (USHHS 2022). The ESI and CI were taken from the Oxford Covid-19 Government Response Tracker (OxCGRT) for USA state level Covid-19 Policy Responses (Hallas et al., 2021). The ESI encapsulates measures that target the economic impacts of Covid-19 at the state level, such as income support and debt relief. The CI focuses on behavioral measures, such as mask mandates, school and gym closings, and restrictions on gathering size and indoor dining, as well as capturing health-related measures such as public information campaigns, contact tracing, and vaccination investment. We include 3 and 6 month lags of the two policy indices to estimate the lasting effect and the possibility that such policies contribute to stronger economic recovery. 3 month gaps were chosen because they roughly align with the start and end of each Covid-19 wave in the US for the study period. Descriptive statistics for all variables are presented in Table 1.

4 Empirical framework

Social network analysis models (SNA) differ from generalized linear models in that they do not assume independence between observations and in most cases estimate different types of structural dependence for a network. A network in SNA is defined by nodes, or units of observations, and edges, or the relationship between the nodes. SNA is ideal for trade analysis because there is good reason to believe that trade relationships are influenced by other relationships in the network, and in addition to accounting for these dependencies, they can provide further insight by estimating

Table 1 Descriptive statistics

Statistic	Median	Mean	St. Dev.	Min	Max
<i>Dec 2018–Feb 2020</i>					
Export disruptions	4	4.409	3.135	0	20
Import disruptions	0.041	0.048	0.035	0.000	0.258
<i>Mar 2020–Nov 2021</i>					
Export disruptions	4	6.590	9.345	0	111
Import disruptions	0.042	0.050	0.039	0.000	0.390
Containment Policy Index	47.427	47.766	11.906	16.167	76.190
Economic Support Policy Index	37.500	38.593	24.105	0.000	100.000
Hospital bed utilization %	0.0538	0.071	0.055	0.001	0.437

N is number of units times number of months. For disruptions, units are state dyads, while vertex variable units are the 50 states.

specific types of dependence. Dependence can take the form of lower-order sender and receiver effects or higher-order effects such as triadic relationships. A common lower-order effect is popularity, which measures how likely a node is to receive more ties for each additional tie it has. For trade this would explain the phenomenon that popular trade destinations are likely to become more popular. A common higher order effect in trade is transitivity. For an undirected network, this is the likelihood that that two nodes will be connected when they are connected to a common partner. This, in effect, captures clustering within a network, which is a common feature in many networks, including trade networks. We have chosen to test our hypothesis using these features of SNA. In the application, states are nodes and shared disruptions of exports for a commodity are the dependent variable edges.

4.1 Exponential random graph model (ERGM) for counts

Existing models of network effects in supply chain risk management are founded on models based on game theory (Wu et al., 2007), firm level cluster analysis (Hallikas et al., 2005), Bayesian network modeling (Ojha et al., 2018), and others (Hosseini et al., 2019). Our paper is first to use a count-valued Exponential Random Graph Model (ERGM) (Krivitsky, 2012) to analyze the spread of export disruptions due to Covid-19 and associated policies.

The ERGM has two key advantages for the purposes of this study. First, the ERGM allows us to model network structure without assuming independence between observations, as is the case with standard generalized linear models (GLM). For example, we include transitivity—also called a clustering coefficient—to model linkages between shared disruptions. The ERGM also allows us to control for deviations from a specified reference distribution, over-dispersion (larger variances), and zero-inflation. Modeling these components is critical because we know that economic disruptions in one state will impact economic conditions in other states due to cross-border ties between intermediate goods, services, and transportation, and because we are agnostic about the distribution of the dependent variable.

The count ERGM, like all ERGMs, does not model unit-level effects as GLMs do, but rather the dependent variable serves to model the entire network using iterative Monte–Carlo Maximum Likelihood Estimation (MC-MLE). This approach employs Markov Chain Monte Carlo methods to draw samples from a set of possible networks to approximate a network probability distribution (Snijders, 2002). This iterative process continues until parameter estimates and the probability distribution of edges converge. ERGM estimates are more accurate because network effects and coefficients on covariates are jointly estimated (Metz et al., 2018). Other statistical modeling approaches could be used to account for network dependence while estimating covariate effects [e.g. latent space methods (Matias & Robin, 2014), stochastic block modeling with covariates (Sweet, 2015), or quadratic assignment procedures (Robins et al., 2012)], but these alternative methods do not permit estimation and testing of specific network effects. Given that one of our research objectives is to test for transitivity effects, we adopted an ERGM-based approach using the implementation made available in the `ergm.count` (Krivitsky, 2016) package for the R statistical software (R Core Team, 2021). This valued-ERGM approach is effective in measuring similar networks, such as those formed by foreign direct investment, communication, and migration (Pilny & Atouba, 2018; Schoeneman et al., 2022; Windzio et al., 2021).

For the count ERGM, the probability of the observed $n \times n$ network adjacency matrix \mathbf{y} is:

$$\Pr_{\theta;h,g}(\mathbf{Y} = \mathbf{y}) = \frac{h(\mathbf{y}) \cdot \exp(\boldsymbol{\theta} \cdot g(\mathbf{y}))}{k_{h,g}(\boldsymbol{\theta})} \quad (1)$$

where $g(\mathbf{y})$ is the vector of network statistics used to specify the model $\boldsymbol{\theta}$; is a vector of parameters that describes how those values relate to the probability of observing the network; $h(\mathbf{y})$ is a reference function defined on the support of \mathbf{y} and selected to affect the shape of the baseline distribution of dyadic data (i.e. reference measure, such as the Poisson distribution); and $k_{h,g}(\boldsymbol{\theta})$ is a normalizing constant.

Our main models include several base level convergence related parameters, network parameters, and parameters on covariates. Base-level parameters include the sum of edge values, analogous to the intercept in a GLM model, as well as the sum of square root values to control for edge value over-dispersion. For the network effects, we include a transitive weight term. The transitive weight term is:

$$g(\mathbf{y}) = \sum_{i,j \in \mathcal{Y}} \min[\mathbf{y}_{i,j}, \max(\min(\mathbf{y}_{i,k}, \mathbf{y}_{k,j}))] \quad (2)$$

This term accounts for the degree to which edge (i, j) co-occurs with pairs of large edge values with which edge (i, j) forms a transitive triad with weighted, undirected two-paths going from nodes i to k to j . In this application, transitivity measures the likelihood that when states i and j share a disruption in a commodity with the same state, k , states i and j share a disruption in a commodity. Note that, given that the network is undirected, cyclical and transitive triads are indistinguishable. Exogenous covariates are included by measuring the degree to

which large covariate values co-occur with large edge values. Our only dyadic measure is that of shared and weighted import disruptions and is defined as:

$$g(\mathbf{y}, \mathbf{x}) = \sum_{i,j} \mathbf{y}_{i,j} \cdot \mathbf{x}_{i,j} \quad (3)$$

Lastly, we specify statistics that account for node (i.e., state) level measures of Covid-19 intensity and policy measures. These parameters take the product of the node's covariate value and a sum of the edge values in which the node is involved, defined as:

$$g(\mathbf{y}, \mathbf{x}) = \sum_i \mathbf{x}_i \sum_j \mathbf{y}_{i,j} \quad (4)$$

5 Results

There are several significant findings from the monthly models, shown in Figs. 1 and 2. It is important to note here that the reported disruptions are not cumulative disruption effects, but shared disruptions across states, meaning that we are illustrating the propagation of disruption, not disruption overall. There is, of course, some overlap, given that any increase in common disruptions will coincide with an increase in the likelihood of disruption overall.

First, for the intercept (Fig. 1, Panel a), we establish a baseline for pre-Covid disruption. What we see is that disruptions spiked at the beginning of the pandemic before trending towards pre-pandemic levels of disruption until 2021, when disruptions mounted again, although not reaching the same levels of disruption as were seen at the start of the pandemic. This finding suggests that supply chain issues are far from over, which in turn limits our ability to draw conclusions about long-term solutions. The variance of disruptions (Fig. 1, Panel b) also spiked at the beginning of the pandemic, but quickly returned to pre-pandemic levels indicating that, while supply-chain issues are not over, they are experienced more evenly. The final network term, transitivity, or the clustering coefficient (Fig. 1, Panel c), shows a pre-pandemic downward trend, but remains statistically significant for all models except for half of the disruptions in April 2020. Two months prior to the start of the pandemic in the US there was a spike in transitivity. This is possibly explained as the impact of the pandemic on industries connected to parts of the world where the pandemic had already taken root. After this spike, both disruption levels show a significant drop for transitivity before recovering and stabilizing. A possible explanation for this is the breakdown of Just-in-Time (JIT) manufacturing that caused disruptions to spread chaotically rather than through industrial and regional ties. Different disruption levels tend to follow the same trends in all three cases. While the transitivity coefficient does switch some of the months, stronger disruptions tend to be more clustered, indicating strong effects of industry and regional ties as a contributing factor for larger export disruptions.

For the Covid-19 impact variables, import disruptions (Fig. 1, Panel d) are relatively stable. This finding was anticipated, given the importance of supply chain inputs for US

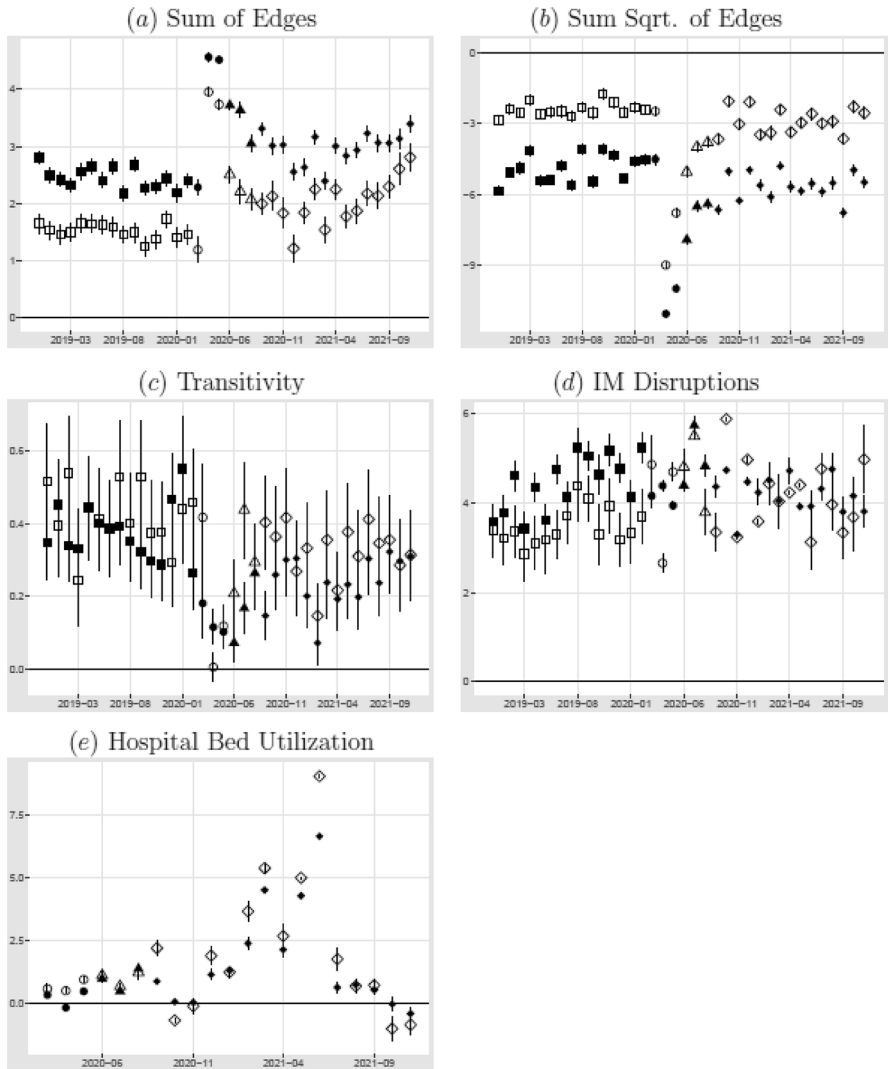


Fig. 1 Y-axes are the coefficient estimates of network terms and Covid-19 impact variables in Poisson ERGMs. Bars span 95% confidence intervals. For some models, the confidence intervals are not visible due to being small and the large range of the coefficient estimates. Squares are pre-covid months, circles are first 3 months of Covid-19 pandemic, and diamonds are post-6 months from start of pandemic. Filled points are for disruptions with 75% drop threshold, non-filled points are for disruptions with 50% drop threshold

exports. However, the relationship between Covid-19 hospital bed utilization (Fig. 1, Panel e) and export disruptions is quite volatile. The relationship is significant and positive for most months of the pandemic, but it occurs around the time that vaccinations became widely available the impact of hospitalizations grew sharply by around 600% before sharply dropping off at the beginning of the Delta variant’s dominance in the

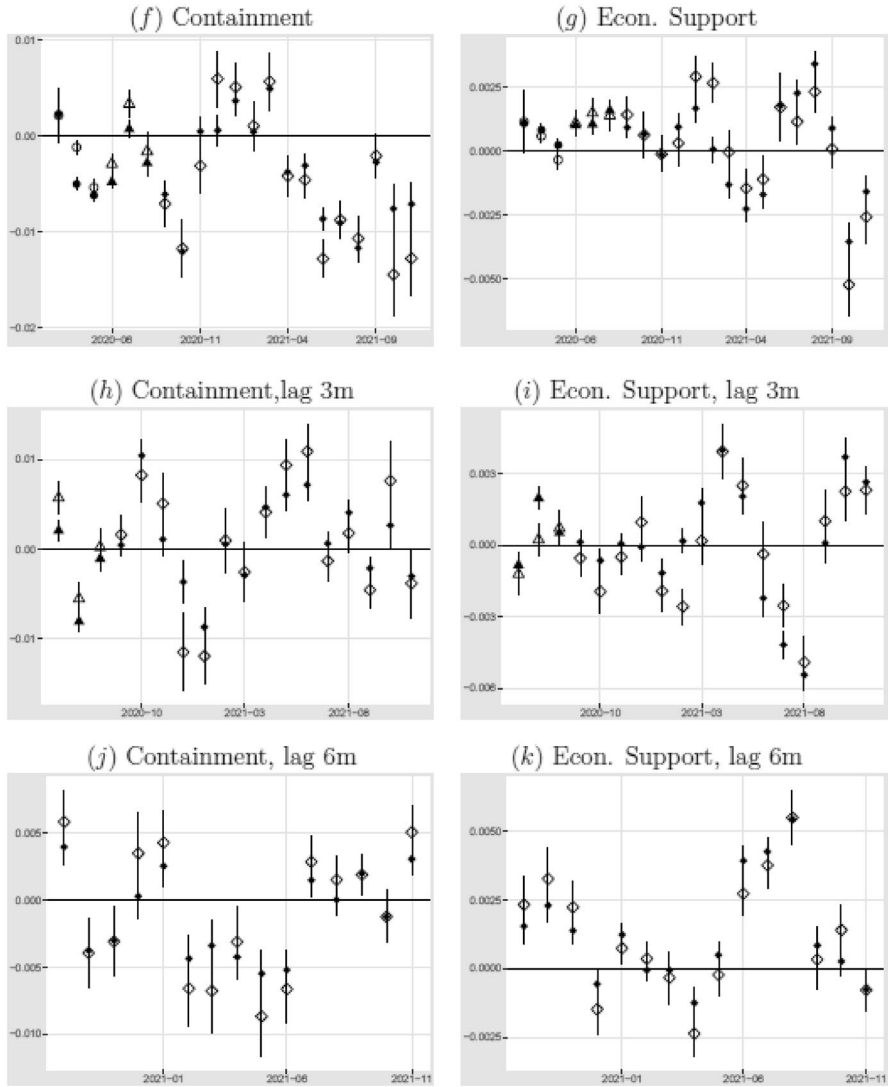


Fig. 2 Y-axes are the coefficient estimates of Policy Variables in Poisson ERGMs. Bars span 95% confidence intervals. For some models, the confidence intervals are not visible due to being small and the large range of the coefficient estimates. Squares are pre-covid months, circles are first 3 months of Covid-19 pandemic, and diamonds are post-6 months from start of pandemic. Filled points are for disruptions with 75% threshold, non-filled points are for disruptions with 50% drop threshold

US. Looking at the comparison of overall hospitalization levels in the US, we see that hospitalizations had the strongest positive relationship with export disruptions when they were at the lowest level since the onset of the pandemic, indicating that Covid-19 intensity’s impact was much more acute then. This supports the assertion that, when pandemic intensity is strong at the country level, local hospitalization level matters less

because the likelihood that disruptions across the country are affecting a firm regardless of local levels is high.

Lastly, for non-pharmaceutical policy interventions and their related lags (Fig. 2, Panels f–k), there is no clear relationship throughout the pandemic. The containment variable has substantially larger coefficients than economic support and could be sizable if a state were to move from the lowest level of intervention to the highest level of intervention. However, this is an unlikely scenario given that some level was implemented and no state ever hit 100. The relationship drops in half by the 6 month lag. Economic support's relationship with export disruptions is more stable, but much smaller in size ranging from a quarter to a third in magnitude of containment. However, by the 6 month lag, the coefficient sizes are comparable and economic support is, on average, positive. Taken together, these results suggest that the impact of non-pharmaceutical intervention on export disruptions is difficult to interpret, is likely minor, and should not be a governing factor in determining policy.

6 Robustness checks

While there is not a direct comparison between GLM and undirected networks, we conduct robustness tests using regression analysis on the bipartite edgelist panel and a modified collapsed edgelist (Table 2). For models (1) and (2), the units of observation are monthly export disruptions for HS code 4-digit level commodities. While many of the policy variables are statistically significant, the coefficients shrink in magnitude once state fixed effects (FE) are included, and significance is lost for many of the coefficients. For models (3) and (4), the unit of observation is the monthly state dyad's shared export disruptions for HS code 4-digit level commodities. Because OLS cannot control for node level variables the same way an undirected ERGM can, policy variables had to be modified as the sum value for the dyad rather than the individual state value. Adding dyad FE in model (4) results in a substantial increase in the adjusted R^2 , providing an important robustness check. Dyad FE would capture most of the relationship between states, including most economic ties.

To show that transitivity is an important predictor of export disruption spread, we compare the predictive validity of the ERGM results with FE OLS. We use one step ahead prediction, which estimates coefficients using one month and then predicts the disruptions of the next month. Figure 3 includes the normalized RMSE (NRMSE)

$$NRMSE = \frac{\sqrt{(\sum_{i=1}^N (x_i - \hat{x}_i)^2 / N)}}{y_{max} - y_{min}} \quad (5)$$

and the Coefficient of Variation of the RMSE (CVRMSE):

$$CVRMSE = \frac{\sqrt{(\sum_{i=1}^N (x_i - \hat{x}_i)^2 / N)}}{\bar{y}} \quad (6)$$

Table 2 OLS results

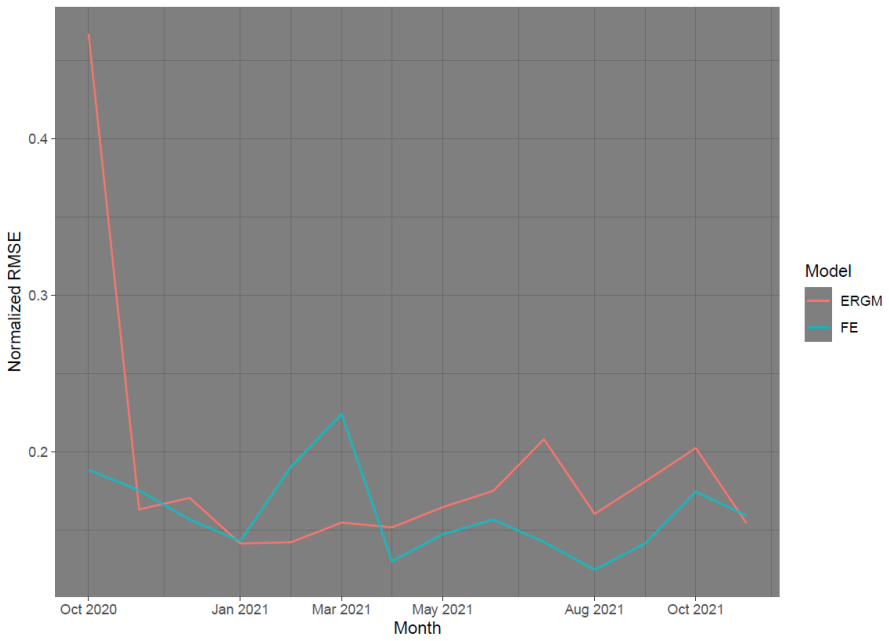
	Dependent variable			
	EX disruptions		Shared EX disruptions	
	(1)	(2)	(3)	(4)
EconomicSupportIndex	0.0004** (0.00002)	0.0001** (0.00002)	0.002* (0.001)	0.008** (0.001)
EconomicSupport_lag3m	0.0001** (0.00002)	−0.0001** (0.00002)	0.011** (0.001)	−0.006** (0.001)
EconomicSupport_lag6m	0.0001** (0.00002)	0.00002 (0.00002)	−0.002* (0.001)	−0.0002 (0.001)
ContainmentHealthIndex	0.001** (0.00002)	0.00001 (0.00005)	0.027** (0.002)	0.009** (0.002)
ContainmentHealth_lag3m	−0.001** (0.00002)	0.0001 (0.0001)	−0.006* (0.002)	−0.004 (0.002)
ContainmentHealth_lag6m	−0.0005** (0.00002)	−0.0001 (0.0001)	−0.034** (0.002)	0.016** (0.003)
Covid hospitalizations	0.189** (0.005)	0.098** (0.006)	8.936** (0.294)	0.707* (0.357)
Import disruptions	0.075** (0.001)	0.053** (0.001)	28.385** (0.684)	−0.163 (0.594)
Constant	0.081** (0.0003)	0.072** (0.003)	1.839** (0.166)	3.165** (0.614)
Observations	2,208,600	2,208,600	18,375	18,375
State or Dyad FE	No	Yes	No	Yes
Adjusted R^2	0.012	0.043	0.198	0.602
Residual Std. Error	0.301	0.296	2.999	2.112
F Statistic	3,282**	525**	567**	23**

* $p < 0.05$ ** $p < 0.01$

The NRMSE shows that both models have roughly the same error in prediction across the range of disruptions, presented as a percentage, but when considered against the average level of disruption, the ERGM has significantly lower levels of error.

We also tested several different dependent variable specifications and other modelling approaches to control for network dependency, which can be found in the Appendix. None of the results from these models differed substantially from the conclusions we draw in this paper.

(a) Normalized RMSE



(b) Coefficient of Variation of RMSE

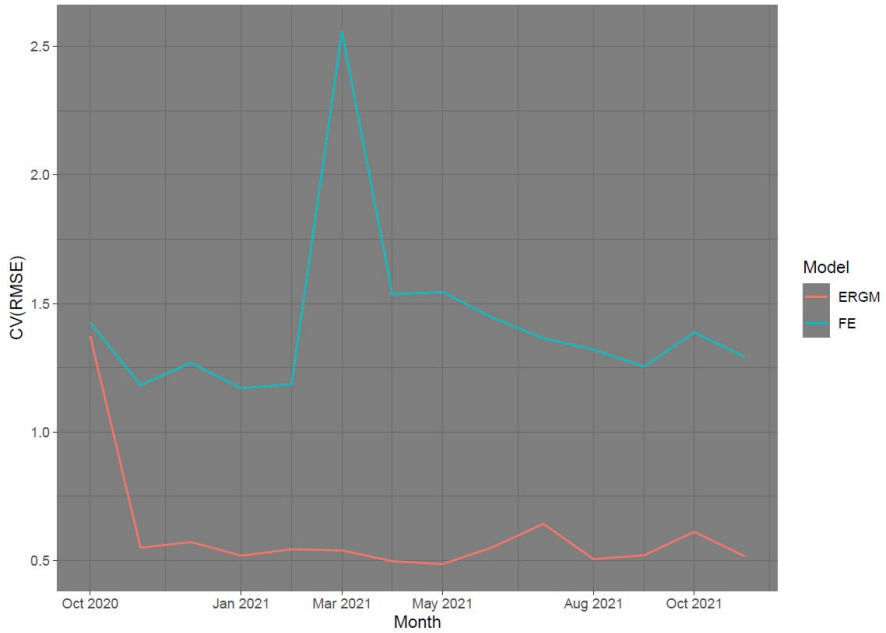


Fig. 3 NRMSE and CV (RMSE) for one-step ahead prediction

7 Conclusion

It would be difficult to overstate the impact of the global pandemic in terms of both the human suffering it has wrought and the severe repercussions for consumers, producers, and the global markets and supply chains that connect the former to the latter. It would appear that some of the most serious disruptions occurred early on in the pandemic, as consumers targeted very specific product categories in what can only be described as a panic-driven buying frenzy, while some countries engaged in rather ill-advised policy responses that further undermined supply chains. One important lesson to be drawn is that global supply chains are very different now than they were at the time of the 1918 pandemic, and we can consequently not rely on models developed on the basis of that crisis to predict the impact of the current pandemic on economies around the globe. This has sparked new debates on supply chain integrity and security and a variety of means through which the stability of at least some critical supply chains might be guaranteed e.g. by physically moving some manufacturing back to our shores.

Covid-19 has posed a unique and unprecedented challenge to supply chains in the globalized environment in which modern economies operate. Our study was intended not only to examine the impact of the pandemic on global supply chains, but to do so using a novel methodology for this application. Network analysis that allows us to examine closely the manner in which shocks travel along network connections. We hypothesized that supply chain disruptions would travel along industry connections in recognizable patterns, and this study appears to support that hypothesis and while Covid-19 was the shock for the disruptions we analyze, this finding has implications beyond pandemics.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s40812-023-00271-3>.

Acknowledgements The authors appreciate the constructive comments reviewers provided. DL research was supported by the Sparks Chair in Agricultural Sciences & Natural Resources, the United States Department of Agriculture Hatch Project #NE-2249, and Oklahoma Agricultural Experiment Station Project #OKL03125. LL research was funded by the United States Department of Agriculture Hatch Project #W4190 and Oklahoma Agricultural Experiment Station Project #OKL03216.

Data availability Data are from publicly available sources. Dataset used for analysis is available upon request.

Declarations

Conflict of interest The authors declare no competing interests.

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