The COVID-19 Pandemic and Trade in the US: How Policy Response and Industry Ties Relate to Export Disruptions

John Schoeneman (john.schoeneman@okstate.edu)
Oklahoma State University

Marten Brienen
Oklahoma State University

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The COVID-19 Pandemic and Trade in the US: How Policy Response and Industry Ties Relate to Export Disruptions

John Schoeneman[1] and Marten Brienen[1]

Oklahoma State University, Stillwater OK 74078, USA,
john.schoeneman@okstate.edu,**
marten.brienen@okstate.edu

Abstract. Using a social network analysis model, we examine for each of the United States how aspects of the COVID-19 pandemic led to the propagation of export disruptions. We specifically measure the impact of import disruptions, COVID-related hospitalizations, subsequent policy responses, and structural network effects. In addition to looking at contemporaneous effects, we also include lagged policy response variables to see if these result different disruption recovery trends. Our results show that disruptions will noticeably cluster along industry connections. Our results are also consistent with past work that shows that non-pharmaceutical policy interventions have had limited contemporaneous effects on trade flows and extend these findings to show that up to six months after policy interventions, the impact of pandemic-related policy on exports disruptions is limited.

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** Correspondence emails should be sent to this address

1 Introduction

COVID-19 has caused both significant demand and supply shocks in international trade. It is not unreasonable to suspect that the latter have resulted both from policy interventions intended to slow the spread of the pandemic by, among other interventions, temporarily halting or slowing production as well as from labor shortages caused by the spread of the pandemic itself. Likewise, the former may have been attributable in part to increased demand for some goods and decreased demand for others. Moreover, shifts in consumption patterns, such as where goods are consumed, have resulted in distribution challenges, especially for foodstuffs. In this research project, we propose using social network analysis to model the trade networks that connect each of the United States to the rest of the world in an effort to capture trade shocks and supply chain disruption resulting from the COVID-19 pandemic and, more specifically, to capture how such disruptions have propagated through those networks. We postulate that the high levels of interconnectedness in global trade make it likely that trade shocks and disruptions of supply chains will propagate primarily along industry-level trade networks. Modeling those networks along with trade shocks and supply chain disruption as we propose here will allow us to show not only the structure of trade networks themselves, but also how disruptions and shocks travel along them. While we have chosen to focus on the United States due to the severity of its COVID-19 outbreak in the time sample and the availability of high-quality data, we do expect that many of the findings will be generalizable for complex economies, due to the homogenization of global trade structures.

2 Theory

2.1 Industry Linkages and Disruption Propagation

Prior to the COVID-19 pandemic, most discussions on supply chain disruption focused on natural disasters, geopolitical events, changes in technology, cyber-attacks, and transportation failures as threats to supply chain stability. The literature divides the causes into quadrants based on controllability and whether they are internal or external to the firm experiencing the disruption [1]. Agriculture and foodstuffs figure prominently in the literature due to their vulnerability to uncontrollable external disruption, but the COVID-19 pandemic has shown that most, if not all, industries are at risk of a global disruptive event. This coincides with a general trend among firms to underestimate levels of risk to their supply chain, often leaving them unprepared to respond to disruptions as they occur [31]. Moreover, while the literature indicates that both the costs associated with such disruptions and their frequency have increased globally, the underlying assumption has long remained that they tend to be rooted locally. This has meant that conventional mitigation strategies do not account for global disruptions [26]. An important outlier has been the work of Nassim Taleb, whose assessment of vulnerabilities in global supply chains that hinge on Just-In-Time manufacturing caused him to advocate for fail-safes and backup systems [25].

In this paper, we not only look at all industries, but control for interaction of disruptions at the global and local level to fill the aforementioned gap in our understanding of supply chain vulnerabilities.

There are a number of extant measures for the robustness of supply chains worldwide. For example, the Euromonitor International publishes a supply chain sensitivity index that combines existing measures of sustainability, supply chain complexity, geographic dependence, and transportation networks [10]. Sharma, Srinastava, Jindal, and Gupta's comprehensive assessment of supply chain sensitivity combining 26 factors, found that dependence on critical part suppliers, location of suppliers, length of supply chain lead times, the fixing process owners, and mis-aligned incentives were the most critical factors in supply chain robustness [21]. While they both identify important aspects of supply chain vulnerability, they fail to fully account for the manner in which supply chain risk compounds as disruption spreads along industry connections. Past literature has provided theoretical grounding for this, depending largely on qualitative case studies to map out how disruptions propagate through industry-based supply chain triads of suppliers, manufacturers, and consumers [18]. Zhu et al., mapping industrial linkages using the World Input-Output Database, found that on a global scale, the asymmetrical industrial linkages could see local shocks causing serious disruptions along the supply chain [2]. Stephany, Stoehr, et al. performed an analysis looking at the risk of supply chain disruption due to COVID-19 in certain industries through the creation of the CoRisk-Index [23]. In this study, we extend the theoretical framework, albeit in a simplified operationalization, using quantitative analysis for a large national market and its global connections. Moreover, while the CoRisk-Index can be a useful tool in this type of analysis, its industry breakdown into three main categories is fundamentally incompatible with our reliance on trade data using HS-4 commodity codes. We hypothesize that *industry connections will be a significant vehicle for the spread of disruptions between US states*. This effectively builds on earlier work we have done, in which we also looked at the propagation of supply chain disruptions due to the COVID-19 pandemic and the significance of policy interventions [19]. The current study expands significantly on that earlier work by looking at a significantly longer span of time, including pre-pandemic and lagging the policy variables in an effort to look much more closely at the expectated outcomes of policy interventions due to the limitations of the literature, much of which goes back to the 1918 Influenza pandemic.

2.2 Effectiveness of Policy Interventions

Due to the highly exceptional nature of pandemics on a scale such as this, limited analysis exists of the economic disruption they cause and of the impact of policy measures intended to mitigate against them. The last comparable global pandemic in terms of severity and the number of economies affected was the Spanish Flu of 1918. In the limited literature available to us, policy assessments have found that public health interventions such as economic support and lockdowns did not have adverse economic effects and that these areas recovered

more quickly [3]. The emerging literature assessing the efficacy of lock downs for COVID-19 show that stay at home orders did not impact trade, whereas workplace closures did negatively impact trade [6]. This suggests a limited impact for policy measures controlling adverse economic impacts on trade flows. This previous study by Hayakawa and Mukunoki was focused on country-level variation and focused on stay-at-home orders and workplace closures. We build on this work by looking at domestic propagation of disruption, while including potential policy confounders such as economic support and network confounders such as cluster effects. Likewise, our earlier work upon which this paper builds, found limited impacts for policy variations [19].

3 Data and Research Design

The monthly U.S. state-level commodity import and export data used in our analysis were collected by the US Census using the U.S. Customs' Automated Commercial System [28]. In this paper, we extend our analysis from a period spanning between March 2020 to December 2020 to one that spans from December 2018 to November 2021. This broader timeframe allows us to investigate several important aspects of trade disruption that we were not able to capture in our earlier study. First, it provides a baseline for disruptions prior to the COVID-19 pandemic. Second, it allows us to investigate longer trends and lagged effects of policy interventions.The import and export data are reported in total unadjusted value, in US Dollars. All 50 states are included as nodes in the final networks.

To construct the dependent edge-level variable used in our models, we first constructed a bipartite graph with states as the first mode and exports at the four-digit level commodity code of the Harmonized System (HS-4) as the second mode. The edges in the bipartite graph are a measure of export disruptions, comparing export value of the current month to a three-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 one for a disruption. Beginning in 2021, however, 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 of US states where the edges are counts of the number of shared disruptions a state has with other states at the same HS-4 commodity level. We collapse the data primarily for methodological reasons[1], but since our goal is to measure trade disruption spread through industry ties, this step does not lose information relevant to our purposes. For robustness, we repeat this process using a 50% minimum value threshold. We did not include time-pooled models, in part because we were primarily interested in time variation, but also

[1] It is common in 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 [17].

due to the fact that our earlier analysis showed no major differences along this dimension [19].

3.1 Covariates

In addition to using US Census data for our export disruption dependent variable, we also use the import data to control for import disruptions of inputs for the export industries. The variable is constructed as a weighted count using the 2014 World Input Output Database (WIOD) [27]. 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 tables to convert HS-4 codes to match International Standard of Industrial Classification (ISIC) codes to then calculate the commodity's input value as a percentage of the total output value for an industry. Since the weights were percentages based on values in the WIOD and applied to counts of disruption, not trade values, no transformation was necessary to match real USD values. Last, they were collapsed to match the monopartite network. In this update, we made changed how the weights were assigned. The disruptions for each commodity were calculated at the state level, but the weights were calculated at the country level with a max of one (since disruptions cannot exceed 100%) and then multiplied by the state level disruption binary value. This step was included to capture the unavailability of inputs within the entire country and to measure industry input disruption more broadly as it is not uncommon for states to buy inputs for commodities across state lines.

To measure the impact of COVID-19 and COVID-19 related policies, we include hospital bed utilization, an Economic Support Index, and a Containment Index. Hospital bed utilization is a monthly average of the percentage of inpatient beds being utilized by COVID-19 positive patients. Data were accessed at the official US government's website for COVID-19 related data [13].The Economic Support index and the Containment index are taken from the Oxford COVID-19 Government Response Tracker (OxCGRT) for USA state level COVID-19 Policy Responses [4]. The Economic Support index includes measures that lessen the economic impact of COVID-19, including and weighting state level variation in measures such as income support and debt relief. The Containment index focuses on behavioral lockdown 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. To estimate the lasting effect and the possibility that policy contributes to strong economic recovery, we include three and six month lags of the two policy indices.

3.2 Model and Specification: The Count ERGM

Existing models of network effect in supply chain risk management have relied on complex models based in game theory [30], firm level cluster analysis [5], Bayesian network modeling that defined edges as causes of disruption [14], and

myriad others [7]. In this paper, to the best of our knowledge, we are the first to use the count-valued Exponential Random Graph Model (ERGM) [8] to model the spread of export disruptions. This model has two key advantages for the purposes of our study. First, it allows us to model network structure without assuming the independence of observations, as is the case with the majority of generalized linear models (GLM). For example, we include transitivity, also known as the clustering coefficient, to model the linkages between shared disruptions. Moreover, this model allows us to control for deviation from the specified reference distribution, including larger variance and zero inflation. These are both critical, as we know that economic disruptions in one state will impact economic conditions in other states, while that dependent variable distribution rarely follows a specific distribution perfectly.

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 an iterative estimation method (MC-MLE) in which, given starting values for the parameter estimates, a Markov Chain Monte Carlo method is used to sample networks in order to approximate a probability distribution [22]. This iterative process continues until the parameter estimates and probability distribution converge. Because the ERGM family of models allows the researchers to specify both network effects and covariate effects in the model, both end up being more accurate estimates [12]. While other statistical modeling approaches could be used to account for network dependence while estimating covariate effects (e.g., latent space methods [11], stochastic block modeling with covariates [24], and quadratic assignment procedure [16]), these alternative methods do not permit precise estimation and testing of specific network effects. Given that one of our research objectives is specifically to test for transitivity effects, we have adopted an ERGM-based approach, using the implementation made available in the `ergm.count` [9] package in the `R` statistical software. This valued-ERGM approach has shown to be effective in measuring similar networks, such as those formed by foreign direct investment, communication, and migration [20, 15, 29].

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

$$\Pr_{\boldsymbol{\theta};h;\boldsymbol{g}}(\boldsymbol{Y} = \boldsymbol{y}) = \frac{h(\boldsymbol{y})\exp(\boldsymbol{\theta} \cdot \boldsymbol{g}(\boldsymbol{y}))}{\boldsymbol{\kappa}_{h,\boldsymbol{g}}(\boldsymbol{\theta})}, \tag{1}$$

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

Our main models include a number of base level convergence related parameters, network parameters, and covariate parameters. 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 dispersion in edge

values. For network effects we include a transitive weight term. The transitive weight term is specified as:

$$\text{Transitive Weights} : \boldsymbol{g(y)} = \sum_{(i,j)\in\mathbb{Y}} \min\left(\boldsymbol{y}_{i,j}, \max_{k\in N}\left(\min(\boldsymbol{y}_{i,k}, \boldsymbol{y}_{k,j})\right)\right),$$

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. Note that, because 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, weighted import disruptions and is defined as:

$$\text{Dyadic Covariate} : \boldsymbol{g(y, x)} = \sum_{(i,j)} \boldsymbol{y}_{i,j} x_{i,j},$$

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:

$$\text{Node Covariate} : \boldsymbol{g(y, x)} = \sum_{i} x_i \sum_{j} \boldsymbol{y}_{i,j}$$

4 Results

There are a number of significant findings from the monthly models, shown in Figure 1 and Figure 2. It is important to note here that the disruptions here are not overall disruptions, but shared disruptions across states, meaning that we are illustrating the spread of disruption, not overall disruption. There is, of course, some overlap, given that any increase in shared disruption will coincide with an increase in the likelihood of disruption overall. First, for the intercept (Panel a), we establish a baseline of pre-covid disruption to compare against. 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 began rising again, but not reaching the same levels of disruption as were seen at the beginning of the pandemic, indicating supply chain issues are far from over, which in turn limits our ability to draw conclusions about long-term solutions. Variance of disruptions, (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 being felt more evenly. The final network term, transitivity or a clustering coefficient (Panel c), shows a pre-pandemic downward trend, but remains statistically significant for all models except for 50% disruptions in April 2020. Two months prior to the start of the pandemic in the US there was a spike in transitivity, which could be the

result of the pandemic already impacting industries tied to China and other parts of the worlds that were already experiencing some early effects of the pandemic. 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 manufacturing that caused disruptions to spread chaotically instead of through industry and regional ties. Different disruption levels tend to follow the same trends in all three and while it 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 COVID-19 impact variables, import disruptions (Panel d) is relatively stable, which is expected given the importance of supply chain inputs for US exports. However, COVID-19 positive hospital bed utilization's (Panel e) relationship with export disruptions is quite volatile. It is significant and positive for most months of the pandemic, but roughly around the time that vaccinations became widely available the impact of hospitalizations sharply grew by around 600% before sharply dropping at the beginning of the Delta variant's dominance in the US. Looking at the comparison of overall hospitalizations level in the US, we see that hospitalizations had the strongest positive relationship on 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 the pandemic intensity is strong at the country level, local hospitalization level matters less because the likelihood that disruptions across the country are impacting a firm regardless of local levels is high.

Lastly, for non-pharmaceutical policy interventions and their related lags (Panel f through 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 zero to 100 on the scale, but this would be unlikely given that some level was implemented and no state ever hit 100 and the relationship drops in half by the six 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 six month lag the coefficient sizes are comparable and economic support is on average positive. Taken together, they confirm our first paper's results that NPI's impact on export disruptions is difficult to interpret, is likely minor, and should not be a governing factor in deciding on policy.

5 Conclusion

The global pandemic that has gripped the world since early 2020 has exacted an incalculable toll in human lives, while crippling economies for much of that year. Given the impact of the pandemic as well as of policy responses intended to limit the cost in human lives, trade disruptions were to be expected throughout supply chains. Indeed, beyond policy responses, panic-buying and

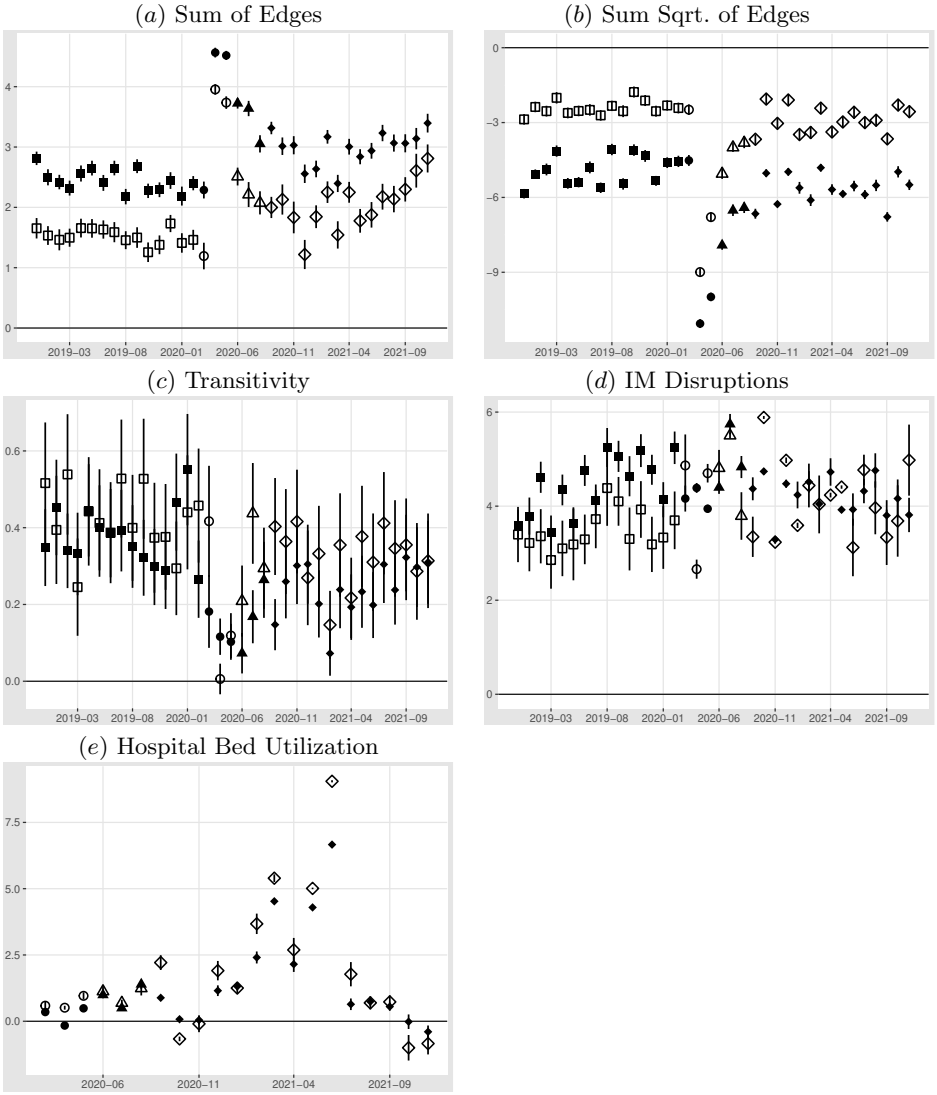

Fig. 1. Coefficient estimates of network terms and COVID-19 impact variables in Poisson ERGMs. Bars span 95% confidence intervals. For some models, the confidence intervals are not visible due to being small and the large range of the coefficient estimates. Squares are pre-covid months, circles are first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

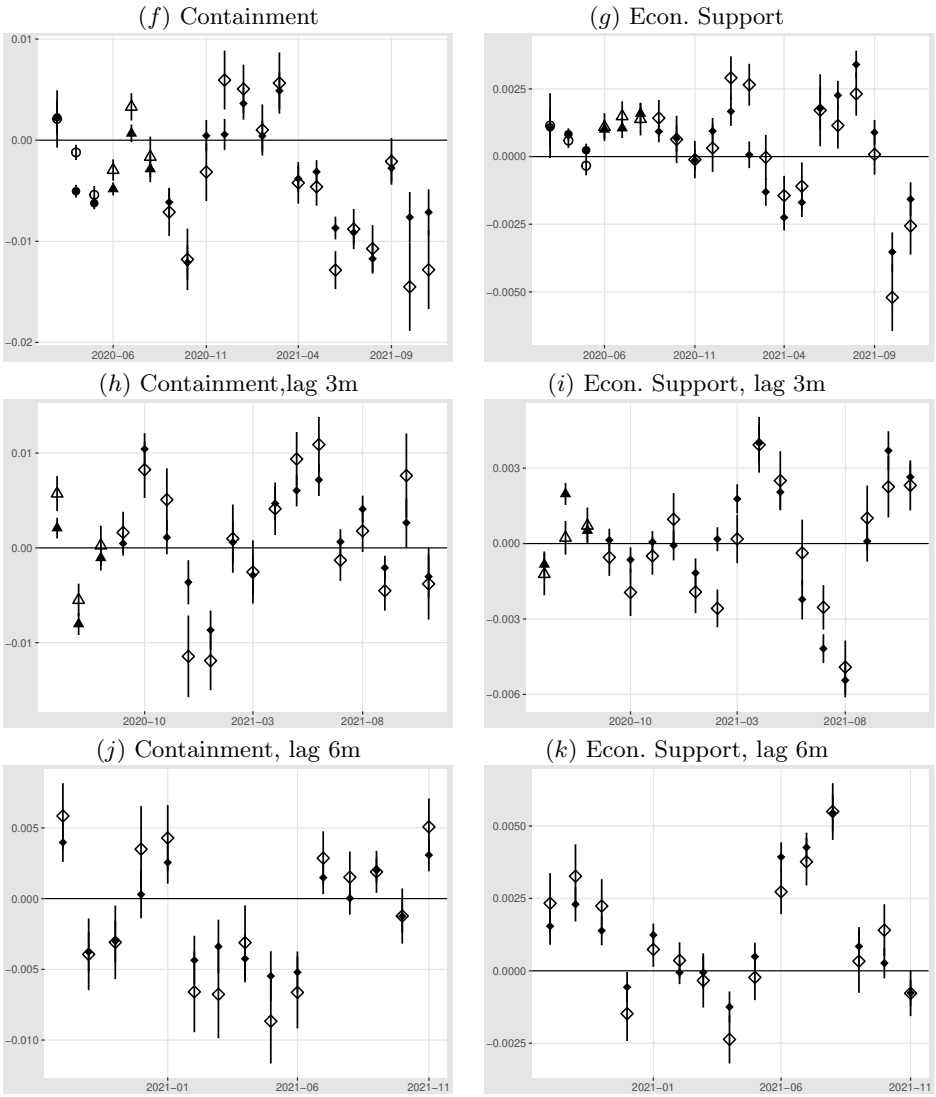

Fig. 2. Coefficient estimates of Policy Variables in Poisson ERGMs. Bars span 95% confidence intervals. For some models, the confidence intervals are not visible due to being small and the large range of the coefficient estimates. Squares are pre-covid months, circles are first three months of COVID-19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

other behavioral oddities caused severe disruptions in very specific supply chains very early on. Given that the previous global pandemic of 1918 took place in an economic environment of much lesser economic complexity, studies examining that event could not accurately predict the manner in which modern economies and industries would be affected. Modern supply chains are, after all, significantly more spread out globally. Indeed, across the globe, new debates have emerged with regard to the perceived need to 're-home' certain key industries as Just-In-Time supply chains dependent on imports from across the globe that have proven to be vulnerable to disruptions in trade over which individual governments have no control.

This pandemic, then, has presented us with a rather unique global challenge, as well as a rather unique opportunity to look at the robustness – or lack thereof – of global supply chains in our modern globalized economic environment. More than just a study into the impact of the current global pandemic on global supply chains, our study was intended to close a hole in the extant and emerging literature, which has not used network level analysis of the manner in which trade shock and disruption moves across networks. It was our hypothesis that disruptions will noticeably move along industry connections, spreading in specific patterns, and our model appears to support this hypothesis. We believe that this is an important finding that has application beyond the context of a global pandemic.

Declarations

Ethics Approval and Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

Data Availability

All data used are from publicly available sources. For replication code and or data, please email author as file size is over 10GB.

Competing interests

The authors declare that they have no competing interests.

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Authors' Contributions

Authors contributed equally to all parts of this article.

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