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Measuring the impact of port congestion on containership freight rates

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ABSTRACT

We examine the impact of port congestion on containership freight rates. Our overall results show that port congestion has a positive and significant effect on containership freight rates. The most important region is Asia, where a 1 % increase in port congestion has a >1 % effect on shipping freight rates. This suggests that the region, being the world's largest manufacturing area and an integral part of the supply chain, has much more importance than previously considered. As such, the results highlight the importance of the manufacturing region in supply chains and are also in line with the derived demand system in shipping. As per the results, a return to the pre-pandemic congestion levels in Asia would lead to at least a 25 % decline in containership freight costs.

1. Introduction

With global seaborne being the leading form of transport (UNCTAD, 2021), global supply chains relied on it for smooth and efficient operations. Over time, the importance of seaborne trade grew since supply chains shipped manufactured goods across the world. Since 90 % of non-bulk dry cargo worldwide is transported by container, container trade volume is closely linked to domestic economic activity (Kilian et al., 2023). For instance, domestic manufacturers depend on imported raw materials and intermediate goods shipped in containers, while consumers frequently buy finished products that arrive in their home countries via container. Given that, China became the largest manufacturing country in the world, seaborne trade patterns shifted and trade routes from China and to the US and the EU became the norm (Stopford, 2013). Furthermore, vessel optimization for these routes provided even more efficiency (Ancona et al., 2018; Beşikçi et al., 2016; Jimenez et al., 2022; Meng et al., 2016).

While the above was the norm for approximately the last two decades, the coronavirus pandemic (March et al., 2021) and, to a lesser extent, the Russia-Ukraine war (Michail and Melas, 2022) have provided the global economy with a new conundrum that pertains to supply chain disruptions. While disruptions have wide implications for the whole economy (Masodzadeh et al., 2022), the lack of consistent data since the 2000s has made it difficult for the academic community to study such events. The temporary closings of Chinese manufacturers and ports in the beginning of 2020 stopped the free flow of products, while vessels waited for days in port anchorages (Alamoush et al., 2022; Karunathilake, 2020; Lenzen et al., 2020). At the time when the production side of the economy

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was adversely affected by the pandemic, the demand side was not equally diminished. Recent studies have shown that not only demand was unaffected, but higher demand pushed freight rates higher (Michail et al., 2022).

The combination of vessels remaining in the anchorages for long periods (Millefiori et al., 2021) with the underperforming ports (Xu et al., 2021) has created congestion in the world's most important ports. While vessel waiting is a usual phenomenon (Stopford, 2013), the duration of the endeavor during the coronavirus period turned this into an abnormal event (Komaromi et al., 2022). Combined with other events such as the temporary close of the Suez canal and the Russia-Ukraine war (Al-Yafei et al., 2022) exacerbated the pressure on global supply chains.

Given the recent events and their importance on the broader economy (Michail et al., 2022), the need for a clear quantification of the effect from port congestion is evident. While some studies have provided some insights into the behaviour of various economic agents, linking the overall state of the turbulence in supply chains with its economic implications (Bourghelle et al., 2021; Mariotti, 2022; van Bergeijk, 2022), there has not been an answer yet to how this disruption is affecting the freight rates per se.

This study fills several gaps by measuring, for the first time in the literature, the impact of port congestion in different areas of the globe on containership freight rates. Our results show that port congestion tends to have a positive effect on containership freight rates. Port congestion shock in Asia has the strongest pass-through to freight costs, namely due to the region's importance as the world's leading manufacturer. This highlights the importance of the manufacturing region in the supply chain, while it is also in line with the derived demand system in shipping (Notteboom et al., 2021; Pettit et al., 2018). The results also suggest that once congestion returns to its pre-pandemic levels, the 20 % implied drop in Asian port congestion, could lead to more than a 25 % decline in containership freight rates.

Following this introduction, the remainder of this paper is organized as follows: Section 2 provides a review of the literature on the issue, Section 3 describes the methodology and the data used, Section 4 discusses the empirical results obtained, and Section 5 concludes on the findings.

2. Literature review

One of the cornerstones of the supply chain operations is the loading and discharging of raw materials, oil, and final or semi-final goods that take place in the ports around the globe (Hall and Jacobs, 2010; Lam and Yap, 2011; Lu et al., 2016; Wendler-Bosco and Nicholson, 2020). Despite its importance, this has not been particularly covered in the bibliography mainly for two reasons. The first is that the relevant data has only been available since the use of Automated Identification Systems (AIS) in the industry that can track the exact place and load of any given vessel (Yan et al., 2020).

The second reason is that a big part of in the supply chain literature has been devoted to the "last-mile problem", i.e. the transportation from the final hub for a given product to the final consumer (Gevaers et al., 2011; Olsson et al., 2019; Ranieri et al., 2018; Simoni et al., 2020). This, while a major conundrum, is mainly an optimization problem aiming to reach a business-to-consumers solution (Mangiaracina et al., 2019), and has not been adequately researched in the business-to-business context (Browne and McLeod, 2020). While some studies indeed have tried to optimize port congestion, they act primarily as case studies of specific ports, leaving the general macroeconomic environment very under-researched (Abu Aisha et al., 2021; Kweon et al., 2022; Raad et al., 2022).

Furthermore, studies on port congestion are rather new in the bibliography given that this problem has not been extensively documented until the last few years. Nevertheless, the negative impact of events such as the ones previously mentioned, have turned the academic community to look into the consequences of port congestion on vessel waiting time (Bai et al., 2024), shipping emissions (Li et al., 2024) and route planning (Zhang et al., 2024). Still, it was not until the recent lockdowns that researchers have started to investigate the matter, with an emphasis mainly around the optimization problems that arise (Aydin et al., 2017; Elchahal et al., 2013; Molavi et al., 2020; Zhen, 2016).

The novel work of Cerdeiro et al. (2020), using an AIS dataset, has been stepping stone for researchers to look into the problems that exist when it comes to the loading and unloading process in the global ports. In a catch-up paper, Komaromi et al. (2022), using the same dataset, show that during the Covid-19 pandemic, shipping delays were 1.5 days higher than the previous period, which is about a 25 % increase in travel times. In a similar manner, Peng et al. (2022) have used high-frequency container port congestion measures, counting vessel movements for 3957 containerships from March 2017 to April 2017 to show that the inclusion of port congestion can improve prediction performance. Finally, Lin et al. (2022) have examined three different port congestion strategies, namely, epidemic prevention alliance strategy, shared berths strategy, and their hybrid, around adjacent ports and their actual fitness for prevention of congestions during the coronavirus pandemic, with results supporting the first option.

Apart from the optimization problems that have been faced during the pandemic, only one previous study, at least to our knowledge, has been conducted concerning the effect of port congestion on international trade. In particular, Steinbach (2022) shows that the U.S. exported 24.5 percent fewer containers between May and November 2021, as a result of port congestion, amounting to export losses of $15.7 billion, due to the port congestions in the US ports. Given the importance of containership trade for the economy (Michail et al., 2021) the impact on the overall economy is expected to have been large.

As of the time of writing this article, there are no studies that measure the magnitude of the impact of port congestion on freight rates, despite the latter's importance to the world economy, and especially inflation (Michail et al., 2022). To extend the very limited literature on how port congestions affect freight costs, we use time-series data for port congestions in Europe, Asia and North America, and estimate their impact on containership freight rates, employing additional macro-variables for control purposes. The methodology we use in this paper is outlined in the following section.

3. Methodology

Following its introduction to the shipping industry by Michail and Melas (2020b), we propose the use of a Bayesian Vector Auto-Regression (BVAR) model. The benefits of this model are twofold: first, under the original Vector Auto-Regression (VAR) setup of Sims (1980), it allows us to capture the co-movement between variables, without imposing any (major) assumptions with regards to the causality structure and without falling under the Lucas Critique (Favero and Hendry, 1992). In particular, the endogeneity issues that usually affect econometric models do not come to play here, under the proposed specifications.

Second, the BVAR model, which is an extension of the original VAR model, allows us to impose a different prior distribution structure to that of normality, which allows us to better capture the peculiarities of data, especially in cases where availability is limited, as is usually the case with shipping time-series. In particular, if the time-series dimension is small, coefficient estimates can be imprecise under the standard VAR framework (Weale and Wieladek, 2016). As such as per their introduction by Litterman (1986), Bayesian methods allow for more parsimonious estimates which alleviate any small sample issues. At the same time, the imposition of a different prior allows for the data to have a strong impact on it and thus shift it in the proper direction, while still maintaining a statistically robust estimation.

More formally, the specification follows that of Sims (1980), where $y_{i,t}$ denotes a matrix with i variables. As such, the VAR representation becomes:

$$\Delta y_t = a + \sum_{j=1}^{k} \beta_j \Delta y_{t-j} + \varepsilon_t,\ \varepsilon_t \sim N(0, \Sigma) \tag{1}$$

where y_t is a matrix of endogenous variables, Δ is the first difference operator, j is the appropriate lag length and ε_t denotes the vector of serially and mutually uncorrelated structural innovations, with variance-covariance matrix Σ. As already discussed, while in the standard VAR literature the Σ matrix follows a standard normal distribution, in the BVAR setup, we can deviate from this restrictive assumption and use something that is more suitable for our dataset. Finally, the β_j are the relevant coefficients that correspond to the *j-th* lag of the matrix of dependent variables. For example, $\beta_{1,2}$ is the first lag of the second variable included in the y_t matrix.

For the purposes of this analysis, the y_t matrix includes the Brent oil price, the Wilshire 5000 total market index, port congestion indices in North America, Europe, and Asia, as well as the containership freight rates.[1] Excluding the port congestion indices, which have not been used extensively in the past, the above variables have been found to be important in explaining a large part of the behaviour of freight rates by the recent literature (Melas and Michail, 2021; Michail et al., 2021)

As elaborated in said literature, the Brent oil price serves as a proxy of costs for containerships and bulk carriers (with a different double effect for tanker vessels as Michail and Melas (2021) have demonstrated), while the stock market serves as a proxy for the global macroeconomic environment, i.e. for capturing the overall demand side for vessels. As Stopford (2013) underlines, shipping is a derived demand system, where higher demand for goods would lead to a greater need for transport, while demand for transport on its own is non-existent. As such, both variables are expected to have a positive effect on freight rates: as Brent prices increase, these will be passed on to the shipper via an increase in freight rates. Similarly, higher economic growth means higher demand for goods and hence higher vessel freight rates, ceteris paribus.

To our knowledge, there is some limited research regarding port congestion but more research is needed given the supply chain disruptions that have occurred over the last three years. Our prior expectation is that port congestion should have a positive effect on freight rates, given that this would effectively lead to higher lead times and thus inhibit any just-in-time practices used by firms, in a similar manner that longer average haul (i.e. longer distances traveled by a vessel) increases freight rates as it reduces supply of vessels. This would, in turn, require higher inventories by firms, which would then imply the need for an increase in transport quantity to ensure that they do not run out of goods (Mosca et al., 2019; Qu et al., 1999).

The above should hold more when it comes to more regional effects: it could naturally be the case that congestion in one region does not affect freight costs in the same manner as congestion in another. For example, higher freight costs in the US may not have an impact on European freight rates. To address this, we employ port congestion indices in three different regions, namely North America, Europe, and Asia.

With regards to data sources, Brent oil prices and the S&P500 index were obtained from the Federal Reserve of St. Louis database (FRED), while all remaining variables were sourced from the Clarksons Intelligence Network database. Following Michail and Melas (2020a), we also employ a Covid-19 dummy to account for the one-off disruption related to the pandemic. The data range from January 2016 to October 2024 at a monthly frequency, limited by data availability. More information regarding the variables used can be found in Appendix 1.

Concerning estimation methods, as already suggested, the BVAR is especially convenient when it comes to smaller samples. In our case, the 106 available observations of our series are in-between what we would normally classify as a small or a large sample. While the original formulation by Litterman (1986) presented a new way to assist in the estimation for short samples, that particular prior comes with a major disadvantage: in particular, the main assumption is that we have a known variance-covariance matrix and hence tends not "let the data speak" as it dominates their information. Without going into much detail, other prior distributions (e.g. the

[1] Given the high correlation between freight rates, we use the Europe-China rate as a proxy. Robustness checks, available upon request, were conducted with the China-Mediterranean, and the China-North America freight rates.

non-informative Normal-inverse Wishart) also have important issues, such as creating dependencies between the error term variance and the coefficient variance (the interested reader may refer to Uhlig, 2005; Weale and Wieladek, 2016; Dieppe et al., 2016).

To avoid this potential drawback, we employ an Independent Normal-Wishart (INW) prior with unknown Σ and arbitrary variance-covariance matrix, Ω_0, which overcomes the previously-mentioned issues (see Dieppe et al., 2016 for more details). As a result, the standard prior distribution for the INW prior is specified such that, $\beta \sim N(\beta_0, \Omega_0)$, where the β_0 defined as following the Litterman (1986) prior, where the first lag of each endogenous variable with itself is assumed to have the largest impact (specified with ones in the prior vector), while further lags and cross-variable lag coefficients are signified with zero, meaning that their starting impact is assumed to be very small (Dieppe et al., 2016). As already suggested, the data can, naturally, shift the prior from its original specification and push it to a completely different structure. Ω_0 is also assumed to take the form of the original Litterman (1986) prior covariance matrix. In simpler words, this is prior-within-prior structure allows us to both be agnostic with regards to the effects, but to also account for the potential that the sample would lead us to a different effect than the one first envisaged via the prior imposition, given the specificities of the data structure.

As per the derived conditional distributions for the posterior distribution of the parameters of interest, i.e. the INW prior plus the data, the researcher can use the Gibbs sampler to draw randomly from that distribution and obtain the final coefficient estimates (Dieppe et al., 2016). To ensure that the original randomness of the estimates is dealt with, common practice suggests that the first 1000 iterations designate the burn-in sample and are thus discarded. Given an overall total number of 2000 iterations used for the convergence of the Gibbs sampler algorithm, we are left with a total of 1000 iterations in the final estimates.

Common practice in the literature has been to use standard hyperparameter values, in order to obtain comparable estimates. In this, following Michail and Melas (2020b), we use an autoregressive coefficient of 0.8, with a tightness of 0.1, a cross-variable weighting of 0.5, a lag decay of 1 and 100 for the exogenous variable tightness. These values suggest that coefficient estimates would be less easily affected from only a few data points, as the tightness implies that not much room for manoeuvre exists. Naturally, more data points would allow for a larger shift of the estimates. At the same time, the literature is more relaxed with the exogenous variables, given the large variable tightness imposed. Similar to what we have discussed before, a high value for the autoregressive coefficient is suggested (0.8), and the lag decay suggests that the original assumption is that further lags will have a smaller effect on the variable. Again, these are all prone to at least some change, depending on the data structure and the dataset length.

As per the literature, structural identification is achieved through the standard Cholesky decomposition which places emphasis on variable order when it comes to further analysis of the effects from a shock, i.e. for impulse responses (see Michail and Melas, 2020b). In particular, impulse responses answer the question of "what happens in the system of equations when a shock, exogenous to the system, affects one variable". For example, what happens when port congestion increases not due to macroeconomic conditions but as a result of Covid-19 social distancing protocols (Michail and Melas, 2021a)? Given that Covid-19 is exogenous to our system of equations, this can be answered via the imposition of a one-standard deviation error shock on the particular port congestion equation and watch it evolve over the system.

To do so, we need to impose a particular ordering structure in the estimates, given that the higher up in the structure a variable is, the less it is affected by another variable's change, albeit only for the first period of the shock. The structure does not affect any of the variables in the subsequent periods. In more detail, we have ordered the variables in a way that is economically rational, with developments in oil prices ordered first, as they would tend to move more by OPEC's discretionary decisions or other events (wars, production issues, etc.) rather than directly follow macroeconomic developments. Given that oil developments affect the macroeconomic environment (see Michail et al., 2022), global macroeconomic environment (i.e. the stock market) is ordered second. Port congestion across the three regions is ordered next, while freight costs, which are affected by all of the previously mentioned factors, are ordered last.

Finally, the lag length was specified to one, which is both in line with the literature and the log-likelihood function results, while VAR stability was confirmed as all roots of the characteristic polynomial lie within the unit circle. The impulse responses that correspond to how an unexpected shock can impact the system of equations in the BVAR setup above can be found in the following section.

Table 1
Descriptive Statistics.

	Oil	S&P500	Freight	Cong_AS	Cong_EU	Cong_NA
Mean	67.6	3465.4	1927.3	0.89	0.85	0.57
Median	66.7	3228.2	1104.2	0.90	0.81	0.50
Max	122.7	5762.5	5721.2	1.17	1.30	1.28
Min	18.4	1932.2	635.0	0.72	0.63	0.31
Std. Dev.	19.9	1010.6	1505.1	0.10	0.15	0.21
Skewness	0.20	0.41	1.39	0.23	1.21	1.18
Kurtosis	3.04	2.14	3.43	2.41	4.08	4.18
Jarque-Bera (Prob)	0.68	6.32	35.04	2.52	31.14	30.53
	(0.71)	(0.04)	(0.00)	(0.28)	(0.00)	(0.00)
Obs	106	106	106	106	106	106

4. Empirical estimates

To motivate our discussion, we first offer a quick glance at the variables used, via the descriptive statistics in Table 1. In particular, it appears that while port congestion has been chronically high in Asia (Cong_AS), the dispersion in the values is much lower compared to Europe and North America. In particular, while the peak change is at 21.4 % higher in Asia, it stands at 32.5 % in Europe and 64 % in North America. At the same time, Fig. 1 also shows the co-movement of freight rates with Asian port congestion, even though the former responds with a lag. Still, the effect appears to be quite important.

To empirically test for the impact of port congestion on freight rates, Fig. 2 shows the impulse responses from the BVAR model, as described in the previous section, with the shaded region signifying a one-standard deviation interval. In particular, the estimates confirm the previous findings of the literature, that the usual bi-directional relationship between oil prices and the stock market exists, with the latter having a larger and longer-lasting impact on the former. While a 7 % shock in oil prices has a <1 % effect on the stock market which becomes insignificant almost immediately, a 4 % permanent shock in the market results in a >2 % persistent increase in the price of oil. This sort of behaviour is only natural, given that the stock market acts as a proxy to world demand.

In a similar manner, the Brent oil price and the stock market have a positive effect on freight costs. As before, our proxy for the global macroeconomic environment (the S&P500) has a stronger effect, with an almost one-to-one response registered; put simply, following a 1 % increase in global stock markets, a long-run impact of around 1 % is expected on the containership freight rates. This impact also appears to be long-lasting, with the impact stabilizing at its peak, at around 20 months from the initial shock. Such a behaviour can also explain why shipping investors tend to delay their decisions for a few months until they confirm that the increase in demand in permanent, in order to reduce their loss potential (Michail and Melas, 2021b). On the other hand, oil price shocks tend to have a smaller (0.2 % per 1 % shock) impact, with the effect lasting for only a month. This result is also intuitively appealing, given that oil price changes tend to be immediately embedded in freight rates but do not reflect longer-lasting tendencies.

The most interesting part of the estimation comes from the response of freight rates to the port congestion indices. In particular, it appears that less half of the shock is passed on to freight rates in the case of North America. At the same time, the effect appears to be short-lived, as the response become insignificant around five periods after the shock. On the other hand, port congestion in the EU does not appear to have an effect on freight rates.

The largest impact on freight rates takes place from port congestion in Asian ports, with a 4 % transitory shock causing a hump-shaped response in freight rates, with the peak standing at around 8 months after the shock. Interestingly, the effect on freight rates is still significant at least 20 periods after the initial shock, and despite the fact that initial effect has faded. With regards to the magnitude

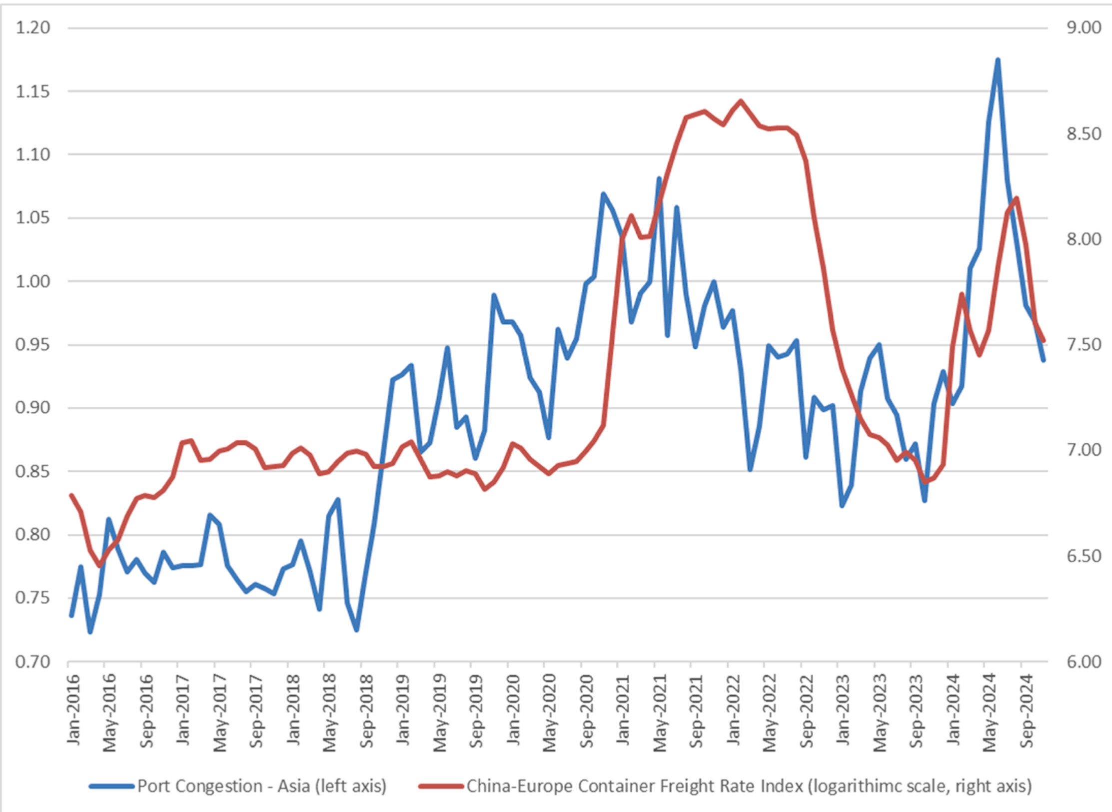


Fig. 1. Port Congestion in Asia and Freight Rates.

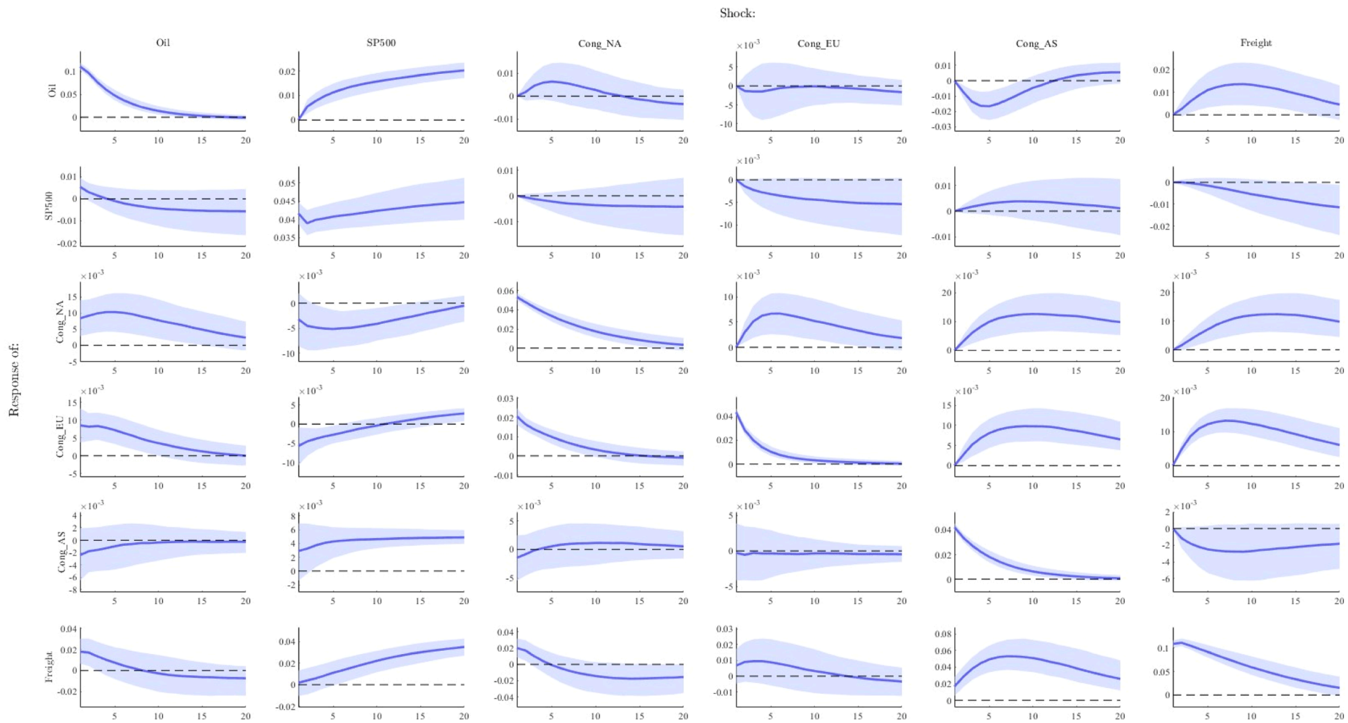


Fig. 2. BVAR Impulse Responses.

of the effect, a 4 % shock in port congestion in Asian ports results in a 5 % maximum impact on freight rates, at approximately 8 months after the shock. Interestingly, higher port congestion in Asian port also spills over to other regions, with small increases also observed in North American and European ports.

To put the figures into perspective, the 17.6 % easing in Asian port congestion in the June 2024-October 2024 period coincides with a 26 % decline in freight costs over the same period. Of that decline, as per the model, around 20 % can be attributed to the easing of port congestion and the remainder to other factors. If port congestion returns to its pre-pandemic levels (around 20 % lower than its current level), then a >25 % decline in freight rates can be expected. Naturally, while port congestion cannot assist in explaining the whole movement in freight rates it can provide a view on how disruptive port issues can become.

The differences point to a significant conclusion: while port congestion is a significant determinant of freight costs, it is more significant if it arises from the manufacturer's side. As Asia has become the world's leading manufacturing centre, with regards to goods, the balance of trade shifts towards this region. Thus, a congestion shock in the main importing countries has a stronger passthrough to freight costs than a shock in Europe. This is intuitively appealing since shipping is a derived demand system, and without a strong desire to import goods the whole necessity of the service declines.

This is also evident from a Forecast Error Variance Decomposition (FEVD) exercise, as can be observed in Fig. 3. Focusing on the effects of other factors on freight rates, the bars suggest that the largest effect (after the own shocks) comes from Asian port congestion, that ends up explaining around 25 % of the total variance of freight rates. The S&P500 explains around 7 %, with the remaining variables explaining <5 % of the variation. Thus, the FEVD also supports the view that port congestion in Asian ports is a significant determinant of freight rates.

To further elaborate on how the impact from port congestion evolves over time, we also provide time-varying estimates of the impulse responses in Fig. 4. As the figure suggests, the broad conclusions still hold; for example, freight rates rise following a shock in the stock market, while congestion, regardless of the region of the port that it is occurring in, causes an increase in freight costs. Asia still holds the reigns in terms of the impact on freight costs, with approximately a 0.8 % response to a 1 % shock across time. On the other hand, the EU and North America congestion shocks appear to cause half of the reaction, again supporting the full sample estimates. A shock in European port congestion appears to have as negative information for world stock markets, likely due to the overreaction of stock market investors to news that are considered to be negative as a whole (de Bondt and Thaler, 1987; Veronesi, 1999).

In order, to further elaborate on our findings, we have proceeded to robustness checks that can been found in the Appendix section. More precisely, we have used the SSE Composite Index in addition to the S&P500 to capture more Asian dynamics in our impulse responses estimations. As far as the definition of freight rates is concerned we have furthered examined our results with the variable of freight rates being Vessel Earnings and SCF Index. Finally, we have also examined how our relationship holds when we have included the demand for the containership trade. All of the above Tables can be found in Appendix 1,3,4 and 2.

Overall, our results are in accordance with the current literature that suggests that the demand side of the equation is far more important than the supply side when it comes to supply chains. The latter has been documented in the production (Tiedemann, 2020), the warehousing (Baker, 2007) and the procurement (Edler and Georghiou, 2007; Wagner and Bode, 2006) sections, with the work of Komaromi et al. (2022) providing similar results for ocean-going transports. In this work, we emphasise that the demand side is one of the main criteria when it comes to the cost of logistics. Heavy congestion in the place where most of the goods are located, will ultimately increase the price of the freight, irrespective of whether alternatives are available.

5. Conclusions

In this paper, we have elaborated on the relationship between port congestion and containership freight costs, using a Bayesian Vector Autoregression (BVAR) model. The results show that congestion shocks Asian ports tend to have a stronger effect on freight rates, with >100 % passthrough. Asian port congestion also has a permanent impact, lasting for >2.5 years (30 months). The results suggest that if congestion returns to its pre-pandemic levels, the implied 20 % drop in Asian port congestion could lead to more than a 25 % decline in freight rates.

The implications from the estimates are straightforward. While port congestion is a significant determinant of freight costs, it is more significant if it occurs in the manufacturing region. As Asia has become the leading manufacturing hub of the world, it is only reasonable that its importance as a determinant of freight rates has grown. This is intuitively appealing since shipping is a derived demand system and, without a strong desire to transport a good the whole necessity of the service declines. Additionally, the results suggest that a shock in port congestion does not have a meaningful impact on oil prices.

While the results bear implications both for the supply chain sector but also for the shipping industry, more research is needed in this area. For example, this research paper does not use AIS data to further examine the port congestion in a disaggregated level, which would allow for either port-specific or route-specific results. The use of other data sources, such as the CCFI could also complement the results for other freight rates, while employing alternative types of vessels (e.g. tankers, dry bulk, etc.) may also provide a more disaggregated view. Finally, the use of non-linear techniques could also assist in extending our knowledge with regards to the potential for changes in the relationship between congestion and freight rates.

CRediT authorship contribution statement

Nektarios A. Michail: Writing – original draft, Software, Methodology, Funding acquisition, Data curation, Conceptualization. **Konstantinos D. Melas:** Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Conceptualization.

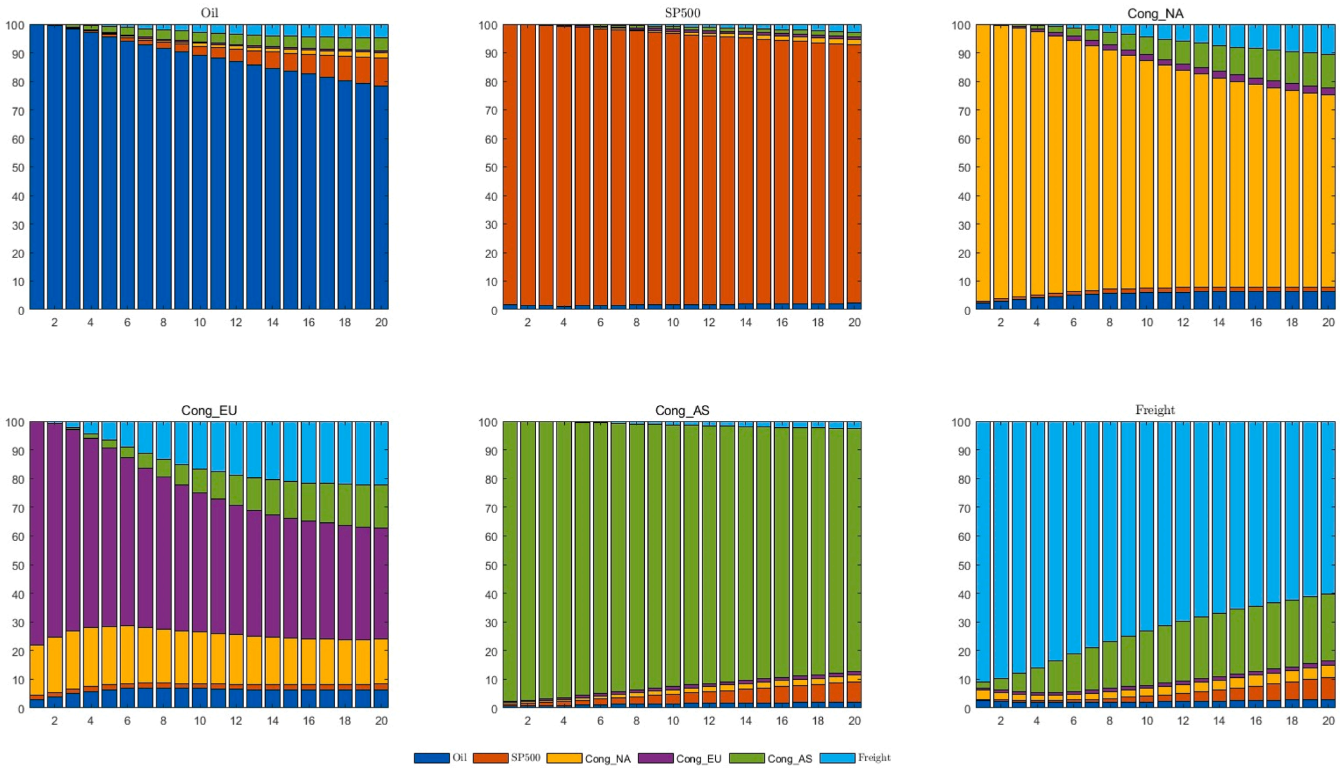


Fig. 3. Forecast Error Variance Decomposition.

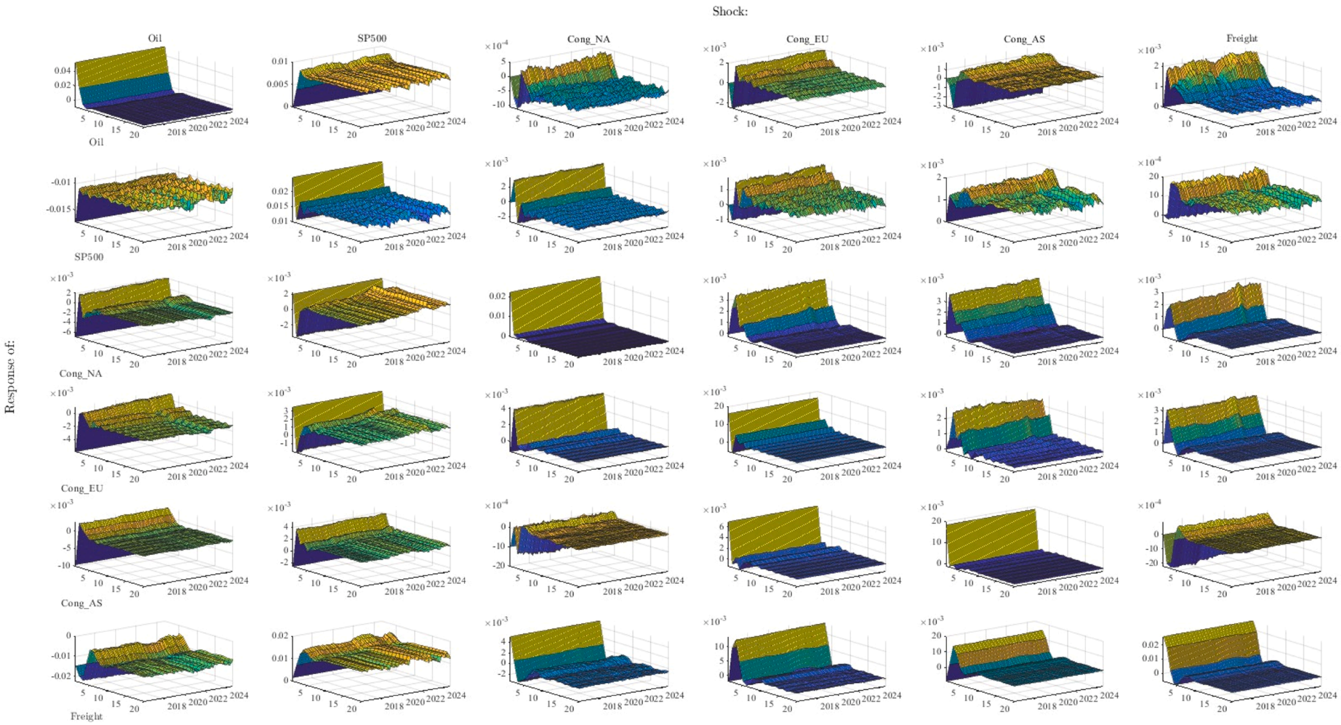


Fig. 4. Time-Varying Impulse Responses.

Declaration of competing interest

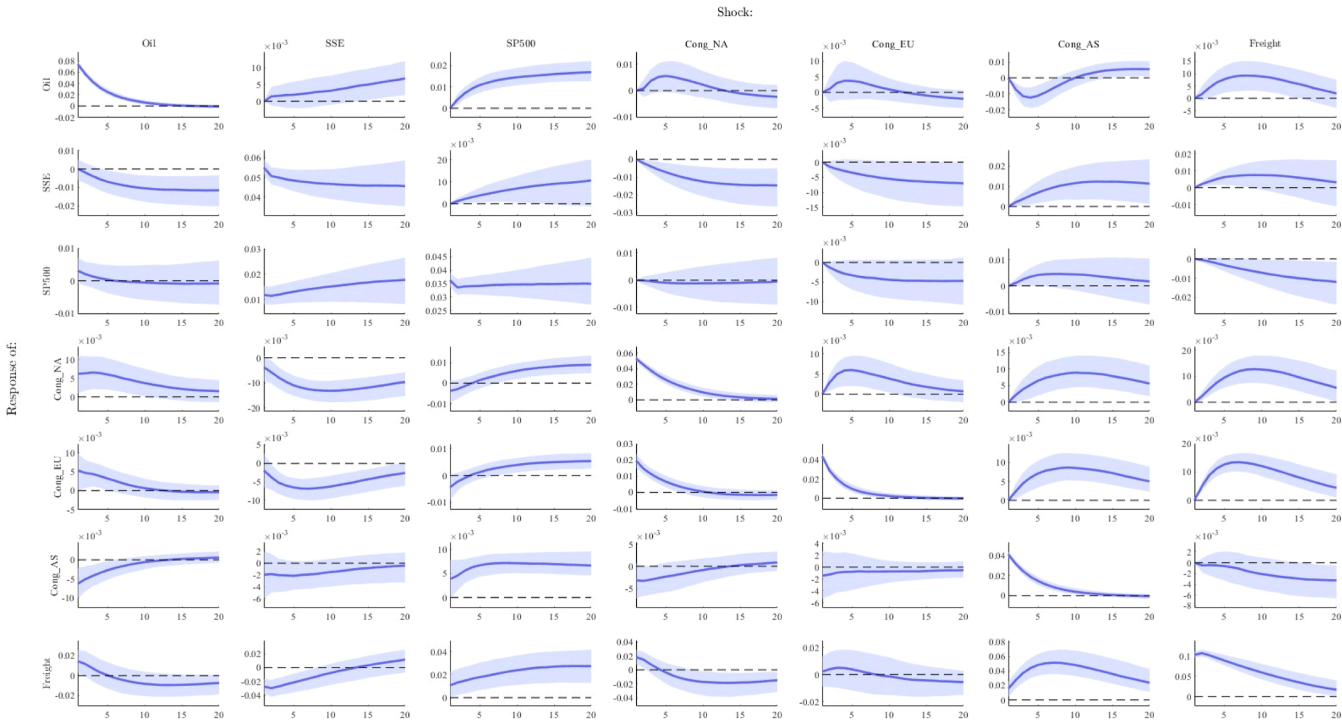
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix – Data Sources

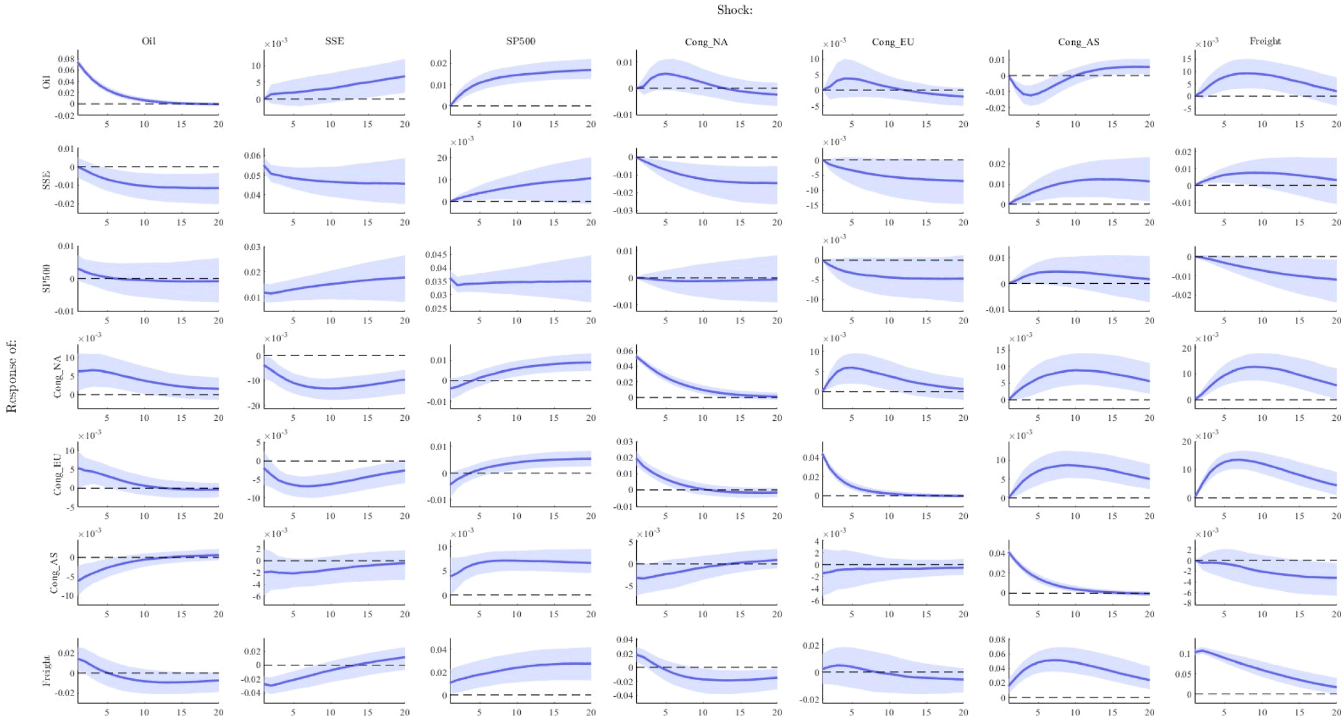
Short Name	Variable Name	Description	Source	Unit of Measurement
Freight	CCFI China-Europe Freight Index	Containerships freight rates between China to Europe	Clarksons Shipping Intelligence Network	Index
Cong_NA	Port Congestion Index - Containerships In Port, East Coast North America, m.TEU, 7dma	Port congestion in North America – East Coast	Clarksons Shipping Intelligence Network	Index
Cong_EU	Port Congestion Index - Containerships In Port, Europe, m.TEU, 7dma	Port congestion in Europe	Clarksons Shipping Intelligence Network	Index
Cong_AS	Port Congestion Index - Containerships In Port, South East Asia, m.TEU, 7dma	Port congestion in South East Asia	Clarksons Shipping Intelligence Network	Index
SP500	S&P 500 Market Index	Stock Market	Federal Reserve of St.Louis Database (FRED)	Index
Oil	Brent Oil Price (Europe)	Brent Oil Price	Federal Reserve of St.Louis Database (FRED)	Dollars per barrel

APPENDIX – Robustness Checks

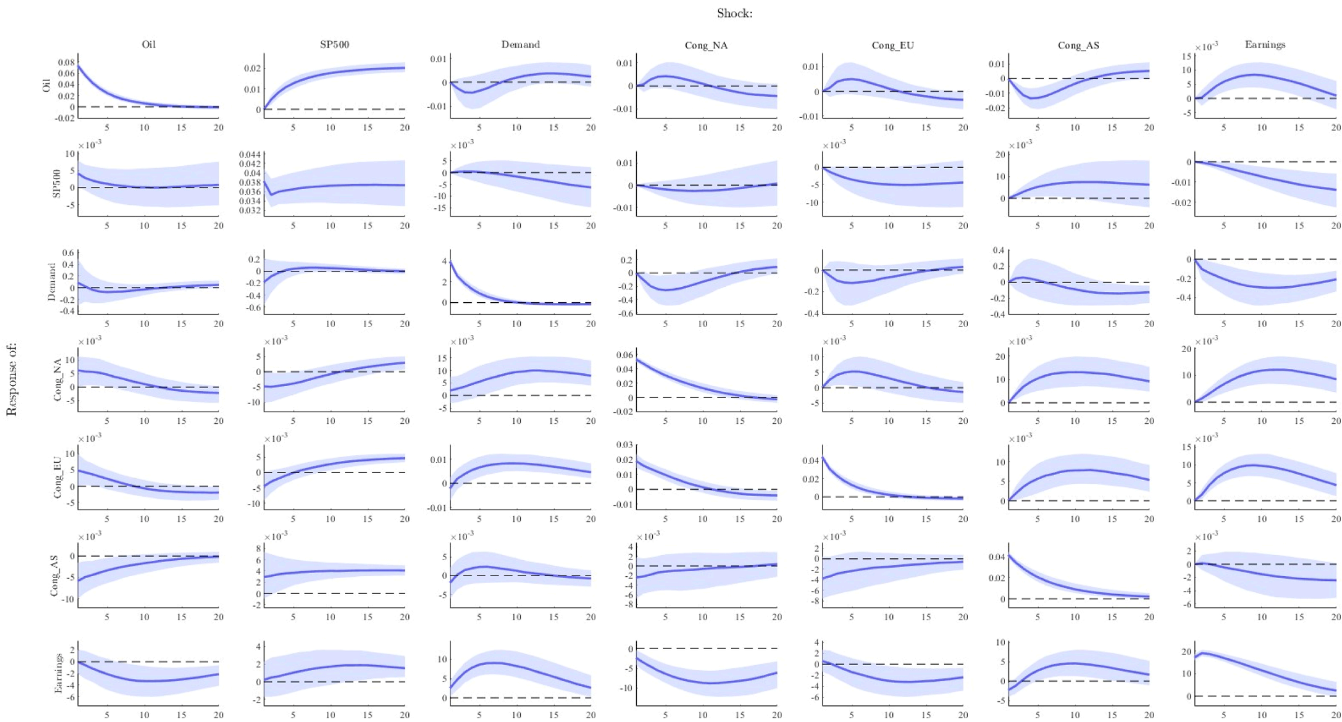
1. Using the SSE Composite Index in addition to the S&P500 to capture more Asian dynamics (Source: investing.com)



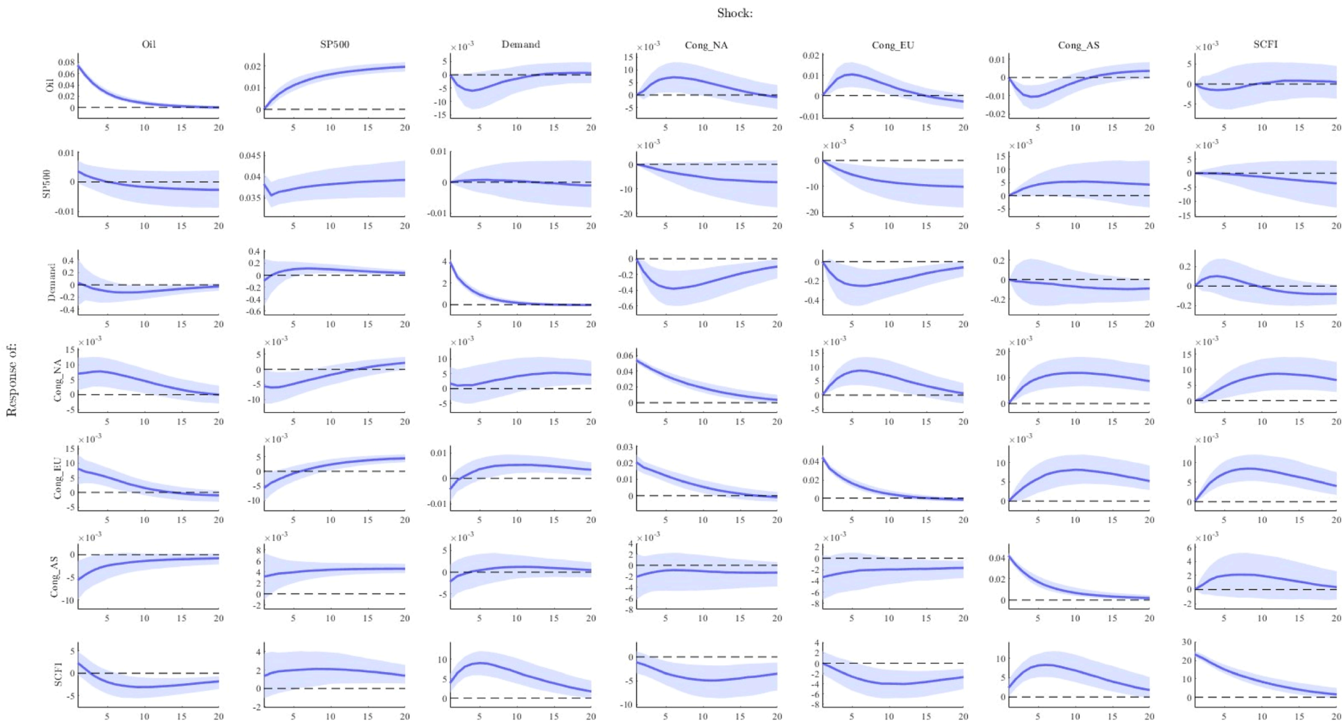
2. Including demand for containership trade (Variable Definition: Monthly Global Seaborne Container Trade Indicator Volume Index, Source: Clarksons Shipping Intelligence Network, Variable ID: 546,202)



3. Including alternative definitions for freight rates (Variable Definition: Vessel Earnings, Source: Clarksons Shipping Intelligence Network, Variable ID: 97,737)



4. Including alternative definitions for freight rates (Variable Definition: SCF Index, Source: Clarksons Shipping Intelligence Network, Variable ID: 98,483)



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