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# Spatio-temporal Spread of Disruptions in Interconnected Supply Networks

Matthias Winter[1] and Johannes Scholz[2]

[1]Logistikum, University of Applied Sciences Upper Austria, Steyr, Austria
[2]Department of Geoinformatics, University of Salzburg, Salzburg, Austria

Correspondence: Matthias Winter (matthias.winter@fh-steyr.at)

**Abstract.** The article investigates the spatio-temporal propagation of disruption effects in supply networks using shipment data from an international retailer during the year of 2021, marked by various disruptions in the global shipping industry. Events such as the COVID-19 pandemic and the blockage of the Suez Canal caused significant disruptions, including congestion and temporary shutdowns of ports. The network effect of such disruptions is measured as network connectivity using node strength in a weighted graph. Analysis of the data reveals a decrease in mean traveling speed and an unexpected decrease in speed variation following the Suez Canal blockage. The impact of the typhoon in China, while notable, was less significant than that of port closures due to COVID-19, likely due to its shorter duration. Evaluation of the spatio-temporal spread indicates, that port shutdowns due to COVID affected some routes from Asia to Europe and Australia, while others remained unaffected, potentially due to company-specific factors or differing supply patterns in various destinations. Future research aims to extend the analysis to include hinterland transportation to distribution centers and stores, where clearer spatio-temporal patterns may emerge, potentially confirmed through tests for spatio-temporal autocorrelation.

**Keywords.** spatio-temporal analysis, supply chain disruptions, global shipping network

## 1 Introduction

Disruptions in global supply networks (SN) are manifold. They can have natural, geopolitical, and other human, or health-related origins (Umar and Wilson, 2024; Gunessee et al., 2018; Srai et al., 2023; Jiang et al., 2023).

However, the production of goods in global economy depends primarily on these SN, consisting of a huge number of buyer-supplier relations (Choi et al., 2001; Wiedmer and Griffis, 2021). As part of these networks, material is shipped all over the world. The performance of SN is prone to disruptions, since the breakdown of central supply links can lead to production failures that spread in the network. This effect may be spatially visible over the globe (Ivanov and Dolgui, 2020). The lack of semiconductors in the automotive industry is only one example of a disruption at a single company, that lead to problems in production plants of other regions (Burkacky et al., 2021). The spatio-temporal propagation of the effects from COVID-19 measures and climate-related disruptions are investigated in the global maritime transport network using AIS data (Dirzka and Acciaro, 2022; Verschuur et al., 2023). However, SN are investigated mostly with the help of simplified models - where only minor parts of an SN are considered. From a macro perspective the Global Supply Chain Pressure Index reflects several events that affect global SNs especially since COVID-19 occurred (Benigno et al., 2022). It is measured by global shipments of raw material, container shipments, and the extent to which delays in supply affect producers. However, this kind of data is too coarse to derive spatial propagation of events.

The purpose of this research is to evaluate the spatio-temporal propagation of the effects of disruptive events. Can we use shipment data to describe the spatial propagation of a disruption's effect? Since shipment data provided by logistics service providers usually include origin-destination ports and time stamps, but not the exact vessel trip that was taken, the data is extended by other geographical data that is publicly available. We use these open data to estimate the approximate route and travel distance. The specific disruptions that are taken into account, are measures taken to mitigate health consequences of the COVID-19 crisis and the Suez Canal blockage (Khan and Rahman, 2021; Kuźmicz, 2022).

The paper is organized as follows. Section 2 gives an overview of the relevant literature in disruption propagation. In section 3 the method used for the analysis in this article is described and in section 4 the results are presented. Since this is a work-in-progress paper, the discussion and conclusion, drawn in section 5, give an outlook of how this work will be continued.

## 2 Literature

In supply chain management, the propagation of disruptions is known as the ripple effect (Dolgui et al., 2018). Quite some methods are applied to investigate the ripple effect in supply networks (Ivanov and Dolgui, 2021). Blackhurst et al. (2018) use Petri nets and assessed vulnerability of supply chains. Ojha et al. (2018) applied Bayesian network modeling to evaluate the propagation of risk in supply chains. Consideration of geographical aspects in supply chain disruption propagation has been part of more recent papers. Yue et al. (2023) states that most companies of the TFT-LCD supply network are located in China, increasing the risk of global breakdown of the production if a disruption occurs in China. Brusset et al. (2023) considers spatio-temporal dynamics of COVID-19 infections and its impact on the ripple effect in supply chains. They implement an epidemiological model and link the number of infections to local productivity in a country. However, most disruptions emerge locally and the effects propagate only through dynamics in the supply network. The event of a pandemic is thus not representative for most types of disruptions.

Focusing on transportation, which constitute essential links between supply, production, and retail, a different branch of literature exists. In transportation research, the focus is not on the supply chain, but the latter is seriously affected if transportation is disrupted. The effect of natural disasters and climate-related disruptions on global economy via maritime ports is estimated using vessel tracking data (Verschuur et al., 2020, 2023). Moreover, COVID-19 and its effects on global trade is analyzed, finding that the lockdown measures led to effects in oversea transportation and affected maritime trade (Verschuur et al., 2021). Putting the cart before the horse, Smith et al. (2023) explain that different consumer behavior due to COVID-19 led to congestion at ports, affecting material availability in the hinterland. Other scholars investigate the propagation of COVID's effects along the global shipping network (Dirzka and Acciaro, 2022).

Summarizing, the analysis of a disruptions spatial spread along the entire value chain is an unsolved challenge. Global shipping is an essential part of global supply networks, but the question of how disruptions affect the production in specific regions and what further consequences emerge in other regions is a challenging field of research.

## 3 Data and Methods

To evaluate the effect of disruptive events, empirical data is used. The data is described in this section. Then the measures used to evaluate the data are defined.

### 3.1 Empirical Data and Preprocessing

This research is based on shipment data of a retailer that operates internationally. The focus is set on goods that are shipped from Asia to Australia, Europe, and the USA. These shipments cover about 85% of the data and about 65.000 data points. The data stems from the year 2021 and is provided by the logistics service provider of the retailer.

The data is pre-processed in R, summarizing the orders that were carried on the same vessel. This is done by shipment-key, resulting in individual trips with unique port of loading and port of destination. The timestamps that were recorded at each port by the respective shipping company include data issues. Therefore, the travel time, calculated from actual time of departure and actual time of arrival is not found to be unique in the data. Since most shipments consist of many orders, taking the median of the travel time leads to plausible values.

For the data analysis the origin-destination pairs from the six Asian ports with most shipments are selected (see Table 1). Next, the destination ports are reduced to the following list:

- Australia: Adelaide, Brisbane, Fremantle, Melbourne, Sydney
- Europe: Dublin, Felixstowe, Hamburg, Hull, Koper, Rotterdam
- USA: Long Beach, Los Angeles

The remaining data covers more than 21.000 trips. The number of trips per port of origin is given in Table 1.

**Table 1.** Number of trips per port of origin

| Port of origin | Number of trips |
|---|---|
| Chittagong | 1286 |
| Ningbo | 8436 |
| Qingdao | 1397 |
| Shanghai | 4168 |
| Xiamen | 1812 |
| Yantian | 3978 |

To get the international shipping routes that are usually taken, are extracted from the global map of human impacts to marine ecosystems from the National Center for Ecological Analysis and Synthesis (NCEAS) (Halpern et al., 2008; Halpern et al., 2015). The data is provided in raster format of $1km^2$ and represents roughly 11% of the 30.851 merchant ships >1000 gross tonnage at sea in 2005 as described in Halpern et al. (2008). The value of human impact by shipping per raster cell represents the number of vessel trajectories that passed through the cell. A snippet of the data is given in Figure 1.


**Figure 1.** Human impact to marine ecosystems by merchant vessel shipping.

### 3.2 Measures for Effects of Disruptions

To measure the effect of a disruption we use travel times, mean travelling speed, the number of vessels that departed from a port, and the coefficient of variation (CV) to cover the uncertainty in travel times and speed. Moreover, we apply the graph theoretic measure of node strength to measure the effect of a disruption in terms of network connectivity (Barrat et al., 2004). For the travelling speed, we use the usually taken route from an origin-destination pair to derive the length of the route in $km$. The coefficient of variation as a measure of relative variability is defined as the ratio of the standard deviation and the mean of the data (Cedillo-Campos et al., 2019) - see Eq. 1.

$$CV = \frac{Standard\ deviation}{Average\ travel\ time} \tag{1}$$

We calculate for each measure the mean per week to get proper data for the changes over time. For node strength, the number of shipments that depart each route are taken as arc weights $w_{ij}$. Then the strength $s_i$ is calculated per week as in Eq. 2.

$$s_i = \sum_{j=1}^{N} x_{ij} w_{ij} \tag{2}$$

To account for the size of the respective port, the strength values are normalized per port. All analyses are done in R, except of the calculation of the distances, which is computed in ESRI ArcGIS.

## 4 Results

The travel times and its variance generally fluctuate much. Speaking of the US west coast, the congestion at the ports of Los Angeles and Long Beach (Deeb and Leonardo, 2023) contributed to this fact. The travel time to destinations in Europe increased during the year 2021, reaching the maximum in the summer between week 20 and 35. The respective values per week are given in Fig. 2. This can be explained by port shutdowns due to COVID infections of employees. Moreover, the effect of the events in 2021 might overlap and therefore it is hard to evaluate the effect of a disruption.

At end of March 2021 (week 12) the Ever Given got stuck in the Suez Canal for six days leading to congestion of cargo vessels. Fig. 3 shows the mean and CV of vessel speed on routes via the Suez Canal and not via the Canal. Since the vessels have different ports of departure in Asia, the duration when they reached the Canal after departure is different. Hence the decrease in mean speed, due to waiting time, should affect vessels departing from week 10 on. Indeed, there is a noticeable drop of mean vessel speed. Moreover, the decrease in CV in week 11 could mean that the blockage somehow unified the travel times on routes through the Suez Canal.

To evaluate the spatial propagation of the Suez Canal blockage the travel times to different ports of destination are analyzed. Fig. 2 shows that the blockage affected port of Hamburg and Felixstowe, where the mean travel time and CV increased for vessels that departed in week 10

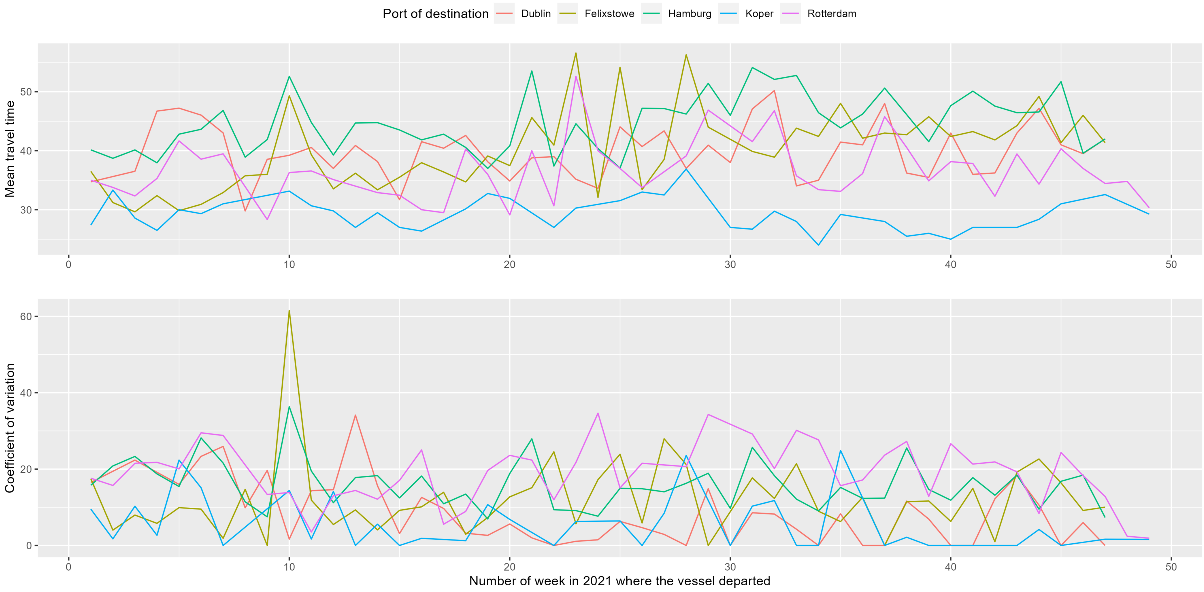


**Figure 2.** Mean travel time and coefficient of variation of shipments from Ningbo and Shanghai to Europe.

from Ningbo or Shanghai. However, there is no effect on vessels to Dublin, Rotterdam, and Koper. An explanation can be that the number of vessels to Koper and Rotterdam is quite small compared to Hamburg and Felixstowe. The number of vessels to Dublin is comparable to Hamburg and Felixstowe, but still no effect can be seen.

The effect of measures to mitigate the COVID-19 crisis is not as easy to analyze, since there were several events over the year 2021 that affected ports in China. Moreover, the Typhoon Chanthu reached the ports of Ningbo and Shanghai in September 2021, resulting in further shutdowns of single terminals at those ports. However, we can see some indications in the data. It was reported that port of Ningbo closed a terminal due to an employee's positive COVID-test in the end of July (end of week 30). The effect can be seen in the strength of the respective nodes (port of Ningbo, port of Shanghai) that decreased in the subsequent week (Fig. 4). This decrease of vessel departures resulted also in a decrease of strength at destination ports in Australia and Europe.

## 5 Discussion and Conclusion

In this article the spatio-temporal propagation of disruption's effects in supply networks is investigated. Shipment data from an international retailer is used to get a first idea, whether such data can be used to analyze spatio-temporal spread of disruptions. The scope is the year 2021, where the global shipping industry experienced a lot of disruption. Starting out with the COVID pandemic, the Suez Canal was blocked for nearly a week leading to congestion. In China, a Typhoon hit some ports, leading to temporal shutdowns of separate terminals. These and other events made the travel times rather volatile. There is evidence in the data that the events led to a decrease in mean travelling speed resulting from longer waiting times along the route due to congestion. Surprisingly, the Suez Canal blockage led also to a decrease of variation in mean travelling speed in the weeks after the blockage. Applying node strength as a measure of connectivity in the network, showed a decrease of node strength after week 30, where a port was shutdown due to a COVID infection. This means that a lower number of vessels departed in that week.

The evaluation of the spatio-temporal spread of the effects showed, that the Suez Canal blockage could potentially affect all routes from Asia to Europe. However, while transportation to Hamburg and Felixstowe was affected, transportation to Dublin, Koper, and Rotterdam was not affected. This might be a company-specific result and other firms in Europe could have a different pattern. As a next step, the data should be extended to hinterland transportation to the distribution centers of the retailer up to the large number of stores. In such data, the spatio-temporal pattern could be clearly visible and a test for spatio-temporal autocorrelation could prove this pattern (Lamieri and Sangalli, 2019; Cheng et al., 2012).

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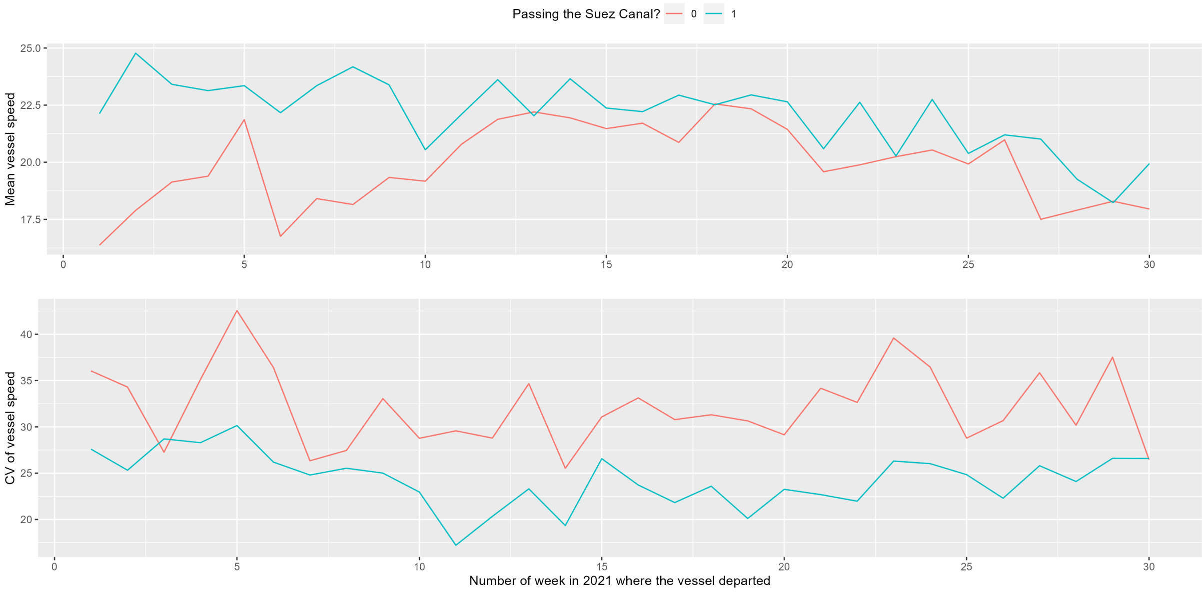


**Figure 3.** Mean vessel speed and coefficient of variation on routes passing the Suez Canal versus not passing it.

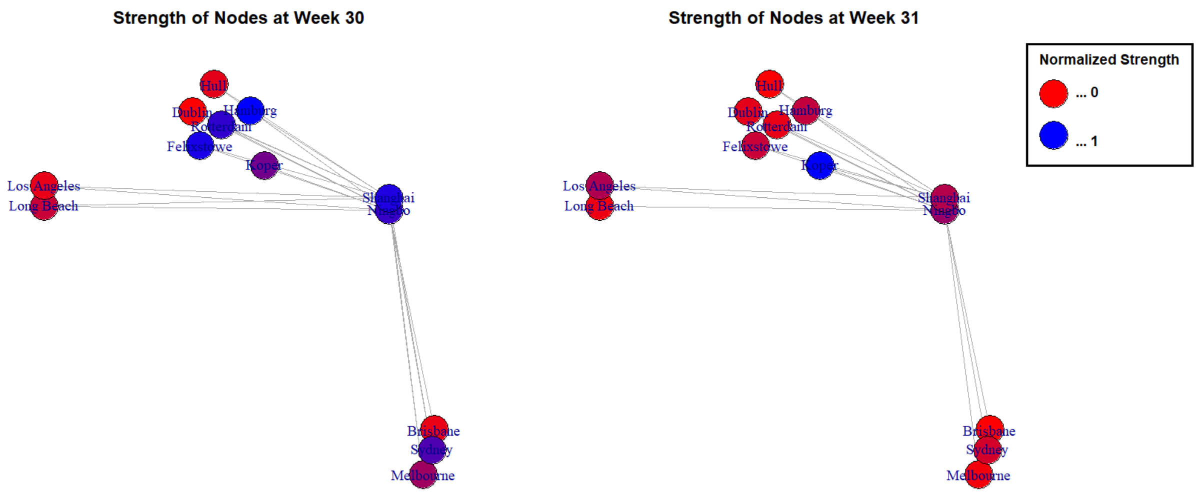


**Figure 4.** Node strength of week 30 and 31 that show the effect of port shutdowns in China.

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