DISENTANGLING DEMAND AND SUPPLY SHOCKS IN THE SHIPPING FREIGHT MARKET: THEIR IMPACT ON SHIPPING INVESTMENTS

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Abstract

We show that demand shocks have a greater effect on real freight rates compared to supply (fleet) shocks both historically and on impact. By contrast, supply shocks have a larger impact on net contracting activity when compared to demand shocks. This paper disentangles for the first time demand and supply shocks driving shipping freight markets and assesses their impact on net contracting activity, a key measure of shipping investments. In the process, we construct novel indices of demand for shipping transportation. Policy related issues are quantified through drawing forecast scenarios for the response of real freight rates to unexpected demand and supply changes. (R41), (E32).

Keywords: shipping freight rates; demand and supply shocks; net contracting; structural VAR.

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1 Introduction

The shipping industry plays an important role in the world economy since over 80% of the world trade in volume terms is carried by sea, according to UNCTAD (2019). One of its sectors is the bulk market that involves the transportation of homogeneous dry and wet bulk commodities - typically raw materials such as crude oil, iron ore, grains, coking and thermal coal, bauxite and alumina etc - on non-scheduled routes, on a one ship-one cargo basis. The bulk sector is important in its own right, as it represents by far the largest shipping segment in terms of both cargo carrying capacity and quantity transported. In 2018, wet and dry bulk vessels carried more than 60% of the world's seaborne trade.

It is not surprising that freight rates are considered indicators of real (physical) economic activity (Kilian; 2009; Kilian and Zhou; 2018); and have been shown to affect the US equity markets (Kilian and Park; 2009). Freight rates are notoriously volatile and have repeatedly undergone periods of boom and bust; Stopford (2009) describes and dates shipping cycles going back close to three centuries, since 1741. Yet, despite their importance for international trade and the global economy, little - if any - is known about the origins of their shocks and fluctuations. Freight rates are driven by distinct demand and supply shocks. In practice, the empirical counterparts that are used as proxies for those shocks are intertwined, thus violating the ceteris paribus assumption. For instance, supply of shipping services is determined by the investment decisions of market participants and is endogenous to the dry bulk industry; it increases through the ordering of newbuilding vessels when freight rates are high, and decreases through the demolition of existing ones when freight rates are low. Demand for shipping reflects the macroeconomic conditions of developing and industrialised countries yet may also be partly endogenous as high freight rates may result in a reduction in demand for seaborne transportation particularly in short-sea trades, where land-based transportation provides an alternative option, on this issue see also Lim, Nomikos and Yap (2019) and Pouliasis, Papapostolou, Kyriakou and Visvikis (2018).

In this paper, we adopt a structural VAR model which accommodates the previous issues and disentangles demand from supply shocks in freight rates. The proposed research design is very flexible and also takes into account the unique features of the shipping industry. First, demand for bulk shipping is considered inelastic to freight rate changes (Stopford; 2009) since the majority of transported commodities are raw materials (e.g. iron ore, coal, crude oil, etc.) or basic food products (grain, corn, rice, soybeans etc.) which typically exhibit inelastic demand curves and shipping provides the most efficient way - if not, the only economically viable way - of transporting them over long distances (Yang, Zhang, Luo and Li; 2020). Second, delivery of a newbuilding order requires substantial time-to-build which can vary from 18 months upwards and depends on prevailing market conditions and available capacity in the shipbuilding industry. As a result, deliveries depend on investment decisions taken in the past (Adland and Strandenes; 2007) and, in the short-term, shipping supply adjusts sluggishly to changes in demand (Greenwood and Hanson; 2015), which often leads to large swings in freight rates (Kalouptsidi; 2014). To accommodate the construction lag in the delivery of new vessels, we examine separately the impact of changes in the number of new contracts for the construction of new vessels and the impact from the delivery of newly-built vessels to the freight market. The number of contracts for newbuilding vessels may deviate from the number of deliveries of these vessels in the future. For instance, this may happen due to cancelling of contracts when market conditions deteriorate (Tran and Haasis; 2015).

In order to capture the discussed features of shipping markets, we use the following variables in our model: global demand for seaborne trade, calculated as a composite index of various seaborne trade demand shifters for the dry bulk (Capesize and Panamax) and tanker (VLCC) sectors; global supply of freight transportation, defined as the rate of global fleet growth for dry-bulk and tanker vessels; and, global price of transportation as measured by Capesize, Panamax and VLCC real earnings. In addition, we consider the impact of those variables to new investments, that is the net new orders that shipowners place for newbuilding vessels.

This paper provides estimates of the dynamic effects of demand and supply structural shocks to dry-bulk and tanker earnings and quantifies their contribution to the evolution of freight rates for the period 1995 to 2018. In the process we contribute to the literature in a number of ways. First, in order to quantify demand for shipping services, we construct novel indices that measure economic activity in the shipping sector using available trade statistics. Second, the model provides a framework through which we can identify mutually uncorrelated supply and demand shocks and thus enables us to answer a number of key questions regarding the determination of freight rates such as: how changes in seaborne trade affect freight rates? what is the response of supply of vessels and net contracting to an increase in freight rates? do shipowners order new vessels following a stronger freight market or stronger demand for shipping transportation? what is the relative contribution of supply and demand shocks in the determination of freight rates and how does this change over time and under different market conditions? Finally, we construct a number of forecast scenarios for unexpected supply and demand changes and evaluate their effect on real freight rates. This provides economic insight regarding the sensitivity of the estimated model to future structural shocks on freight markets and answers important "what-if" shipping policy questions.

Taken together the results reveal that positive demand shocks have a greater effect on real freight rates, compared to negative supply (fleet) shocks, both historically and on impact (impulse responses) across the dry-bulk and VLCC segments examined. By contrast, unexpected supply disruptions exert a larger effect on new investment activity on impact when compared to positive demand shocks. Finally, based on forecasts scenarios, the responses of freight rates are symmetric to substantial positive and negative one-off shocks of the global demand for shipping; while, they are larger in positive rather than negative shocks of global demand based on historical precedence. The pandemic of COVID-19 can be considered a substantial negative one-off demand shock for shipping transportation.

The rest of this paper is organised as follows. Section 2 discusses the research design of the paper and outlines the methodology; section 3 describes the demand and supply drivers and describes the methodology for the construction of demand indices; section 4 presents the empirical results; section 5 assesses the impact of structural freight rate shocks on net contracting; section 6 performs an analysis based on forecast scenarios and section 7 concludes the paper.

2 Identifying shocks to shipping freight rates

We use a three-variate structural VAR model in order to decompose unexpected changes in freight rates into three mutually uncorrelated shocks: a seaborne trade (demand) shock, a fleet supply shock and a freight-specific shock. Specifically, consider a 3x1 vector of endogenous variables:

$$y_t = [Trade_t, Fleet_t, Freight_t]$$

where, $Trade$ is a constructed demand index for shipping services as discussed later in the paper, $Fleet$ measures the growth in the supply of fleet and $Freight$ is the logarithm real earnings for the specific vessel size. Consistent with the theoretical foundations of Maritime Economics (Stopford; 2009), fluctuations to real freight rates are attributed to three structural shocks: Supply shocks (changes in the size of the fleet), shocks to seaborne trade and shocks to the utilisation of the fleet (utilisation shocks). The structural representation of the VAR model of order p is:

$$A_0 y_t = c_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \tag{1}$$

where y_t is a 3x1 vector of endogenous variables, as defined above, A_0 refers to the 3x3 contemporaneous coefficient matrix, c_0 represents a 3x1 vector of intercepts, A_i denotes the 3x3 autoregressive coefficient matrices and ε_t is the 3x1 vector of serially and mutually uncorrelated structural innovations.

A long lag length of 24 months (p=24) is used to allow for potential delays between structural shocks and their effect on the freight market.[1] The structural VAR model of Eq. (1) cannot be estimated directly so we pre-multiply both sides of Eq. (1) with A_0^{-1} which results in the reduced-form VAR model:

$$y_t = c_1 + \sum_{i=1}^{p} B_i y_{t-i} + e_t \tag{2}$$

where $B_i = A_0^{-1} A_i, i = 1, ..., p$, $e_t = A_0^{-1}\varepsilon_t$ and $c_1 = A_0^{-1}c_0$. Based on the reduced-form coefficient estimates of Eq (2) we can recover an estimate of the structural impact multiplier matrix A_0 which enables us to reconstruct the unique structural shocks from $\varepsilon_t = A_0 e_t$ and the structural model coefficient matrices, $A_i = A_0 B_i, i = 1, ..., p$. The final step in this process involves putting restrictions on A_0 so that the coefficient estimates are uniquely identified, as follows:

$$e_t = \begin{bmatrix} e_t^{\text{Trade}} \\ e_t^{\text{Fleet}} \\ e_t^{\text{Freight}} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 \\ 0 & \alpha_{22} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\text{Demand Shock}} \\ \varepsilon_t^{\text{Supply Shock}} \\ \varepsilon_t^{\text{Utilisation Shock}} \end{bmatrix} \tag{3}$$

where, $\varepsilon_t^{\text{Demand Shock}}$ stands for demand-side shock, $\varepsilon_t^{\text{Supply Shock}}$ denotes shocks which are due to fluctuations in the size of the fleet and $\varepsilon_t^{\text{Utilisation Shock}}$ captures utlisation shocks.

The zero restrictions in A_0^{-1} of Eq. (2) are motivated by economic theory as well as market practice in the bulk shipping industry and follow similar applications in commodity markets (Kilian (2009) and Stuermer (2018)). Specifically, the proposed model of the global

[1] Kilian (2009) and Kilian and Park (2009) show that introducing long lags is important in structural models of the global oil market to take into account the low frequency co-movement between real price of oil and global economic activity. We anticipate this to be equally important for freight markets given the nature of shipping investments and the impact of construction lags.

shipping markets implies an upward sloping freight supply curve and a vertical demand curve. Shifts of the demand curve, driven by trade shocks, result in an instantaneous change in freight rates, as do unanticipated supply shocks that shift the supply curve. The model imposes the exclusion restriction that changes in freight rates will not affect global demand for seaborne trade immediately, but with a delay of at least a month. This restriction is consistent with the view that demand for shipping is inelastic to changes in freight rates, at least in the short-run. In addition, we expect the sensitivity of demand to innovations in freight markets to be relatively small due to the economies of scale provided by ships and the lack of alternative and economically feasible means of transportation.

Turning next to innovations in the stock of fleet, new vessel deliveries increase the size of the fleet and have a negative impact on freight rates; while, vessel demolitions have a positive impact. Supply shocks may be due to accidents and losses, arrests of vessels due to defaults of shipping firms as well as potential disruptions in the operation of shipyards due to say, labour strikes, default of ship yards, cancellation of newbuilding orders etc. Supply shocks may also be induced by technological obsolescence or regulatory changes such as the gradual decommissioning of the single-hull tanker fleet in the 1990s, following the passage of the 1990 Oil Pollution Act by US Congress. Another interesting example of a supply shock is the lockdown of all major recycling destinations in the Indian subcontinent in March 2020, following the Covid-19 outbreak which stalled all ship scrapping activity globally. Supply shocks have an immediate impact on the level of freight rates. On the other hand, the stock of fleet does not to respond immediately to demand or utilisation shocks due to the construction lag in the delivery of new vessels; as a result, $\alpha_{21} = 0$ and $\alpha_{23} = 0$ in Eq. (2). Nevertheless, positive seaborne trade or freight rate shocks trigger investment in new capacity (and thus an increase in deferred supply).

Finally, utilisation shocks are idiosyncratic shocks for each market segment that are not driven by changes in demand or shifts in the stock of fleet and may be attributed to changes in capacity utilisation, i.e. the intensity in the use of fleet. For instance, owners may adjust the utilisation rate through slow steaming. Utilisation shocks may also be caused by factors such as port congestion, strikes of port labour, acts of piracy, geopolitical events that may affect the average haul, like the Iran oil embargo, or shifts in trading patterns over time (Riad, Errico, Henn, Saito, Turunen and Saborowski; 2012). Freight rate shocks are allowed to have an immediate impact on freight rates, but affect with a delay both the supply and the demand for seaborne trade. Capacity utilisation is important in its own right in that respect as it helps distinguish between aggregate demand and aggregate supply shocks (Kilian, Nomikos and Zhou; 2021).[2]

3 Measuring Demand and Supply for Bulk Shipping

The key ingredients in the proposed model are factors that proxy the demand and supply for shipping services. Demand for dry bulk shipping services translates into demand for seaborne trade which, in turn, is driven by a few key factors. Undoubtedly, the most important one is the world economy; as Stopford (2009) documents, seaborne trade is highly correlated with world GDP cycles and is also affected by prevailing conditions in the related commodity trades. Commodity markets affect the demand for shipping in both the short- and long-term. Short-term fluctuations in shipping markets may be caused by the seasonal character of some trades (e.g. in agricultural commodities). On the other hand, long-term fluctuations are due to changes in the economies of the countries that import and export the corresponding commodities. These reflect the drivers of urbanisation, population growth and changing income levels that characterise commodity flows for crude oil, raw materials and agricultural products. Furthermore, changing consumer tastes may also shift commodity demand over time, as technology evolves or as regulations change; for instance, environmental regulations and curbs on emissions may result in the gradual substitution of coal with natural gas for power generation. In addition to those factors, which are exogenous to the shipping industry, demand is also affected by the distance over which commodities are transported, known as the average haul and measured in tonne-miles. Finally, one must also consider random shocks that perturb the shipping equilibrium and result in the well-known shipping boom-bust cycles, generating the extraordinary volatility that characterises the industry. These unique and unpredictable shocks may be caused by economic disturbances superimposed on business cycles - such as the two oil price shocks in 1973 and 1979 and the more recent global financial crisis - or, political events such as wars, revolutions and strikes.

[2] The ordering of the variables and the zero restrictions imposed on the A_0^{-1} matrix are motivated by economic theory and justified on the basis of the discussion here. To check the validity of those restrictions, we calculate the pair-wise correlations among the reduced form residuals for the three series in the SVAR model. These are close to zero in all cases suggesting that the ordering of the variables in the SVAR is immaterial. For instance, for Capesize vessels, the correlation between the reduced form residuals for demand (first series) and supply (second series) is equal to -0.0084; between the demand (first series) and freight rates (third series) is equal to 0.0006 and between the supply (second series) and freight rates (third series) is equal to 0.0032.

The supply component of the shipping mechanism corresponds to the cargo carrying capacity of the dry bulk and tanker fleets. The dry bulk sector is involved in the transportation of homogeneous bulk commodities, typically raw materials such as iron ore, grains, coking and thermal coal, bauxite and alumina, on non-scheduled routes, mainly on a one ship-one cargo basis. The dry bulk sector represents by far the largest shipping segment in terms of both cargo carrying capacity and quantity transported. In this study we consider the two largest segments of the dry bulk shipping sector, the Capesize and Panamax segments, as well as the Very Large Crude Carrier (VLCC) sector of the crude oil market. At the largest end of the range, Capesize carriers have a cargo carrying capacity of about 180,000 metric ton dead-weight (mt dwt) and carry primarily iron ore and coal along a few shipping routes. Panamax carriers have a capacity of about 80,000 mt dwt and serve mainly the coal, grain, bauxite and the larger minor bulk trades. Finally, the VLCC sector consists of oil tanker vessels with a cargo carrying capacity of 260,000 mt dwt that are used exclusively in the transportation of crude oil. According to Clarksons Shipping Intelligence Network (SIN), as of October 2019 the Capesize and Panamax dry bulk sectors accounted, respectively, for 40% and 25% of the total cargo carrying capacity of the dry-bulk fleet, while the VLCC sector represented 40% of the total capacity of the tanker fleet. Therefore these vessel types are representative of the overall bulk fleet and their dynamics can be extrapolated to other segments of the bulk shipping industry.

Measuring demand for shipping services is not an easy task since demand shifts are not observable. To overcome this, we identify sector-specific proxies that capture fluctuations in economic activity in the shipping sector. We also recognise that each sector has unique characteristics and fundamentals; for instance, capesize vessels are used primarily for the transportation of iron ore and coal and rarely carry grains or other agricultural commodities. For this reason, the chosen demand proxies differ across the sectors examined.

There are various approaches for modelling and measuring physical economic activity, as presented in a comprehensive way in Kilian and Zhou (2018). For instance, Kilian (2009) uses an index of global economic activity constructed using dry bulk cargo freight rates. Other studies use proxies of real GDP, measures of global industrial production or production of industrial commodities such as global steel production, as in Ravazzolo and Vespignani (2020). There has also been increased interest in recent years in extracting measures of the global business cycle from the real prices of commodities, as in Alquist and Coibion (2014) and Delle Chiaie, Ferrara and Giannone (2017). Shifts in commodity prices are associated with unexpected fluctuations in physical economic activity. A global business cycle boom tends to lift all real commodity prices, whereas a slowdown tends to lower them.

For the purposes of modelling the demand for shipping transportation, each of the approaches above has its limitations. For instance, although the economic activity index of Kilian (2009) has become a popular choice in the literature for modelling demand for commodities, the index is a coincident indicator of shipping activity as it is constructed using a combination of voyage rates and the Baltic Dry Index (BDI). There are also drawbacks in using the OECD Industrial production index as it excludes emerging economies in Asia, such as China and India, whose demand for industrial raw materials has fuelled the surge in industrial commodity and oil prices, especially during the period 2001 to 2008.[3] In addition, the coverage of our proposed measure should be broader and incorporate shipping-specific aspects of demand, such as seaborne trade and commodity flows, which are not captured by conventional measures of economic activity. Finally, most indicators of economic activity are available at either quarterly or annual frequency, which significantly reduces the available sample size.

Hence, to capture demand for seaborne trade we use a combination of variables that measure *commodity trade flows* and *industrial production*. For instance, for the Capesize market we consider trade flows in the main commodities transported by Capesize vessels, namely Iron Ore and Coal. Specifically, we consider *Seaborne Iron Ore Imports* (comprising imports of China, Japan, South Korea and Taiwan); *Coking Coal Seaborne Exports* that comprise exports of Australia, Canada, US and China; and *Steam Coal Seaborne Exports* that include exports of Australia, Canada, China, Colombia, Indonesia, South Africa, US and Venezuela. These represent the major trade routes in the seaborne coal and iron ore trades. For example, Brazil and Australia are the world's largest iron ore exporters and Australia is the world's largest exporter of coal, exporting 180 million metric tonnes of coking coal, as well as 194 million metric tonnes of steam coal (source: World Coal Association). At the same time, China has experienced rapid growth since its accession to the World Trade Organisation (WTO) in December 2001 and is currently the world's largest importer of raw materials thus driving fluctuations in mineral commodity demand and prices. This rapid economic development has been mainly driven by construction and manufacturing and has thus been highly commodity-intensive: As of 2017, China represented around 11 percent of global oil consumption, 41 percent of global cop-

[3]OECD also estimates industrial production for emerging economies. The index is available since 2006 at a monthly frequency and given its short time-span is not used in this study.

per consumption and 54 percent of global iron ore consumption (source: Reserve Bank of Australia). The data for the above trade flows are available on a monthly basis and are supplemented by ton-mile seaborne trade data for Coal and Iron Ore. The later are only available at an annual frequency and monthly data are interpolated from annual values using cubic interpolation The ton-mile data capture changes in the average haul of the trade and thus supplement the information from the trade flows data.

For commodity production we consider *World Aluminium Production* and *SE Asia Steel Production*: Aluminium production is correlated with the industrialization and urbanization processes of emerging economies and is a reliable proxy of demand for raw materials and, consequently, demand for seaborne trade. Crude steel is a key input in many industries including construction, transportation, energy, packaging, home goods and agriculture. The importance of steel production as a proxy for real (physical) economic activity is emphasised in Ravazzolo and Vespignani (2020), who show that world steel production has strong predictability in forecasting world GDP, oil and fertilizer prices. Furthermore, the steel industry is one of the key drivers in seaborne trade since 50% of dry bulk trade is steel-industry related. Consequently, a measure of steel production of the major importers and users of freight services is expected to track shipping economic activity fairly well. SE Asia steel production includes aggregate production in China, Japan, S. Korea and Taiwan. The various variables used along with their respective sources are listed in Table 1.

For the Panamax demand index we employ slightly modified proxies, since Panamax vessels transport primarily agricultural commodities and coal and are less involved in the iron ore trade. As such, we substitute Iron Ore Imports with *Grain Exports*, calculated as the sum of US, Canada, Australia, Argentina and EU-28 Grain exports. In addition, we consider monthly (interpolated) ton-mile data for the Grains trade. Finally, for the VLCC sector, we consider *Persian Gulf Crude Oil Exports* and interpolated ton-mile data for *Crude Oil Seaborne Trade*.

The proxies reported in Table 1are *demand shifters* since an increase in each one of them would have been preceded by a shift in the demand for shipping services. At the same time, they also reflect the fundamentals of their respective markets. In order to extract the relevant shipping-related information we follow the approach of Kilian (2009) and proceed as follows: First, we compute the logarithmic first differences for all the demand proxies to compute their period-to-period growth rates. Second, we take the equal-weighted average of those growth rates and accumulate them in order to calculate the cumulative effect of the demand index. The final step is to de-trend the series as our interest centres on cyclical

Variable	Source	Capesize	Panamax	VLCC
Coal Seaborne Trade (btm)	(SIN)	✓	✓	
Coking Coal Seaborne Exports (mt)	(SIN)	✓	✓	
Crude Oil Seaborne Trade (btm)	(SIN)			✓
Global Primary Aluminum Production (mt)	(IAI)	✓	✓	
Grains Seaborne Exports (mt)	(SIN)		✓	
Grains Seaborne Trade (btm)	(SIN)		✓	
Iron Ore Imports (mt)	(SIN)	✓		
Iron Ore Seaborne Trade (btm)	(SIN)	✓		
Persian Gulf Crude Oil Exports (bbl/day)	(SIN)			✓
SE Asia Steel Production (mt)	(WSI)	✓	✓	
Steam Coal Seaborne Exports (mt)	(SIN)	✓	✓	

Notes: btm stands for billion tonne-miles; SIN is Clarksons Shipping Intelligence Network; mt is metric tons; IAI is the International Aluminium Institute; WSI is World Steel Institute; bbl is barrels. Coking Coal seaborne exports comprise exports of Australia, Canada, US and China; Grain exports comprise Wheat and Coarse Grain Exports of US, Canada, Australia, Argentina and EU-28; SE Asia Iron Ore Imports comprise imports of Japan, S. Korea, Taiwan and China; SE Asia Steel Production includes production in China, Japan, S. Korea and Taiwan; Steam Coal seaborne exports include exports of Australia, Canada, China, Colombia, Indonesia, South Africa, US and Venezuela.

Table 1: Demand Proxies for the Construction of Shipping Demand Indices.

variation in the demand for shipping.[4]

The demand index for the Capesize, Panamax and VLCC sectors is depicted in the first-row of plots in Figure 1. As observed, the demand indices follow similar patterns across the Capesize and Panamax sectors. There is a gradual drop from 1997 to 1999, a period coinciding with the SE Asia currency crisis that also had an impact on shipping. From that point, demand increases steadily until the very sharp drop in demand during the

[4]Kilian and Lutkepohl (2017) show than in a VAR(p) model with p > 1, standard Gaussian inference on individual VAR slope parameters remains asymptotically valid even in the presence of I(1) variables. Furthermore, Kilian and Murphy (2014) show that the potential cost of not imposing unit roots in a model similar to ours, is a loss of asymptotic efficiency, which would be reflected in wider error bands for the reported Impulse Response Functions (IRF's). Since the impulse response estimates presented below in the paper are reasonably precisely estimated, this is not a concern in this study also. Specifically, using the first differences of freight rates results into wider error bands but no other difference for the IRF's reported. The results are available from the authors.

2008 financial crisis. Dry bulk shipping demand recovered most of the lost ground within two years and returned to the pre-crisis levels. Finally, the gradual drop in the demand index from 2014 to 2018 is consistent with lower growth rates in world seaborne trade over the more recent period, keeping in mind that the index is de-trended and the graph reflects deviations from the trend. Similar observations can be made for the VLCC demand index.

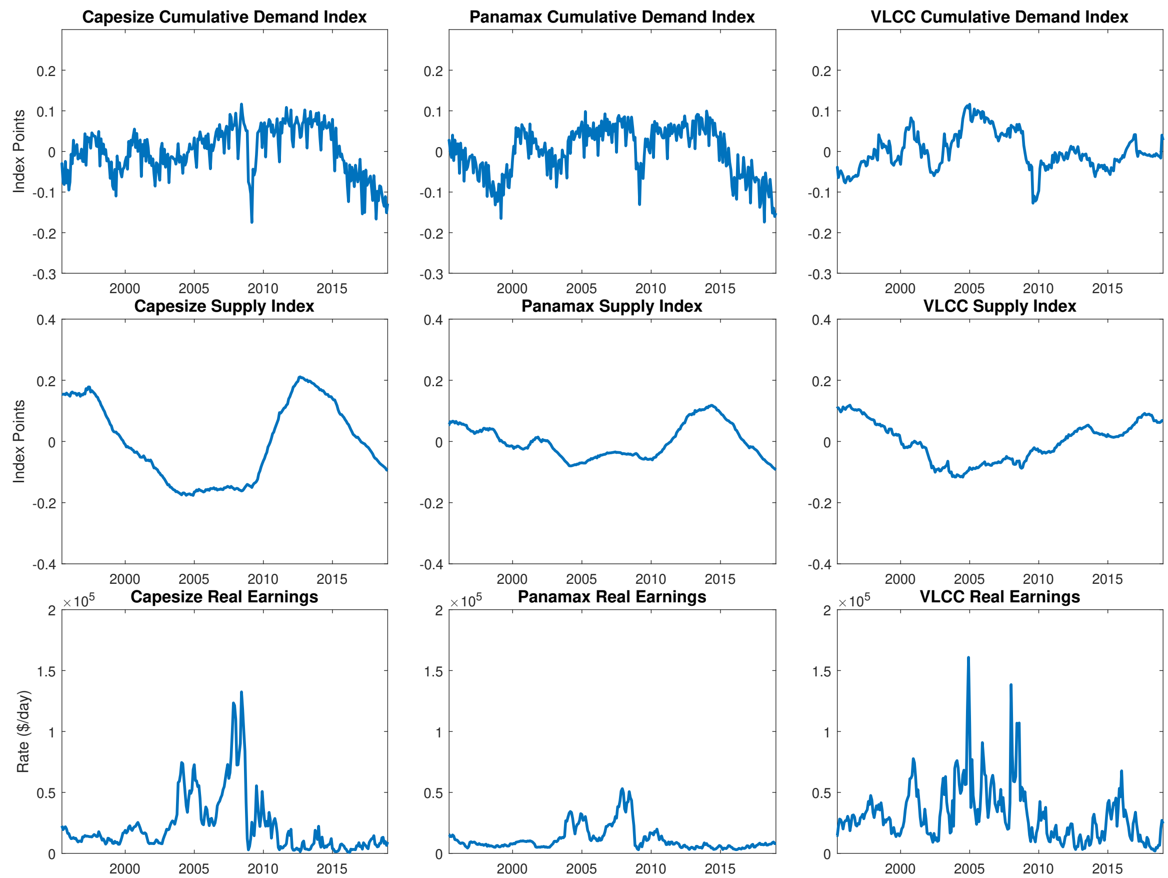


Figure 1: Row-wise: Cumulative demand indices, Supply (fleet growth) and Real freight rates.

On the supply side, we consider monthly percentage changes (log-differences) in the total stock of fleet for the Capesize, Panamax and VLCC sectors. As in the construction of the demand index, we accumulate the growth rates and detrend the supply series and keep the cyclical component. The total stock of fleet (in million dead-weight tons, *mdwt*) measures the maximum possible supply of shipping services at any given point in time. In practice the world fleet is never fully utilised as some vessels may be off-hire for repairs and maintenance, waiting at anchorage to load or discharge cargo, may be in lay-up or even used for floating storage (in the case of VLCC). The detrended cumulative percentage changes in the total stock of fleet for the Capesize, Panamax and VLCC sectors, are depicted in the second-row of sub-plots in Figure 1. We can observe the above average increase in the fleet from 2010 onward, reflecting the orderbook overhang accumulated during the rally in freight rates from 2003 to 2008. This pattern is more pronounced for the Capesize sector.

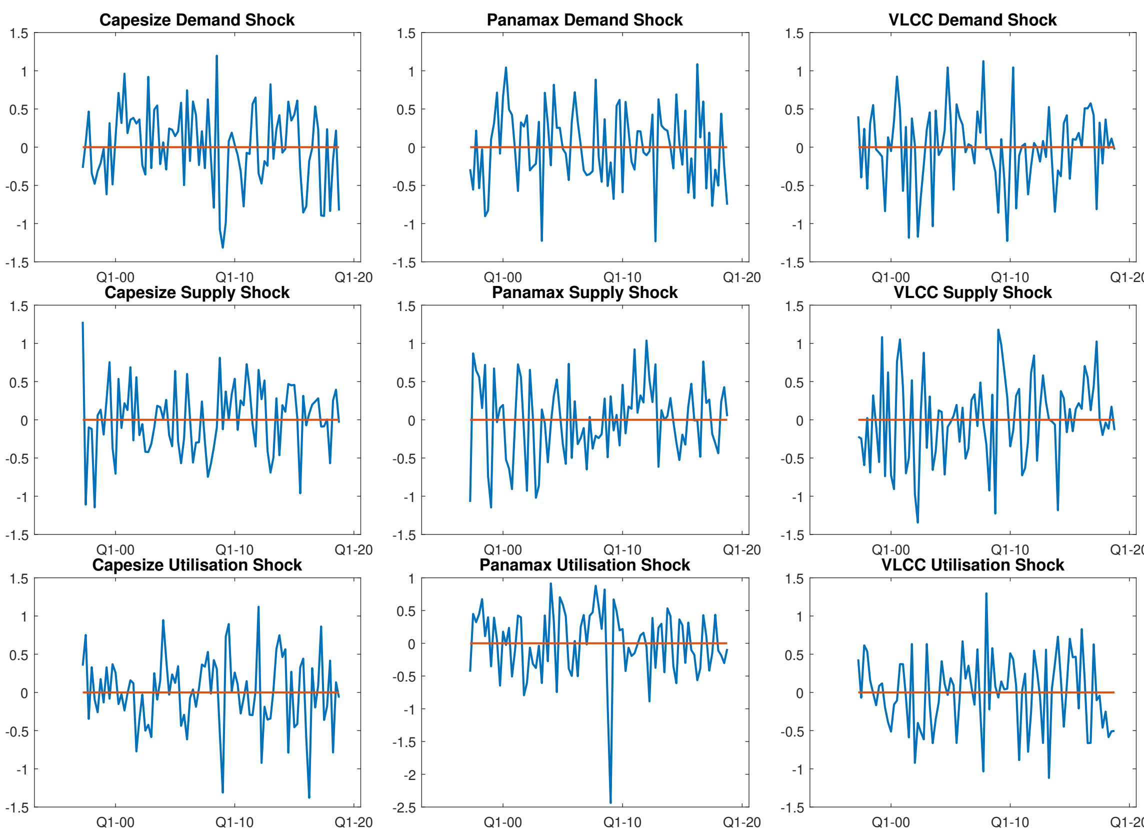
Next, the state of the freight market is expressed by freight rates (earnings), measured in $/day and deflated using the US CPI. We note from the earlier discussion the imbalances that dominate trade in raw materials. Freight costs are largely asymmetric between the front-haul (laden) and back-haul (ballast) routes (see as well Behrens and Picard (2011), Brancaccio, Kalouptsidi and Papageorgiou (2020) and Friedt and Wilson (2020)). For instance, China and Brazil are, respectively, the world's largest importer and exporter of iron ore and trade flows on the Brazil to China iron ore route imply an under-utilisation of shipping capacity on the back-haul leg from China to Brazil. Freight earnings are average net earnings for each vessel type across different round-trip voyages that include a front-haul and a back-haul leg. As such, our choice of freight earnings takes into account both trade asymmetries as well as average distances. Freight rates for Capesize and Panamax vessels, presented in the third-row of plots in Figure 1 increase notably during the period 2003-2005 and then from 2006 to 2008, only to drop sharply during the 2008 crisis. The earnings of VLCC vessels exhibit higher volatility, compared to the Capesize and Panamax vessels, with notable peaks in 2005 and 2008 and smaller peaks in 2002 and 2015. We can also note that real freight rates have become more volatile following the financial crisis of 2008.

Apart from the time-series used and their sources to construct demand indices which are presented in detail in Table 1, supply and freight rates data are from Clarksons Shipping Intelligence Network (SIN) for the period January 1995 to December 2018 (289 observations).

4 Empirical results

The reduced-form VAR model is estimated first using least squares and the estimates are subsequently used to construct the structural representation of the VAR model. We start our analysis by computing the structural shocks. Figure 2 depicts the quarterly averages of the structural shocks implied by the SVAR model of Eq. 3 for the period 1995-2018.

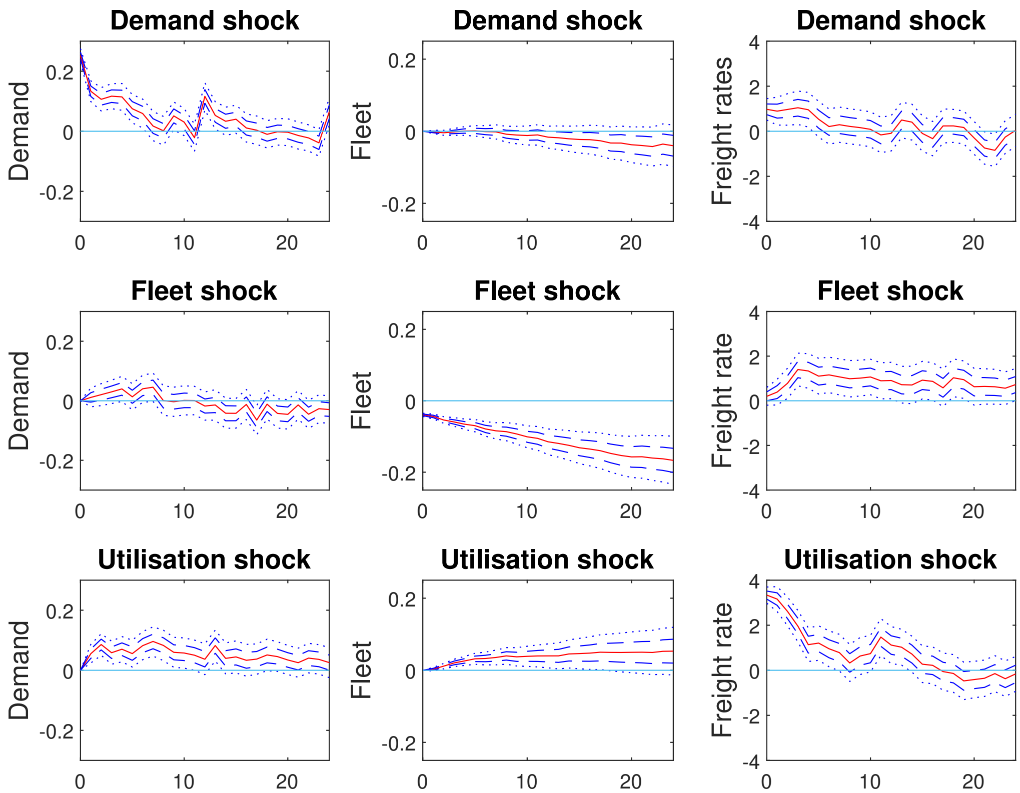
As observed in the first row of Figure 2, several positive demand shocks can be identified throughout the prosperous period of the shipping markets from 2003-2008. We can also note the large drop in shipping demand during the 2008 financial crisis. In the second row, positive supply shocks can be observed for the period 2008-2012 across all segments. This is consistent with the empirical data showing that the large orderbook of vessels created during the period 2003-2008 finally hit the water after 2008 thereby leading to overcapacity. Finally, for Capesize and Panamax vessels, the third row of Figure 2 depicts a series of positive freight-specific (utilisation) shocks over the period 2003-2008, with a pronounced temporary correction in 2005 and a clear significant drop during the shipping crisis in the third quarter of 2008. These patterns are less clear for the VLCC market since the fundamentals drivers are different for each market.



Note: Quarterly averages of the structural residuals of Equation 3.

Figure 2: Historical Evolution of the Structural Shocks, Q1 1998 to Q4 2018.

In order to quantify the effect of the variables of interest to their own structural shocks,

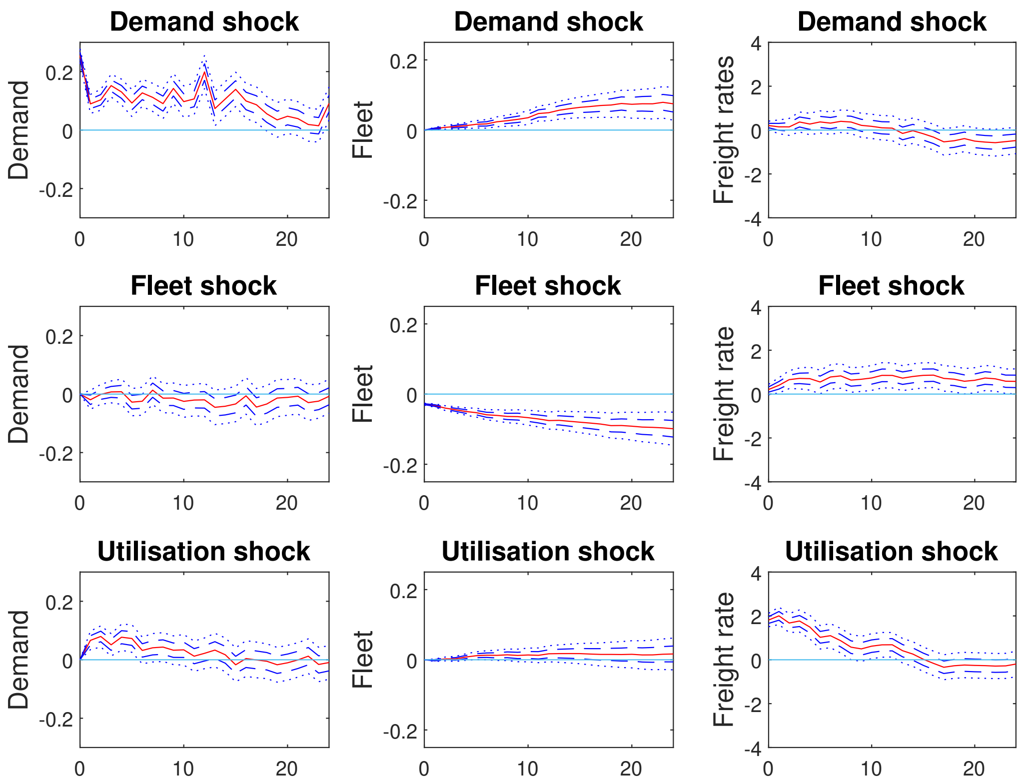


Note: Point estimates with one- and two-standard error bands. The confidence intervals are constructed using a recursive-design wild bootstrap. X-axis measures months after the initial shock.

Figure 3: Responses to one standard deviation structural shocks: Capesize Sector

we calculate their impulse responses to an one standard deviation change. Figures 3, 4 and 5 depict impulse responses of freight demand, freight supply and real freight rates to one-standard deviation structural innovations for the Capesize, Panamax and VLCC sectors, respectively. All shocks have been normalised in a way that an innovation will cause freight rates to increase. The graphs also present one and two-standard deviation bounds for the impulse responses, estimated using a recursive-design wild bootstrap (WB) procedure with 2,000 replications as in Goncalves and Kilian (2004). The recursive-design WB is a modification of the ordinary bootstrap which generates a pseudo time series y_t^* according to the autoregressive process:

$$y_t^* = Y_{t-1}^{*\prime}\hat{\phi} + \hat{\varepsilon}_t^* \tag{4}$$

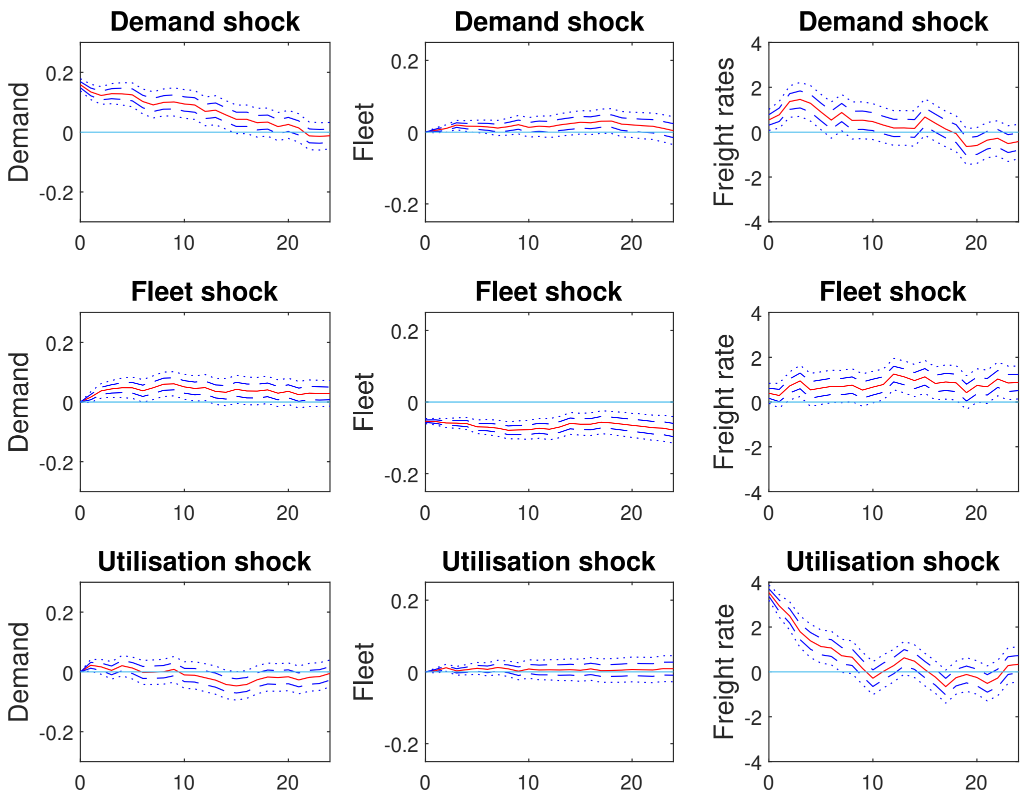


Note: See notes in Figure 3.

Figure 4: Responses to one standard deviation structural shocks: Panamax Sector

where $\hat{\varepsilon}_t^* = \hat{\varepsilon}_t \eta_t$, $\hat{\varepsilon}_t = \hat{\phi}(L) y_t$ and η_t is an i.i.d sequence with mean zero and variance one.

Taken together, the first rows of Figures 3, 4 and 5 show that an unexpected increase (shock) in demand for freight causes an immediate and sharp increase in global freight rates, followed by a gradual correction of 2-7 months. Demand shocks do not have an immediate impact on the supply of shipping services yet gradually, after about 20 months, fleet supply increases which is consistent with the long construction lags in the industry. This increase in supply also causes freight rates to decrease at the end of the horizon, which is particularly evident for the Panamax and VLCC sectors. Demand shocks are not particularly persistent as they are attenuated after about 10 months. In the second row, unexpected global fleet disruptions cause a gradual, yet mostly insignificant, increase in freight demand that builds-up over the whole estimation period of 24 lags. At the same



Note: See notes in Figure 3.

Figure 5: Responses to one standard deviation structural shocks: VLCC Sector

time they push freight rates higher and this increase appears to be particularly persistent. On average, supply shocks have a longer lasting impact on freight rates, compared to demand shocks, due to the fact that investment decisions in shipping capacity are largely irreversible.

Finally, the third row of sub-plots of Figures 3, 4 and 5 shows that a positive utilisation shock triggers a notable increase in freight demand for the dry-bulk sector yet has no significant effect for the VLCC sector. This could be attributed to the fact that the demand indices constructed for the dry-bulk and VLCC sectors are based on commodities which differ widely. Dry-bulk commodities in particular, such as iron ore, coal and grain are more sensitive to fluctuations in freight rates compared to crude oil.

Next, Figure 6 plots the historical decomposition of real freight rates over the period

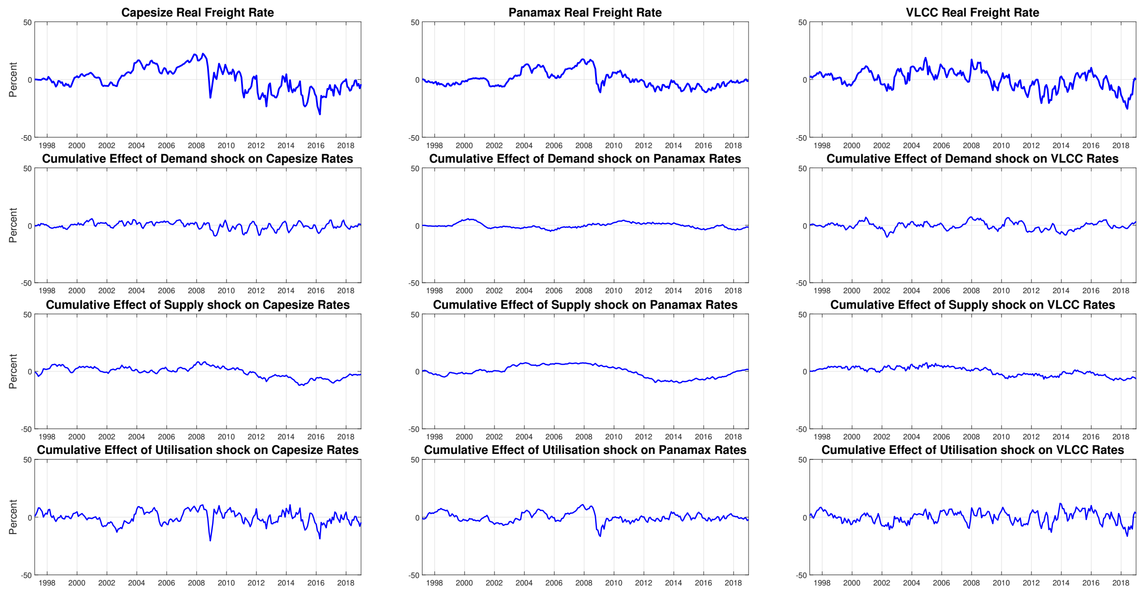
1995:1 to 2018:12. Each observation y of our original data can be re-written as the cumulative sum of the structural shocks which corresponds to the historical decomposition of the variance:

$$y_t = \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-i} \approx \sum_{i=0}^{t-1} \Theta_i \varepsilon_{t-i} \tag{5}$$

where $\Theta_i = \frac{\partial y_{t+i}}{\partial \varepsilon_t'}$ measures the response of y_t to a one-time impulse in structural shocks, ε_t. Historical decomposition is useful in quantifying how much of the observed fluctuations in the variables is explained by a given structural shock. Each sub-plot of Figure 6, depicts the cumulative contribution effect on the real freight rate of one structural shock, while turning off all other shocks. By construction, the sum of the historical decompositions must be approximately equal to the demeaned actual data, presented in the first row. The second row of plots shows that demand shocks exhibit moderate contributions to real freight rates historically across the dry-bulk and VLCC segments. Notable positive contributions can be observed during the period 2004 to 2008 and negative ones during the period 2009 to 2016, with a positive contribution after 2016. The third row of Figure 6 suggests that supply shocks have slightly larger contribution to real freight rates over time when compared to demand shocks. Specifically, supply freight shocks exhibit a clear trend of generally positive but small contributions on real freight rates during the period 2000 to 2010, followed by negative contributions during the period 2012-2018, which coincides with the delivery of the orderbook that had been accumulated previously. Finally, the fourth row of Figure 6 reveals that freight rate (utilisation) shocks have a much larger contribution on real freight rates, compared to demand and supply shocks over time. Notable negative contributions can be observed during 2009, as a result of the global financial crisis and during 2016; while, large positive contributions can be observed from 2004 to 2005. Finally, we can also note that the relative contribution of freight shocks increased following the financial crisis of 2009.

5 Empirical Analysis of Shipping Shocks: The Role of Net Contracting

In this section we obtain further insights into the significance of the shipping structural shocks on other variables of interest. An important issue is whether the distinct demand and supply structural shocks affect the decision of shipowners to order new ships; see



Cumulative Effects of shocks to Real Freight Rates. Estimates derived from model (3).

Figure 6: Historical decomposition of real freight rates (1995:1 - 2018:12)

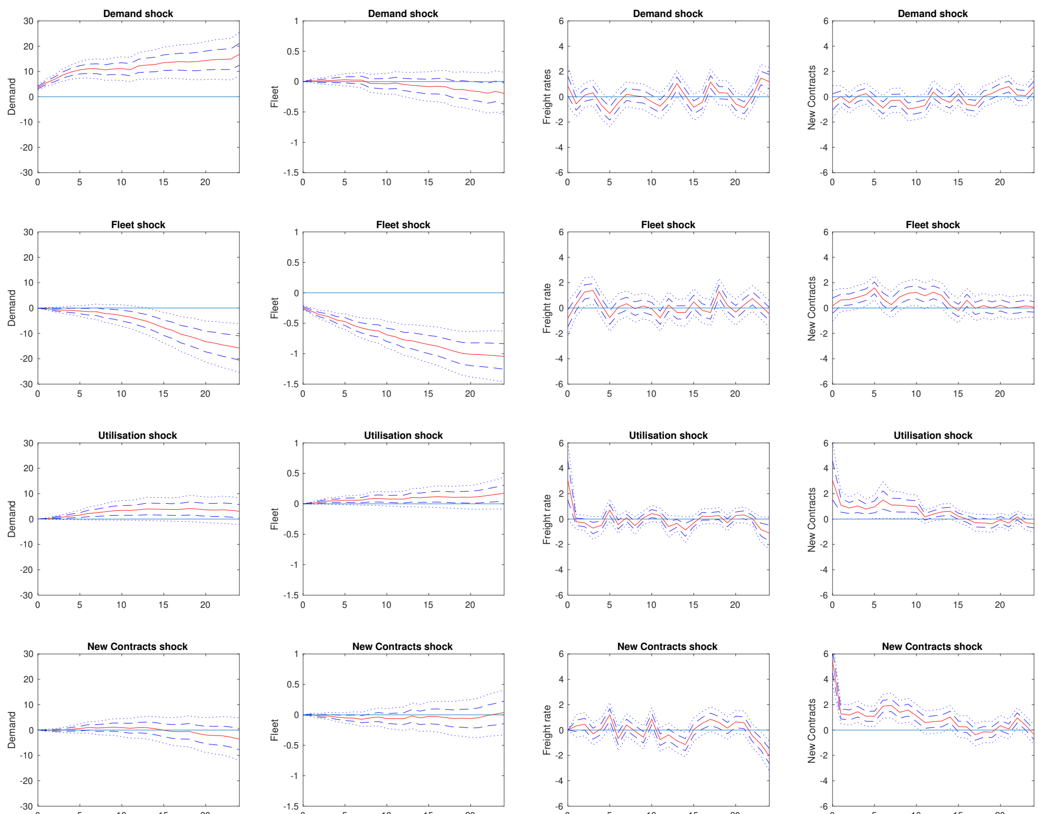
Jingbo, Yijie and Linjun (2019) among others. Thus, we examine the impact of supply and demand shocks on net contracting. Net contracting is the net increase in the order for new vessels over and above what is required to replace the existing fleet and is an indicator of the investment decisions of shipowners. We extend the SVAR model of Eq. (1) to a four-variate model by incorporating net contracting to the vector of variables as follows

$$y_t = [Trade_t, Fleet_t, Freight_t, NetContracting_t]$$

where $NetContracting$ is calculated as the change in orderbook plus deliveries minus demolitions, in million dead-weight tons (mdwt), as defined in Papapostolou, Nomikos, Pouliasis and Kyriakou (2014). The reduced-form errors can thus be decomposed as follows:

$$e_t = \begin{bmatrix} e_t^{\text{Trade}} \\ e_t^{\text{Fleet}} \\ e_t^{\text{Freight Rates}} \\ e_t^{\text{Net Contracting}} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ 0 & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\text{Demand Shock}} \\ \varepsilon_t^{\text{Supply Shock}} \\ \varepsilon_t^{\text{Utilisation Shock}} \\ \varepsilon_t^{\text{Net Contracting Shock}} \end{bmatrix} \tag{6}$$

The identification scheme in Eq. (6) is based on the idea that seaborne trade shocks lead to higher freight rates which in turn trigger investment in new capacity, through net contracting. On the other hand, the non-zero elements in the last row of A_0^{-1} imply that all other variables are treated as predetermined with respect to net contracting. In response to strong demand and/or high freight rates and/or under-supply in the market, owners will place orders for new ships which will be delivered in the market with a delay, due to the construction lag. Hence, net contracting shocks do not have a contemporaneous impact on the rest of the variables. Thus, the set-up of our model helps to identify whether investors place orders for new ships on the back of a strong freight market, a strong seaborne trade demand, an under-supplied market or, a combination of those forces.



Note: See notes in Figure 3.

Figure 7: Responses to one standard deviation structural shocks: Capesize Sector.

Impulse responses for the four-variable VAR are presented in Figure 7.[5] Results for the

[5]We present impulse responses for the Capesize market only. Results for the VLCC and Panamax

first three columns are similar to those reported in Figure 3. Looking at the last column of Figure 7, a positive demand shock has no immediate impact in net contracting. On the other hand, supply-related shocks result in an immediate increase in net contracting activity that lasts up to several months ahead. Similarly, a positive unexpected change in utilisation appears to trigger an immediate increase on net contracting that builds up and persists for up to 10 months ahead, with 1-2 reversals. Finally, a positive net contracting shock has no immediate impact on any of the other variables yet it triggers a slight increase on freight supply, after about 20 months, and a corresponding reduction in freight rates which may reflect the time it takes for an order to be delivered to the market. This suggests that owners are primarily influenced by changes in the level of freight rates and fleet size when deciding to invest in new ships. On the other hand, they appear to be less responsive to changes in seaborne trade.

6 Forecast Scenarios

In this section we use the estimated four-variate structural VAR model of the freight market to generate forecasts of real freight rates. Forecasting freight rates is of interest to policy makers and industry practitioners alike. At the same time, forecasts generated by the widely used reduced-form and time-series regression models are sensitive to the underlying assumptions for the future structural demand and supply shocks. In particular, these forecasts represent the expected change in real freight rates under the assumption that the expected value of all future shocks is equal to zero.

To address this issue, we use alternative forecast scenarios about future shipping demand and supply shocks and quantify their impact on real freight rates. As discussed in Baumeister and Kilian (2014) there is a strict correspondence between standard reduced-form VAR forecasts and forecasts from the structural moving-average representation for a given data set. One may consider prespecified sequences of future structural shocks into the structural moving representation of the VAR model when predicting real freight rates. The sequences of those future structural shocks are the forecast scenarios and may be based upon historical sequences of supply (or demand) shocks or may be purely hypothetical, reflecting likely developments in the market. Building upon the work of Waggoner and Zha (1999) and Baumeister and Kilian (2014), who apply similar models to the oil markets, we consider different scenarios for the evolution of the supply and demand for freight rates and

sectors are qualitatively similar and are available from the authors.

assess by how much real freight rates may change, compared to an unconditional baseline scenario. Forecast scenarios are extremely useful for quantifying impacts emerging from likely outcomes in the fashion of a 'what-if' question. This type of analysis is of special interest for policy institutions (e.g. central banks), consultancy and financial firms. For example, market participants may be interested in how a given increase in the size of the fleet or a reduction in ton-mile demand will affect real freight rates.

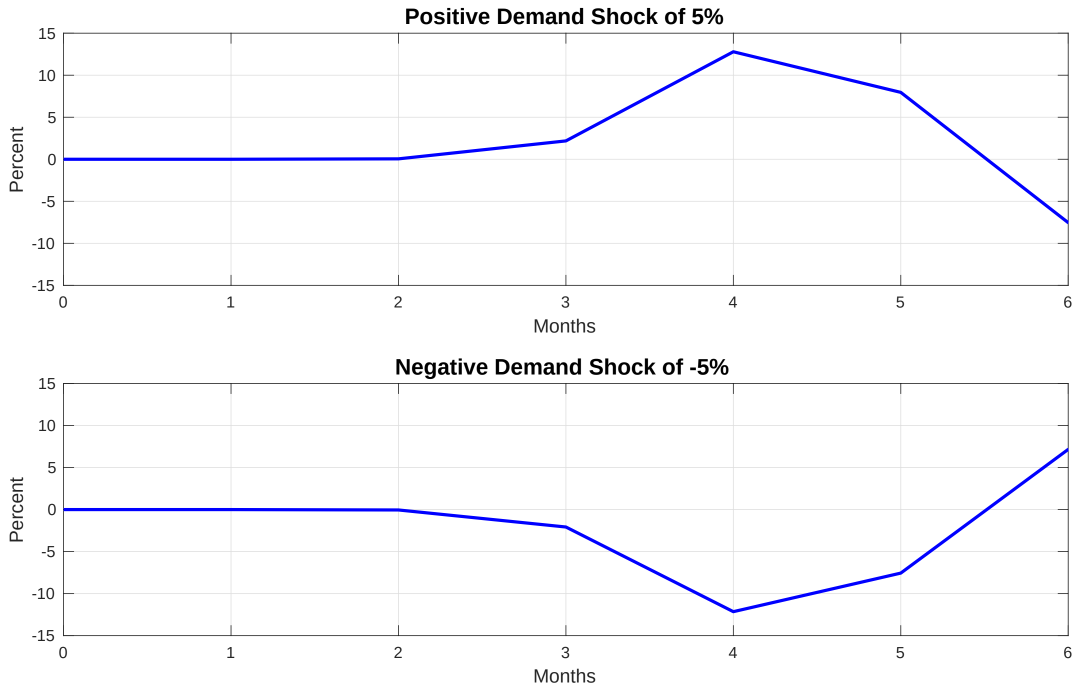
As in Baumeister and Kilian (2014) we use the historical decomposition of the variance as a basis for the scenario analysis and combine it with the stuctural freight shocks identified earlier. In other words, we quantify the cumulative contribution of the structural shocks that occured over the sample period to the actual series, i.e. multiply the size of the shock by its impact effect. Then the forecast scenarios are obtained as:

$$y_{t+h} = \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t+h-i} = \sum_{i=0}^{h-1} \Theta_i \varepsilon_{t+h-i} + \sum_{i=h}^{\infty} \Theta_i \varepsilon_{t+h-i} \tag{7}$$

where y_{t+h} denotes the dependent variable h periods in the future which can be written as the sum of two terms. The first term of the RHS of Eq. (7) captures the cumulative effect of all structural shocks that have yet to occur between $t+1$ and $t+h$. The second term captures the cumulative effect of all structural shocks that have already occurred between $-\infty$ and t and are known at time t.

Figure 8 plots the responses of Capesize real freight rates to positive and negative hypothetical one-off shocks in the global demand for shipping transportation. We compute the effects of each of the two shocks by calibrating an one-time structural shock in the global demand for shipping service such as the impact response is equal to +5% and -5%, while setting all other future shocks to zero. Such shocks are caused by large exogenous shifts in demand. For instance, the pandemic of COVID-19 can be considered a substantial negative one-off demand shock for shipping transportation. Similarly, the trade war between US and China is an obstacle on free trade, resulting into lower demand for seaborne transportation. The first sub-plot of Figure 8 shows the resulting stimulus in real freight rates expressed as percentage deviation from the baseline scenario. As observed, real freight rates increase quickly but subsequently this increase fades away completely after month 6. The second scenario involves an unexpected drop of 5% in global demand. As observed in the second sub-plot of Figure 8, real freight rates temporarily decrease by as much as 10% relative to the baseline forecast but revert to their baseline level after 6 months.

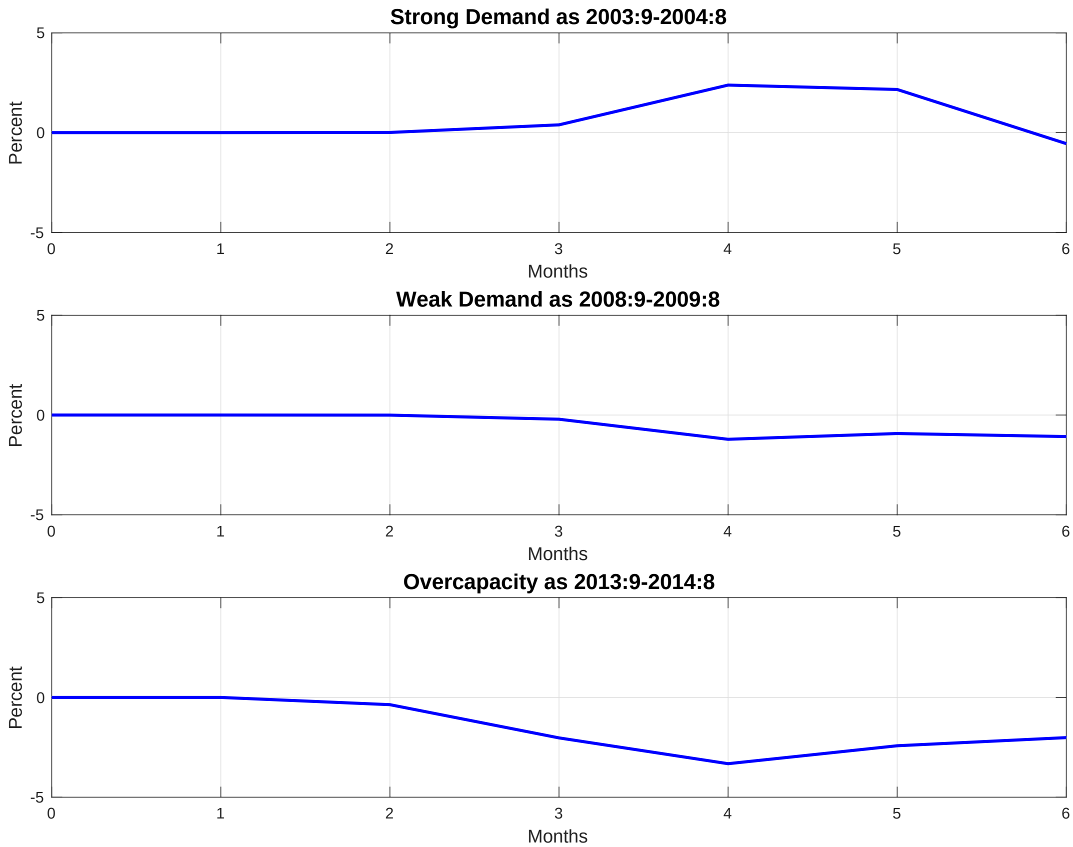
Next, Figure 9 considers three scenarios of consecutive freight rate structural shocks based on historical precedence. The first sub-plot of Figure 9 depicts the responses of



Note: The two forecast scenarios are based on two hypothetical one-off shocks of an increase (5%) and decrease (5%) in global demand for shipping transportation.

Figure 8: Forecast scenarios for the real freight rate: Percent deviations from the baseline forecast for the Capesize Sector

real freight rates to unexpected changes in the global demand for shipping over the period September 2003 to August 2004. This period was characterized by strong demand as a result of, among other factors, China's accession to the World Trade Organization (WTO) in December 2001; an event that is widely considered to have changed the dynamics of the global seaborne trade over the period 2003 to mid-2008. When feeding in the model the estimated sequence of global demand shocks from September 2003 to August 2004, while setting all other future structural shocks equal to zero, real freight rates increase up to 3% compared to the baseline scenario of no shock. However, this increase is only achieved after a period of almost 4 months, possibly because the increased demand is met in the short-term by more efficient utilisation of the existing fleet and re-activating vessels that are in lay-up. In other words, it seems that a persistent increase in demand is required in order to have a strong increase in real freight rates. Next, the second sub-plot of Figure 9 considers the scenario of a weak global demand for shipping as the one observed during the months after the default of Lehman Brothers, i.e. over the period September 2008 to August 2009.



Note: The three forecast scenarios are based on historical precedence of a sequence of shocks: The first sub-plot corresponds to the sequence of shocks over a period of strong global demand, such as the period between September 2003 and August 2004; the second sub-plot refers to the sequence of shocks over a period of weak global demand, such as the period between September 2008 and April 2009; the third sub-plot corresponds to the sequence of shocks over a period of oversupply of vessels, such as the period between September 2013 and August 2014.

Figure 9: Forecast scenarios for the real freight rate: Percent deviations from the baseline forecast for the Capesize Sector

As is widely accepted, this period was characterized by high uncertainty in the global economy and a free-fall drop in the demand for shipping. As observed, real freight rates decrease in response to weak demand and reach a maximum drop of 2% around 4 months ahead. This suggests that a series of negative demand shocks may affect freight rates but with a delay reflecting the inherent lag in this process. Finally, an alternative scenario is the possibility of a positive supply shock (oversupply) which, according to anecdotal evidence, has been the case for the dry-bulk markets over the period 2013 to 2017, resulting into depressed dry-bulk freight rates. We consider this forecast scenario of oversupply as the one observed over the period September 2013 to August 2014. As such, we feed in the model the estimated sequence of vessel supply shocks, while setting all other future structural shocks equal to zero, and present this scenario in the third sup-plot of Figure 9. We note that in this case, real freight rates decrease with a lag of 4 months and up to a maximum drop of 3.5% when compared to the baseline scenario of no shock. The drop appears to be higher compared to the low demand case in Panel B.

7 Conclusion

The shipping industry plays an important role in the world economy, since more than 80% of the world trade is transported by sea. In this paper, we use a structural VAR model to identify mutually uncorrelated demand and supply shocks and examine their impact on real freight rates and net contracting; the latter being a key measure of shipping investments. The set-up of the model is flexible and takes into account key features of the industry such as inelastic demand for shipping services and construction lags in the delivery of newbuilding orders. In order to quantify demand for shipping services, we construct indices that measure economic activity in the Capesize (dry-bulk), Panamax (dry-bulk) and VLCC (tankers) sectors using trade statistics.

We show that freight rates are driven by distinct demand and supply shocks and their origin alters their effect on net contracting activity; features neglected by earlier studies. Results reveal that, overall, positive demand shocks impose a greater effect on real freight rates when compared to negative supply (fleet) shocks both historically and on impact (impulse responses) across all segments examined. By contrast, unexpected supply disruptions exhibit a larger effect on impact on net contracting activity when compared to positive demand shocks. These findings provide interesting insights into the behaviour of market participants. For instance, it seems that owners are more sensitive to changes in the level of freight rates and fleet size when making investment decisions, while they appear less responsive to changes in seaborne trade. Finally, based on forecasts scenarios, the responses of freight rates are symmetric to substantial positive and negative one-off shocks of the global demand for shipping; while, they are larger in positive rather than negative shocks of global demand based on historical precedence. Similarly, the findings presented here can be used in planning and scenario analysis in the shipping industry.

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