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# Disentangling Supply and Demand Shocks in the Tanker Shipping Market

*A structural vector autoregressive analysis of freight rate shocks and global stock returns*

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# Foreword

This thesis completes our Masters of Science in Economics and Business Administration at the Norwegian School of Economics (NHH).

When deciding on a topic for the thesis, we wanted to combine our individual interests. Through a term paper in the course "Econometric Methods and Applications in Macroeconomics and Finance", Snorre developed an interest for the possible applications of structural vector autoregression (SVAR). Wanting to combine this with Haakon's growing interest for shipping, it was decided in cooperation with our supervisor, Roar Aadland, that applying SVAR to the tanker shipping market would make for an interesting thesis. To better incorporate a highly econometric topic with our majors in finance, we decided to extend this idea by including a study of the potential relationship between freight rates and the global stock market. Being a much discussed, but little-researched topic, we wanted to contribute to the literature on the potential of freight rates as a leading indicator.

To the best of our knowledge, utilizing SVAR to disentangle supply and demand in a shipping market has never been done prior to this thesis. Motivated by the challenge, we faced several difficulties on the way. One of our most demanding issues was related to the complexity of our model, which complicated the task of finding suitable variables. The process of increasing our understanding of shipping market mechanisms has been highly educative and rewarding.

We would like to extend our deepest gratitude to Roar Aadland for invaluable discussions and insight into the shipping industry. In addition, we also wish to thank Øivind Anti Nilsen and Gernot Doppelhofer for sharing generously of their insights on econometrics.

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# Abstract

This paper utilizes structural vector autoregression to analyze the dynamics of the tanker shipping market. Inspired by Kilian (2009) we suggest a structural decomposition of the real tanker freight rate into three components: total tanker supply shocks; global aggregate demand shocks; and tanker-specific demand shocks. To our knowledge, this is the first study to disentangle and estimate the dynamic effects of supply and demand shocks to the real tanker freight rate. The response in the freight rate is found to differ considerably depending on the type of shock impacting it. Additionally, it is shown that the tanker-specific demand shocks are most important in determining real tanker freight rates. However, through a historical decomposition, the paper demonstrates that the relative importance is subject to the market conditions of specific time periods. Through an extension of the model used to disentangle the supply and demand shocks, the paper investigates the potential of the real tanker freight rate as a leading indicator. The results do not indicate a reliable relationship between global total stock market returns and the real tanker freight rates.

# 1. Introduction

This study aims to investigate the shipping tanker market through a structural vector autoregressive (SVAR) model. The first objective is to identify and quantify the underlying demand and supply shocks in the tanker shipping market. This is done through disentangling freight rate shocks into supply and demand shocks and then analyzing how the different shocks affect the freight rate. The second objective is to perform an analysis of the effect unanticipated tanker freight rate shocks might have on global total stock returns.

To our knowledge, this paper is the first to disentangle the supply and demand shocks in the tanker market. Earlier work has focused on the response in market variables like ship prices, time to build and investment activity to exogenous shocks in the freight rate. Such identification strategies fail to account for potential existence of reverse causality between the explanatory variables and the freight rate. As a result, it becomes difficult to believe that the effects are causal. Further, freight rate increases may have different interpretation dependent on the underlying cause. Evidently, one would expect that a price increase from e.g. the demand boom in China over the last two decades, is different from an increase caused by the scrapping of single-hull tankers between 2005 and 2010. Hence the underlying cause is important when considering the dynamics of the tanker market and the freight rate's eligibility as a leading indicator.

The importance of understanding the underlying factors of varying freight rates is especially relevant for a shipping nation like Norway. With a contribution to GDP of around 8.4%, shipping is one of Norway's most important industries (Norwegian Ministry of Trade, Industry and Fisheries, 2017). Shipping is known for its highly cyclical nature, continuously impacted by political events and regulatory changes (Norwegian Shipowners´ Association, 2017). Further, the large number of factors impacting the freight rate and its volatility, underpins the complexity and uncertainty of future prices. Hence, studying the impact of different types of unanticipated shocks, and how they affect the freight rate mechanism, can contribute to a better understanding of the dynamics in the shipping market.

While the freight rate mechanism is well understood, the impact of endogenous supply and demand shocks to the freight rate has not yet been investigated. Theoretically, when the level of cargoes is low, the supply curve of shipping is relatively flat in the short and intermediate term. This is due to the flexibility available to shipowners through adjusting the speed of the ships and reactivating idle ships. In sluggish markets, the speed can be decreased to save on fuel. Likewise, shipowners can increase the speed to meet higher demand in the short run, at the cost of higher fuel usage. If the demand for sea transports shifts outwards due to increased economic activity, the supply curve steepens sharply once all available ships are running on full speed. When a shift in inelastic demand meets inelastic supply, the impact on freight rate is drastic. The high freight rates from an increase in demand, can only be adjusted in the long-run through additional ship-building. Furthermore, many of the new ships will often be delivered once the impact of increased economic activity has decreased. Therefore, a global business cycle upswing will likely be followed by a persistent trough period in the shipping market due to prevailing excess capacity. The balance will only be regained through gradually scrapping of older ships, and new upswings in the economic activity. (Kilian, 2009)

Further, a consequence of increased globalization is the rapid growth in international trade. From 1950 to 2011, import and export as a percentage of world GDP increased from 19% to 59%[1]. Furthermore, close to 90% of the world's trade is shipped using seaborn transportation (International Chamber of Shipping, 2017). In an increasingly globalized world, domestic indicators may be losing some of their ability to predict economic activity (Fitchner, Rüffer & Schnatz, 2009). Hence, it becomes increasingly important to identify global indicators. The link between freight rates and stock market performance has mainly been discussed in pop literature (Rothfeder, 2016). In addition, a few researchers have published articles suggesting that the Baltic Dry Index has properties of interest as a leading indicator of future stock performance (e.g. Alizadeh & Muradoglu, 2011; Bakshi, et al., 2011). Although the Baltic Dry Index has been covered more thoroughly, this paper explores whether the tanker freight rate could be considered a leading indicator of future global total stock returns.

Inspired by Kilian (2009), we propose a structural decomposition of the tanker freight rate into three components: tanker supply shocks; shocks to the global aggregate demand; and demand shocks that are specific to the tanker market. To study the impact of shocks, variance decomposition is often used to estimate how much each type of shock contributes to the total variance on average. In addition to a variance decomposition, this paper estimates the cumulative effect of a given structural shock on each variable at each given moment in time, through a historical decomposition. This offers unique insight on the interpretation of the different shocks' relative proportion of the variance. The same analytical tools are applicable studying the relation between freight rates and stock returns.

[1] This data is retrieved from the Penn World Tables version 8.1.

The remainder of this thesis is structured as follows: Section 2 presents relevant literature and states this paper's contribution as such. Thereafter the methodology and model setup are presented in section 3. The data is presented in section 4, before we perform the empirical analysis in section 5. Finally, the concluding remarks of our paper are discussed in section 6.

# 2. Literature review

In the examination of existing literature, research related to the use of structural vector autoregressive (SVAR) models will be reviewed first. Thereafter, we examine some of the literature related to the shipping industry, and its potential link to the stock market.

VAR models were introduced by Sims (1980) as an alternative to the traditional macroeconomic models. His main objective was to enable a transition from structural equations with one equation at the time to a joint timeseries approach for all variables. Sims focused on developing a model that allowed all included variables to be endogenous. In his paper he argues that the traditional macroeconomic model approach on identification is "[…] inappropriate, to the point at which claims for identification in these models cannot be taken seriously" (Sims, 1980).

The earliest uses of VAR models were not focusing enough on what the causal effect was. Consequently, variables without a causal relationship were used to explain phenomena. This was addressed by Cooley and LeRoy (1985) and spurred the development of SVAR models that impose non-recursive identifying restrictions (see e.g. Sims, 1986, Bernanke, 1986; Blanchard & Watson, 1986). Since then, VAR models have continuously been researched, and new ideas and insight are still being generated (Kilian, 2011).

SVAR has become a popular tool, especially in macroeconomic research studying monetary policy and sources of business cycle fluctuations (e.g. Abraham & Haltiwanger, 1995; Bernanke & Mihov, 1998; Gali, 1999; Kilian, 2009). Abraham and Haltiwanger (1995) used SVAR models in their study of the business cycle and cyclicality of real wages. They focused on the importance of identifying and quantifying the factors in the business cycle that are important in determining the movements of the variables of interest. Further, they underpin that identification and quantification is the direction research should be heading. Studying the business cycle and oil market dynamics, Kilian (2009) published an article where he disentangled oil price shocks into supply and demand shocks using SVAR. His model consisted of three variables; oil production; an index representing global real economic activity; and the oil price. The purpose of his study was to investigate whether shocks in the oil price resulting from supply and demand shocks, have different effects on the economy. After his decomposition of supply and demand shocks to the crude oil market, new literature based on his approach has emerged (e.g. Kilian & Park, 2009; McPhail, Du & Muhammad, 2012; Qiu et al., 2012; Aastveit et al., 2015; Baumeister & Kilian, 2016). McPhail, Du & Muhammad (2012) studied the corn price volatility through a SVAR model disentangling the innovations in corn price into; global demand, speculation and energy. Qiu et al (2012) extended this model by including the supply and demand variables for gasoline, ethanol and corn. These studies show that the framework in Kilian (2009) is appropriate in markets with features similar to the commodity industry. It may be that markets trading homogenous goods, are easier to represent by the simplified model disentangling supply and demand, than markets with heterogenous goods.

The literature studying factors that influence demand and supply in shipping services is extensive. One of the earliest contributions to explain and predict freight rates in shipping with econometric applications was Tinbergen (1934). Further, the first to set out a broad economic framework of the international shipping business was Martin Stopford, when he published the first edition of *Maritime Economics* in 1988. Covering how the shipping market is organized, explaining the market cycle and the mechanisms of shipping freight rates, Stopford laid the groundwork for further research of the shipping industry (Stopford, 2009).

Furthermore, several studies have focused on the shipping markets as a static mechanism where a system of variables connects supply and demand (e.g. Beenstock & Vergotti, 1993; Strandenes & Wergeland, 1980; Klovland, 2004; Taylor, 1976; Hawdon, 1978; Wijnolst & Wergeland, 1996). Beenstock and Vergotti (1993) describe a static economic model that may be used to forecast the global shipping market and explain the behavior of vessel prices. Strandenes and Wergeland (1980) developed the NORBULK model within the framework of a competitive market equilibrium. A distinct feature of the NORBULK model is the specification of the relationship between trade and the global economic activity. This relationship is found significant in Klovland (2004) as well. He showed that cycles in economic activity are major determinants of the short-run behavior of shipping freight rates in the years between 1850 and WWI.

Compared to the papers studying the shipping market as a static mechanism, a crucial difference is how we in this paper are treating all variables endogenously. Some similarities can be drawn to Veenstra and Franses (1997), who develops a VAR model using a sample of only the dry bulk freight rates themselves, to asses a long-term forecast of the freight rates. Finding that the specification of these long-term relationships does not improve forecast accuracy neither in the short- nor the long term, they interpret the results as a corroboration of the efficient market hypothesis.

Randers and Goluke (2007) focused on dynamic systems that exploit the development of econometric techniques. After more than 30 years of research they proclaim an endogenous perspective on global shipping, and place much of the booms and busts of the industry on the industry itself. Kalouptsidi (2014) studies the market dynamics in bulk shipping by quantifying the impact of *time to build* and demand uncertainty on investment and prices. She finds that moving from time-varying to constant to no time to build, reduces prices while significantly increasing both the level and volatility of investments. Greenwood and Hanson (2015) studied the link between boom and bust cycles and returns on capital in the dry bulk shipping industry. They showed that high current ship prices are associated with high prices for used ships and increased investment in new ships, while also forecasting low future returns.

Kilian and Park (2009) builds on the seminal work of Kilian (2009) on disentangling supply and demand in the oil market to study how different types of shocks might affect the U.S. stock market. Using VAR models to study economic factor's link to stock returns is well covered in the literature (e.g. Campbell & Shiller, 1987, 1988a, 1988b; Hagmann & Lenz, 2004; Binswanger, 2004; Cochrane, 2008).

The freight rate has by some researchers been suggested as a leading indicator of the stock market. Motivated by shipping's important role in the earliest phases in the supply chain of goods, it can be argued that it is one of the first industries to be affected by changes in global economic trends. Fitchner, Rüffer & Schnatz (2009) argue that a potential problem with many of the existing leading indicators, is that they are domestic. In an increasingly globalized world, they argue that several domestic leading variables have lost some of their ability to predict economic activity, due to greater international dependency.

The real price of oil is the most commonly used macro-economic factor to predict stock market returns among the alternatives to domestic indicators (Alizadeh & Muradoglu, 2011). The literature on the impact of oil prices on stock market returns is extensive (see e.g. Jones & Kaul, 1996; Mussa, 2000; Nanda & Faff, 2008; Kilian & Park, 2009; Sørensen, 2009; Kang, Ratti & Yoon, 2014). However, there has been no consensus on the direction nor magnitude of the relationship between the two (Kilian & Park, 2009).

Alizadeh and Muradoglu (2011) argue that shipping freight rates must contain information that should be reflected in stock returns. Their findings show that changes in freight rates are reflected in the stock market with a lag, due to information diffusion between industries, making it a leading indicator. They propose that investors are slow to respond to changes in the shipping industry, due to the availability bias. First documented by Tversky & Kahneman (1973), the availability bias states that decisionmakers tend to rely on the information most available to them.

In light of the above, the contributions of our thesis are threefold. Firstly, this paper offers new insight to the understanding of the underlying effects of the freight rate mechanism, as it is the first to disentangle the supply and demand shocks in the tanker market. Secondly, our utilization of SVAR allows the variables to endogenously affect each other. Through this we resolve the problem of potential existence of reverse causality between the explanatory variables and the freight rate. This is one of the major drawbacks of earlier papers. Thirdly, we show that previous papers on the freight rate's potential as a leading indicator, seem to neglect the importance of the underlying cause of freight rate fluctuations.

# 3. Model Setup

This paper performs a structural vector-autoregressive approach where we disentangle supply and demand in tanker shipping to study the dynamics of the shipping market. In addition, we extend our model to incorporate global stock returns to analyze how different types of shipping shocks may affect the returns. The SVAR model is especially useful when there is mutual dependency between the variables, since it allows the variables to be endogenous. The model is built so that the estimate of a given variable depends on its own lags, as well as both contemporaneously and lagged values of the other variables in the system (Kilian, 2011).

First, the theoretical groundwork for SVAR models will be introduced. Secondly, the general methodology of a SVAR model will be explained thoroughly. A short introduction of how to interpret shocks, variance decomposition and historical decomposition will be presented before we specify this paper's two models. Thereafter, assumptions and model restrictions for both models will be presented. Finally, we discuss the robustness of the variables and the choice of lag length.

## 3.1 Introduction to structural vector autoregressive models

SVAR models take a different approach than traditional dynamic simultaneous equation models to achieve identification. Identification in econometrics is the process of converting observed data and assumptions into parameters of interest. These parameters are then put into the reduced form VAR and transformed into a behavioral interpretation of the real-world dynamics. In other words, the SVAR model aims to identify the structural innovations within a system, and then study the interactions between variables in the VAR model (Gottschalk, 2001). Impulse response functions (IRFs) represent the reactions of the variables to shocks hitting the system (Lütkepohl, 2010). However, it is often not clear which shocks are relevant for studying a specific economic problem. Thus, structural information must be used to specify meaningful shocks (Lütkepohl, 2010).

It is essential for the reader to be aware that the causal relationships between the variables are not formally tested in the model, but are simply imposed by the structure. The ordering in the models is constructed based on our institutional knowledge, economic theory and other a priori knowledge of how the variables affect each other. Thus, only to the degree that the reader believes our assumptions are plausible, should our results be recognized as reliable.

## 3.2 Theoretical setup

This section will present the theoretical setup of a structural vector autoregressive model, as introduced by Sims (1980). Since we are interested in studying how the variables in $y_t$ are affected by the shocks, it is necessary to differ the structural shocks from the reduced form VAR shocks. Hence, we estimate the transformation matrix, $A_0$, by performing a Cholesky decomposition of the covariance matrices to the shocks on reduced form, $\sum_e$. Cholesky decomposition orthogonalizes the shocks on reduced form to be able to differ them from the fundamental reduced-form VAR shocks. Orthogonalize means in this case that the error terms in the VAR model become uncorrelated. The recursive structural model created by Cholesky decomposition, is used to obtain the structural shocks and impulse response functions of interest. (Kilian, 2011)

Reduced form VARs can be seen as general representations of structural models on the form

$$(1) \qquad A_0 y_t = \alpha + \sum_{i=1}^{L} A_i y_{t-i} + u_t \quad , \quad for\ i = 1, \dots, p$$

In this expression, $y_t$ is a vector $(K \times 1)$ consisting of the endogenous variables at time $t$. Furthermore, $\alpha$ is a constant term, L is the desired lag length, $A_i$ is the matrix of coefficients on lag $i$, and $u_t$ are the structural errors at time t. The structural errors, $u_t$, are assumed orthogonal, meaning that an innovation in one variable does not affect the current value of any other variable (Kennedy, 2003).

To estimate the impulse response functions we are interested in, it is necessary to express the model on reduced form. The key to uncover the structural parameters of the model is to find ways of identifying $A_0$ from the data. Thus, we need to express $y_t$ as a function of historical values of $y$. This enables us to determine the linear combination of reduced form shocks, from which we decompose the structural shocks.

To do this, we use Cholesky decomposition with the assumption that the transformation matrix $A_0$ has a lower triangular structure

$$A_0 = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix}$$

Given the ordering of the variables within the vector $y_t$, a lower triangular structure will impose a hierarchical structure on the contemporaneous correlations between $y_{1t}, y_{2t}, y_{3t}$.

To express the model on reduced form with orthogonalized residuals, we multiply each side of the structural VAR with its inverse matrix, $A_0^{-1}$

$$(2) \qquad A_0^{-1} A_0 y_t = \alpha + \sum_{i=1}^{L} A_0^{-1} A_i y_{t-i} + A_0^{-1} u_t$$

$A_0^{-1}$ is often referred to as the structural impact multiplier matrix. Since the product of a quadratic matrix and its inverse is equal to the identity matrix, $I_K$, the reduced form VAR model could be expressed,

$$(3) \qquad y_t = c + \textstyle\sum_{i=1}^{L} \phi_i y_{t-i} + e_t$$

where $c = A_0^{-1} \alpha$ , $\phi_i = A_0^{-1} A_i$ for $i = 1, \dots, L$ and $e_t = A_0^{-1} u_t$.

We have now imposed a recursive structure on the structural impact multiplier matrix, $A_0^{-1}$, such that the reduced-form errors, $e_t$, can be expressed as a linear combination of the structural errors. As a result, the VAR shocks on reduced form relates to the structural shocks through the equation

$$(4) \qquad e_t = A_0^{-1} u_t$$

The covariance matrix of is then

$$E(e_t e_t') = A_0^{-1} \Sigma_u (A_0^{-1})'$$

$$\Sigma_e = A_0^{-1} \Sigma_u (A_0^{-1})' \quad , \quad where\ \Sigma_u = I_K$$

$$(5) \qquad \Sigma_e = A_0^{-1} (A_0^{-1})'$$

Equation (4) shows how the dynamic relationships in the economy can be modeled as a relationship between structural shocks in SVAR. The reduced-form VAR shocks $e_t$ could be interpreted as a weighted average of the structural shocks $u_t$, where the weights are given by the matrix $A_0$. Knowledge of the structural-impact multiplier matrix, $A_0^{-1}$, allows us to estimate the corresponding structural impulse response matrices $\Theta_\mathrm{i}$.

IRFs are useful to assess both timing and magnitude of the responses to one-time demand or supply shocks (Kilian & Park, 2009). The effect of a shock will depend on the variables included in the system, the model's structure and restrictions, as well as the observed time period. In this representation, structural impulse responses based on the structural impact multiplier matrix are responses to one-standard deviation shocks. IRFs should be interpreted as a measure of the response in the $k^{th}$ component of $y_t$ to an unanticipated disturbance in the $k^{th}$ component (Jordà, 2003). This interpretation makes IRFs attractive from an economic point of view.

In *Model 1*, we disentangle innovations in the real tanker freight rate into three structural shocks: $u_{1t}$ denotes shocks to the global tanker supply of deadweight tonne; $u_{2t}$ denotes shocks to the real global economic activity; and $u_{3t}$ denotes shocks to the real tanker freight rate. In the extended model, innovations to global total stock returns that are not driven by neither supply nor demand in the tanker market ($u_{4t}$), are added. The interpretation and difference between these shocks will be defined as part of the motivation for our ordering. Disentangling $u_{4t}$ further lies outside the scope of this paper.

Forecast error variance decomposition (hereinafter referred to as variance decomposition) is typically used to make statements regarding the percentage of the variance explained by innovations in the $k^{th}$ variable. Similar to the discussion of impulse response functions, these statements are only sensible if we can attach some structural meaning to the innovation under consideration. Identification of the structural innovations requires the same type of assumptions on the transformation matrix, A, as stated above**.**

Historical decomposition estimates the cumulative effect of a given structural shock on each variable at each given moment in time (Kilian, 2011). We use historical decomposition in the empirical analysis to quantify how much each given structural shock explains of the historically observed fluctuations in the real tanker freight rate. Quantifying the cumulative effect of each factor is important because it uncovers information that cannot be obtained from impulse response functions (Abraham & Haltiwanger, 1995; Edelstein & Kilian, 2009).

From a covariance-stationary VAR model, the historical decomposition can be computed as follows:

$$(6) \qquad y_t = \sum_{\mathrm{i}=1}^{\infty} \Theta_{\mathrm{i}} u_{t-\mathrm{i}}$$

where $y_t$ still refers to the vector of current endogenous observations. We make use of $u_{t-\mathrm{i}} = A_0 e_{t-i}$. Further, $\Theta_{\mathrm{i}}$ is the $K \times K$ matrix of structural impulse responses, at lag $i = 0,1,2,..,L$ , and $u_t$ that denotes the $K \times 1$ vector of mutually uncorrelated structural shocks.

Additionally, we assume that our sample only contains data from 1 to t (equivalent to our sample period 1990.1-2017.9, where i=1 refers to the observation in 2017.9). Hence, we split equation (6) into two terms:

$$(7) \qquad y_t = \sum_{\mathrm{i}=0}^{\mathrm{t}-1} \Theta_{\mathrm{i}} u_{t-\mathrm{i}} + \sum_{\mathrm{i}=\mathrm{t}}^{\infty} \Theta_{\mathrm{i}} u_{t-\mathrm{i}}$$

The first term expresses the value of $y_t$ as dependent on shocks $u_1$, $(\ldots)$ $, u_t$ that can be estimated, while the second term expresses the shocks that corresponds to the pre-sample period and thus cannot be estimated. Since the model is stationary, MA coefficients die out as we move further into the past. Hence, the second term will have a steadily diminishing effect on $y_t$ as t increases. Hence, an approximation of the historical decomposition could be expressed by,

$$(8) \qquad y_t \approx \sum_{\mathrm{i}=0}^{\mathrm{t}-1} \Theta_{\mathrm{i}} u_{t-\mathrm{i}}$$

for each moment in time. Note that since the decomposition is based on past observations the earliest estimates in the sample may contain significant error terms.

Finally, we denote this approximation by

$$(9) \qquad \hat{y}_{\mathrm{t}} = \sum_{\mathrm{i}=0}^{\mathrm{t}-1} \Theta_{\mathrm{i}} u_{t-\mathrm{i}}$$

By decomposing this sum, the cumulative contribution of each shock to each element of $\hat{y}_{\mathrm{t}}$ can be isolated. The results based on this decomposition will be presented in the empirical analysis.

A recursive system, like the one we propose, allows for a causal interpretation since it consists of one-way relations between the variables within the system (Wold, 1952). If there is not a rational economic explanation behind the structure of the SVAR model, the results would be meaningless. Hence, a recursive structure needs an explicit causal ordering of the variables. Believing in this recursive structure is vital for trusting the results of the model, and we will therefore motivate the ordering.

*Model 1* consists of three variables: a *supply variable*, an *aggregate demand variable*, and a *tanker-specific demand variable*. We define tanker-specific demand as innovations to the tanker freight rate that are neither explained by supply nor aggregate demand. Through these three variables, *Model 1* represents the dynamics of the shipping market and imposes identifying assumptions resulting in a recursively structural model of the form,

$$y_t = (\Delta deadweight\ tonne_t, \Delta steel\ production_t, real\ tanker\ freight\ rate_t)$$

where the reduced form errors $e_t$ can be expressed as follows:

$$\begin{pmatrix} e_t^{capacity} \\ e_t^{economic\ activity} \\ e_t^{freight\ rate} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} u_t^{supply\ shock} \\ u_t^{aggregate\ demand\ shock} \\ u_t^{tanker-spesific\ demand\ shock} \end{pmatrix}$$

In *Model 1*, the supply variable, *deadweight tonne capacity in the tanker market,* is ordered causally prior to the global demand variable, *real global economic activity*, which again is ordered causally prior to the tanker-specific demand variable, *real tanker freight rate*.

The supply variable is ordered first in the recursive structure. This implies that supply cannot be contemporaneously affected by shocks in neither real global aggregate demand nor the tanker-specific demand. In other words, supply cannot increase as a response to increases in demand within the same month. Graphically this can be explained by a vertical supply curve in the short term. Changing the supplied capacity is not done overnight and shipowners face long lags between the order and delivery of a new vessel (Kalouptsidi, 2014). Under full capacity utilization, it is practically impossible to deliver an extra shipment of oil within the same month, due to the time to build. Normally, the period from ordering a new ship until delivery lies between 1-3 years (Stopford, 2009). The time to build is important to keep in mind when considering lag length. The time to build increases our belief in the ordering of supply as the first variable. This belief is further strengthened by Kalouptsidi (2014) who finds that supply adjusts sluggishly due to entry costs, time to build, and convex operating cost of ships. Her finding implies that tanker supply may only be affected by a persistent increase in demand, if demand is to have an effect at all.

Global aggregate demand is ordered as the second variable in the recursive structure. Changes in global economic activity that cannot be explained by changes in supply will be referred to as aggregate demand shocks. This second restriction implies that global economic activity can be contemporaneously affected by supply shocks, while it is not allowed to be contemporaneously affected by tanker-specific demand shocks. The connection between global economic activity and freight rate is indomitable (Klovland, 1994;  Stopford, 2009). However, we argue that global aggregate demand only will be affected by tanker-specific demand shocks with a lag of at least 1 month, if impacted at all.

In terms of ordering, freight rate is the last variable, meaning that we allow it to be contemporaneously affected by both supply and global aggregate demand shocks. The tanker-specific demand shock could in principle capture any number of omitted factors. Regardless of the factors captured, the model ensures that all tanker-specific demand shocks must be orthogonal to tanker supply shocks and to global aggregate demand shocks.

In *Model 2*, we expand *Model 1* through adding global total stock returns as a fourth variable. This is done to study how freight rates affect the global total stock returns, and whether this might give insight into whether freight rate could be interpreted as a leading indicator. Adding the fourth variable will result in the following recursive structure,

$$y_t = (capacity_t, economic\ activity_t, freight\ rate_t, world\ total\ return_t)$$

where the reduced form errors $e_t$can be expressed as follows:

$$\begin{pmatrix} e_t^{capacity} \\ e_t^{economic\ activity} \\ e_t^{freight\ rate} \\ e_t^{global\ total\ returns} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} u_t^{supply\ shock} \\ u_t^{aggregate\ demand\ shock} \\ u_t^{tanker-specific\ demand\ shock} \\ u_t^{other\ shocks\ to\ global\ total\ returns} \end{pmatrix}$$

The recursive structure of the top three variables are the same as in *Model 1*. Innovations to global total stock returns that cannot be explained by the other three variables, are referred to as *other shocks to global total stock returns*. This implies that capacity, real economic activity, and the real tanker freight rate are treated as predetermined with respect to global total stock returns.

Global total stock returns can respond contemporaneously to all the other shocks. Since stock prices are published at least as frequently as the freight rate, this motivates our ordering. Further, we believe it is a reliable assumption that shipping-specific information is reflected in the freight rate before it is reflected in stock market returns (see e.g. Alizadeh & Muradoglu, 2011). In addition, we argue that ordering global total stock returns at the bottom serves our analysis the best, as it would allow for contemporaneous responses in global total stock returns to all the other variables.

As a final part of this chapter, we will now discuss robustness of the variables and the choice of lag length. Lagged effects are common in macro series, and important to consider when estimating VAR models. This matters for both estimates of the autoregressive coefficients as well as in IRF analysis. On the one hand, including lags can help reducing autocorrelation in the residuals. On the other hand, VAR models easily become overparameterized. Having too many parameters relative to observations will lead to problems with imprecise estimates after using too many degrees of freedom (Brüggemann & Lütkepohl, 2000). Moreover, including too many lags can lead to overfitting. Thus, choosing the correct lag-length is essential to avoid misspecification whilst still getting a parsimonious model.

A common approach to determining lag length is to use some type of information criterion[2]. For *Model 1*, Akaike's (1974) information criterion (AIC) and Hannan and Quinn's information criterion (HQIC) both recommend a lag length of 12 lags. Schwarz's (1978) Bayesian information criterion (SBIC) on the other hand, suggest only 1 month of lags as the preferred lag length. According to Lütkepohl (2005), the SBIC and the HQIC have a theoretical advantage over AIC since they provide consistent estimates of the true lag order, while minimizing the AIC will overestimate the true lag order with positive probability. Since SBIC penalizes adding more lags harder than the AIC it is not surprising that it recommends a less parameterized model. Further, with 333 observations of each variable, we have a smaller sample than Kilian (2009) had studying the oil market. This contradicts a long lag-length. From this analysis a lag length of 1 year, i.e. 12 lags, could be a reasonable solution.

However, the log-likelihood ratio (LR) indicates that the most appropriate lag length is 24 lags. An important issue with our model is the time to build and hence the period from a structural demand shock occurs until we expect the reaction in supply to be visible. Thus, we argue that

[2] According to Lütkepohl (2005) the constant on the log-likelihood can be dropped because it does not affect inference. The Lütkepohl versions of the information criteria are used in this thesis.

a priori knowledge of the process of acquiring new ships motivates a longer lag-length. In addition, we suspect that the information criterion suggests a lower lag-length due to the first differencing of the series, because differencing makes the variables more difficult to predict.

Furthermore, using a lag length of 12 is somewhat lower than what Kilian (2009) suggests in his paper. Kilian argues that using economic reasoning and knowledge of institutional aspects is the preferred method to choose the number of lags when studying the oil market. As two years of lags are necessary to capture the cyclical nature of the oil market, he argues that 24 lags are suitable. Based on institutional aspects of the oil market, a long lag length is required. In combination with Kilian's arguments, economic reasoning based on a priori knowledge weights heaviest. The LR underpins the viability of this choice.

Turning to *Model 2*, the LR still prefers 24 lags while AIC now recommends 13 lags. SBIC still recommends 1 month of lags, while the HQIC prefers 4 lags. Further, Kilian and Park (2009) used 24 lags when they extended Kilian's (2009) initial model to study the relationship between oil price and stock returns. Thus, we conclude that using 24 lags is the preferred lag length for both models in this paper since we believe it captures the effects more accurately. Increasing the lag length above 24 would cause further parameterization, which is undesirable. In any case, the results with 12 lags are practically identical to the ones with 24 lags. All IRFs for both models are available in the appendix (see A.1).

In terms of stability, both our models satisfy the eigenvalue stability condition, which is required to make reliable interpretations of the IRFs. A SVAR model is stable if all eigenvalues lie within the unit circle (Lütkepohl, 2005). This is shown graphically in our appendix (see A.2). Further, to viably interpret the inference of a SVAR model, all variables must be covariance stationary (Lütkepohl, 2005). We have used Augmented Dickey-Fuller (ADF) and Phillipe-Perron (PP) tests[3] to ensure that our variables are stationary. According to the ADF-tests, neither of the variables representing tanker supply, aggregate demand nor total stock returns are stationary in level form. For these three variables we had to log-transform and difference the series to satisfy ADF and PP. First differencing could throw away information that might be important for our model. However, stationary variables are a prerequisite for reliable inference. Hence, we chose to difference these variables. For the real tanker freight rate, we only had to log-transform the variable to believe in the stationarity condition. After adjustments, all

[3]For a thorough description of the method for these tests we refer to Hamilton (1994) and Phillips & Perron (1988).

variables reject unit root at the 1% significance level. This strengthens the robustness of the model. For further details we refer to the appendix (see A.4).

For a graphical presentation of the residual analysis, we refer to section A.3 of the appendix. Here, we observe clear signs of normality, although some problems may exist in the tails of the distributions. In most of the histograms we observe higher peaks and fatter tails, compared to the normal distribution. This is a sign of a leptokurtic distribution, which indicates that the residuals show signs of stochastic variance, or just a distribution where the kurtosis is higher than in the standard normal. Leptokurtic observations are confirmed by performing the Jarque–Bera skewness, and kurtosis statistics based on Lütkepohl (2005) for both models.

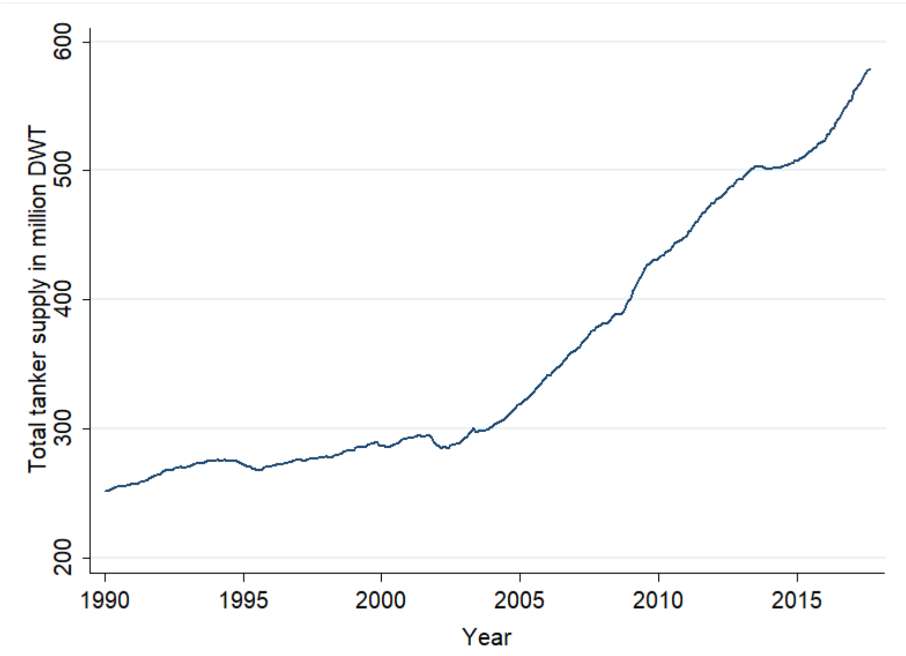
In *Model 1*, the kurtosis test fails to reject the supply residual, and the skewness test fail to reject the tanker freight rate residual. Further, the Jarque–Bera test, which combines the two latter tests, reject the null hypothesis that the residuals in *Model 1* are normally distributed. In *Model 2*, the freight rate residual fails to reject the skewness test. Apart from this it seems to be both skewness and kurtosis in most residuals. This is underpinned by the Jarque-Bera test, which rejects the null hypothesis that the residuals in *Model 2* are normally distributed. These results are coherent with the Shapiro-Wilk normality test. The Shapiro-Wilk test is often preferred to Jarque-Bera when the sample has less than 2000 observations or the residuals has a leptokurtic distribution (Park, 2015). The Shapiro-Wilk test succeeded to reject normality for all the residuals except for freight rate. Rejecting normality of the residuals may reduce the belief in the inference and the confidence intervals of the impulse response functions (Lanne & Lütkepohl, 2006). We will not try to correct for the non-normality of the residuals in this paper, but rather keep it in mind when examining the results.

# 4. Data

After adjustments, the dataset includes four measures: the percentage change of growth in total tanker deadweight tonnage capacity; the percentage change of growth in steel production as an indicator of global economic activity; the real tanker VLCC freight rate; and the percentage change of growth in an index for global total stock returns. All data are quoted at monthly frequency. The main argument for why we need monthly data is the restriction implying that if global economic activity is affected by freight rates, it is only with a lagged effect. At quarterly frequency, it would be more difficult to argue that the relationship could not be contemporaneous. In addition, monthly data will result in more observations and a more detailed description of the relationships between the variables than quarterly or annual data would. The sample period spans from January 1990 up to and including September 2017. While some of the variables have data available from the 1970s, the dataset is restricted by the steel production and freight rate time series, for which we only have data from January 1990. Due to the chosen lag-length and first differencing of the variables, the first estimations will be from February 1992.

The first variable in our ordering is the supply variable. It is constructed based on the development of total tanker fleet size in terms of deadweight tonnage obtained from Clarkson's Shipping Intelligence Network (SIN). More specifically, the series shows aggregate monthly data, reported in million deadweight tonnage for tanker ships larger than 10k deadweight tonnage. Figure 1 illustrates the development in the time series. To make the variable stable it is log-transformed and first differenced. Thus, the variable we use in the models represents the monthly percentage growth in total tanker fleet size. For a graphical presentation of the adjusted series we refer to the appendix (see A.3.1).

*Figure 1) Development in the total tanker supply, measured in million DWT.*



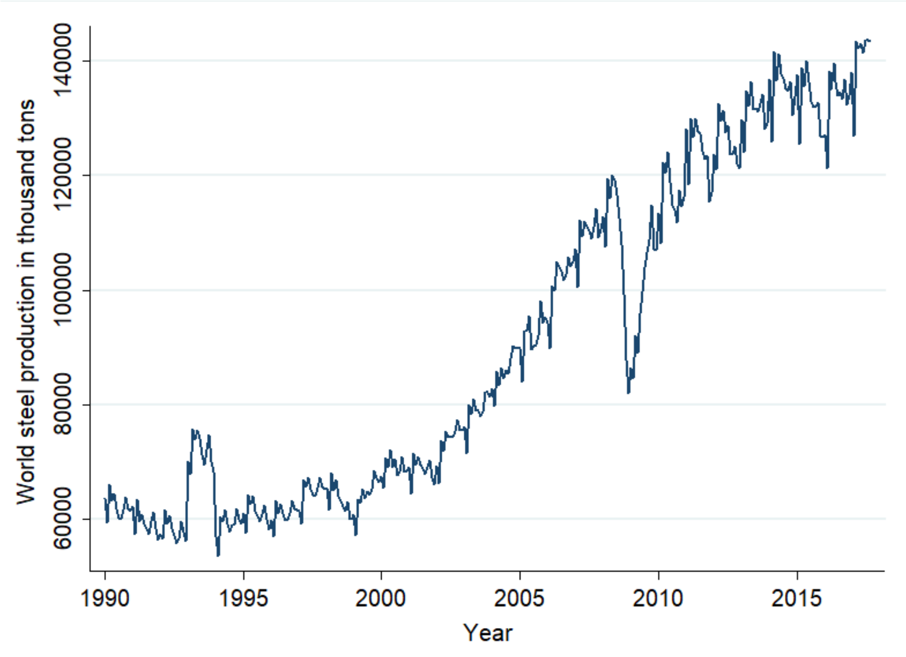

Second in our ordering is global aggregate demand. This variable is constructed with monthly world steel production data retrieved from Clarkson's SIN and the World Steel Association (WSA). The SIN database covers the period 1995.1-2017.9, while WSA have data from 1990.1-2017.9. However, WSA only provide data in hardcopy, hence these had to be entered manually. Thus, we have used global steel production data from Clarkson's SIN, and extrapolated the series with the first five years of data from WSA. To ensure that the data was representative equivalents, a correlation test of the period 1995.1-1999.12 showed a correlation of 0.9978, which is well within required levels.

According to Ravazzelo and Vespignani (2016), two of the most common indicators of global economic activity are OECD’s industrial production index and Kilian’s real economic activity index. However, Ravazzolo and Vespignani argue that world steel production may be a more precise indicator of global economic activity. One of the main advantages achieved with global steel production, is that we can ignore the weighting problem associated with OECD’s industrial production index and Kilian’s index. In addition, the series does not require deflating, as steel production is a real variable. For further discussion, as well as technical details on how the proxy is motivated, we refer to Ravazzolo and Vespignani (2016).

Measuring global economic activity, GDP is both a broadly accepted as well as a frequently used indicator. However, GDP is only reported on a quarterly basis, making it unfit for the SVAR analyses of this thesis. Using Kilian’s real economic activity index could potentially lead to biased results in a model studying tanker freight rates, as it is based on weighted dry bulk freight rates as a proxy for real global economic activity. Hence, choosing the global steel production index ensures avoidance of multicollinearity issues that might occur using a freight based index.

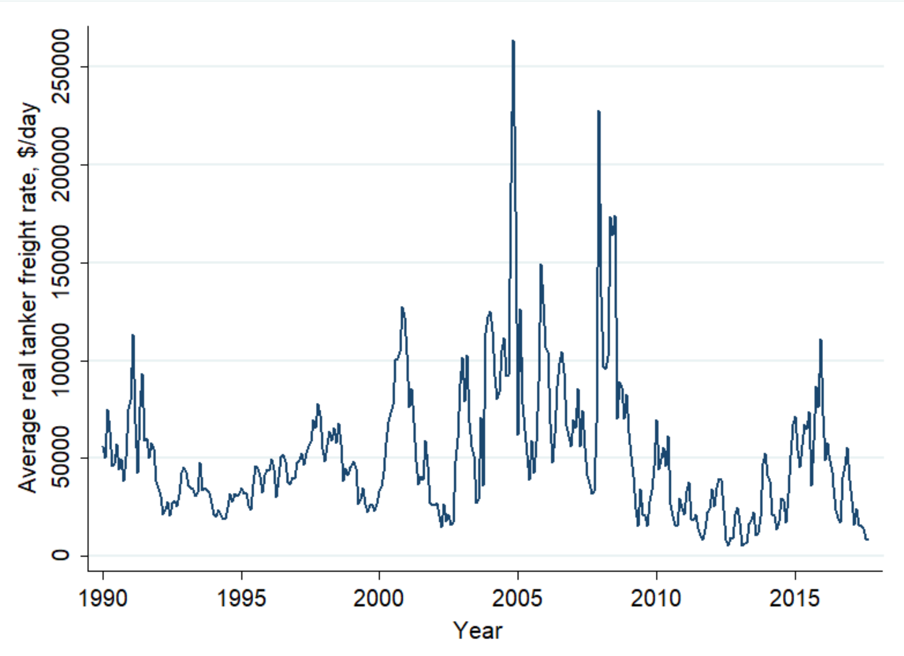
In figure 2, the development in world steel production is illustrated. The series seem to be seasonal with an exponential trend. Hence, we chose to log-transform the variable and then perform first difference to make it stationary, before we incorporated it into our model. Based on Ravazzolo and Vespignani (2016), we do not seasonally adjust the variable. As a result, the variable incorporated in the model should be interpreted as the percentage change in monthly steel production growth. For a visualization of the log-transformed and differenced variable, we refer to the appendix (see A.3.2).

*Figure 2) Development in world steel production, measured in thousand tons produced*



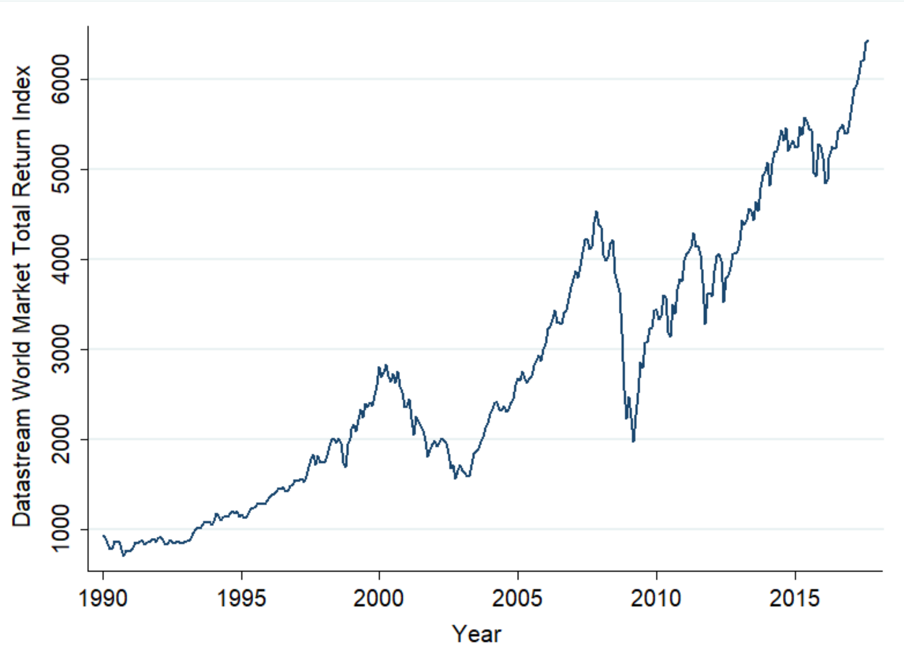

The third variable, tanker-specific demand, is based on the average VLCC long-run historical earnings per day, retrieved from Clarkson's SIN. To construct the real tanker freight rate, the VLCC rate was inflation-adjusted with CPI data provided by the U.S. Bureau of Labor Statistic using the most recent month, September 2017, as base. Deflating the time series eliminates any variation in freight rates caused by inflation. Figure 3 illustrates the development in the average real VLCC freight rate. To satisfy the robustness requirements of our model, the real tanker freight rate is log-transformed, and should therefore be interpreted as the percentage change in the real freight rate.

*Figure 3) Development in the average real VLCC freight rate, measured in USD/day*




To capture the historical performance of the global stock market, the World Market Total Return Index is retrieved from Thomson Reuters Datastream Economics database. More specifically, the index accounts for re-invested dividends, and provides monthly data with base in January 1973. Datastream publishes several regional indices, where each index comprises at least 75 % of the total market value for each market included. Datastream's World Total Return Index utilizes these regional indices to form an aggregate index which is representative for the world market. A graphical representation is presented in figure 4. In our model, we have included the variable as log-transformed and first differenced. Hence, it should be interpreted as the monthly change in percentage growth in global total stock returns.

*Figure 4) Development in the Datastream World Market Total Return Index*




# 5. Empirical Results

In this section we present the empirical results. First, we quantify the evolution of the structural shocks related to the variables in *Model 1* over the selected time period. This is done to compare structural shocks in the three variables to historical events related to the tanker industry. Secondly, we analyze how different types of shocks affect the tanker market to see whether the dynamics of the reactions to shocks correspond to economic theory. Thereafter, the variance of the real tanker freight rate is decomposed, both on average through a variance decomposition, and cumulatively for each specific moment in time through a historical decomposition. This is done in order to identify the importance of the different shocks in determining real tanker freight rates. Further, we analyze how shocks to the tanker market might influence the global total stock returns. Finally, a variance decomposition is used to identify how important the tanker market variables are in determining variation in stock market returns.

Note that in order to perform the empirical analysis, we have mainly used STATA as our statistical software. However, the function needed to perform a historical decomposition is not available in STATA. Hence, we have applied converted MATLAB-code based on Ambrogio Cesa-Bianchi's toolbox for VAR analysis (Cesa-Bianchi, 2017) and created the historical variance decomposition in R.

## 5.1 Dynamics of the tanker market

The analysis begins with a quantification of the evolution of shocks to the tanker market. Figure 5 presents the historical evolution and illustrates the time path of the structural shocks implied by *Model 1,* expressed by the residuals of each variable in the model. The shocks have been averaged to annual frequency to improve the readability of the graph. In reality, fluctuations have higher amplitude and occur at a higher frequency (see A.7 in the appendix). As can be seen from figure 5, the real tanker freight rate responds to a multitude of shocks at any point in time, the composition of which evolves over time. Further we note that the scale on the y-axis of the three types of shocks differ to better present the fluctuations in each shock.

In the beginning of the observed time period, the market expected a supply shortage. During the period 1966 to 1973, the tanker industry was booming, leading to rapid increases in capacity (Stopford, 2009) These large amount of 1970's tankers were expected to be replaced around 1990. However, most of the tankers continued to trade, and in combination with lower demand than expected, the industry went into a recession from 1992 to 1995 (Stopford, 2009, p. 129). From the historical evolution, the recession might be indicated from the fall in aggregate and tanker-specific demand within the same period. In 1997, the Asian financial crisis halted the demand from the emerging Chinese economy, leading to further negative sentiment in the tanker industry. The negative sentiment finally triggered the scrapping of the 1970's tankers in the years leading up to 2000, creating a negative supply shock. Several of these events seems to be reflected in the historical evolution of the tanker supply, indicating a negative supply shock in the period before 2000, and a drastic drop from 2000 to 2001.

Additionally, the historical evolution indicates a positive shock in tanker-specific demand around 2000. At this time, the growth in the Asian economies had recovered and reached record production levels. In 2001, the tanker-specific demand fell drastically before steadily increasing again. This corresponds well with the burst of the dotcom bubble in early 2001, when the collapse in internet stocks precipitated a deep recession in Atlantic and Asian economies. As seems to be reflected in figure 5, the tanker supply shortage recovered from 2001 to 2003. In 2003, the International Maritime Organization (IMO) introduced a new world-wide double-hull requirement[4], leading to the phasing out of single-hull tonnage tankers until 2010. We expect this to have dampened the positive supply shocks, while at the same time increased the need

[4] Regulation (EC) No 1726/2003 of the European Parliament and the Council of 22 July 2003 amending Regulation (EC) No 417/2002 on the accelerated phasing-in of double hull or equivalent design for single-hull oil tankers, Official Journal L 249, 1.10.2003

for new ships. In terms of demand, 2003 was also the year when the Chinese economic activity exploded again (Stopford, 2009). From the evolution of the supply variable, the increased demand seems to have triggered the building of new ships, which balanced out the scrapping of single-hull and older ships from 2003 to 2010.

Between 2007 and 2008, the financial crisis hit the economy. The negative effect on aggregate demand is clear from the historical evolution. However, tanker-specific demand does not seem to have experienced an immediate negative shock from the financial crisis. Rather, figure 5 indicates a positive shock to tanker-specific demand in 2007, lasting into 2008. The shipping industry was not hit immediately by the crisis, and average monthly earnings in 2008 surpassed those of the record year of 2004[5]. However, in the second half of 2008 global oil trade was hit by the economic recession, while new ships kept entering the market. The increase in positive supply shocks and negative tanker-specific demand shocks, as can be seen in the historical evolution, seems to reflect this.

In 2014, the oil market was hit by a supply shock, making the price drop drastically. At the same time the demand for oil from China increased steadily until 2015 (IEA, 2015). This led to increased demand for tanker services, which is reflected in the historical evolution of the tanker-specific demand. The real tanker freight rate increased during the same period, leading ship owners to once again order new ships. These ships started entering the market in 2016 and 2017, as can be seen from the positive shocks in the historical evolution of tanker supply.

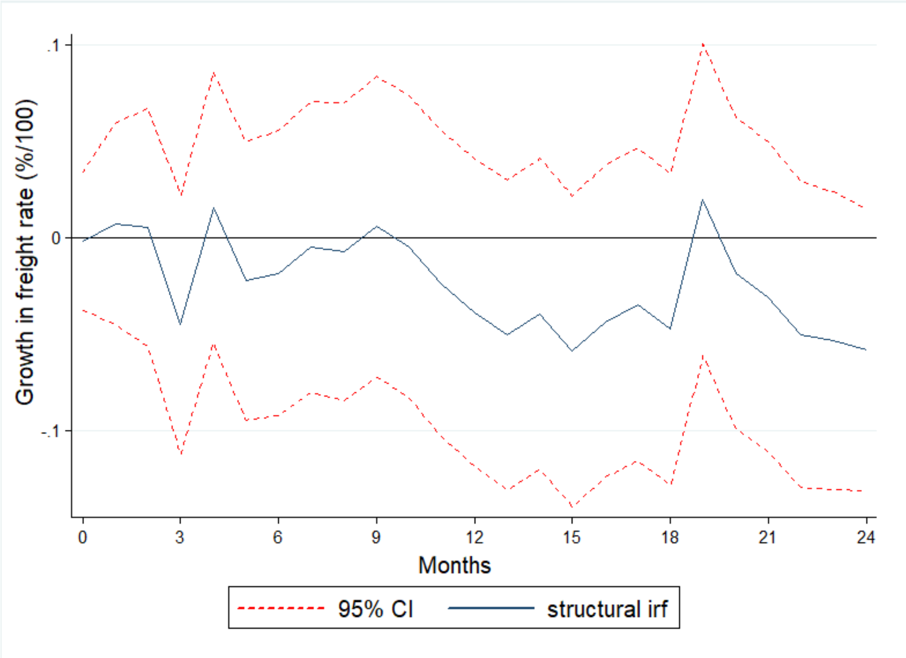
[5] Average VLCC long run historical earnings are found from Clarkson's SIN.

*Figure 5) Historical evolution of the unanticipated shocks to the three supply and demand variables in Model 1*

After quantifying the historical evolution of the shocks, we move on to analyze the tanker-market dynamics through the IRFs of *Model 1*. The analysis looks at the development of the real tanker freight rate over a 24-month period following a positive one-time structural shock.

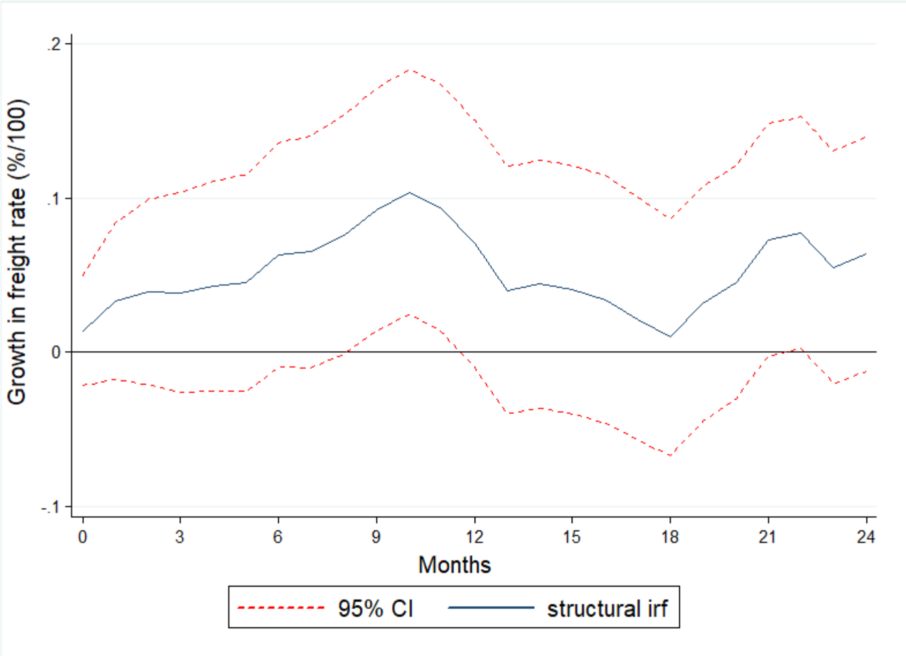
The impact on the real tanker freight rate from a positive shock to the supply of tanker deadweight tonnage, is illustrated in figure 6. A positive supply shock implicates that there has been an unaticipated increase in the supply of deadweight tonnage. Shipowners invest heavily during boom periods, often leading to a surplus in supply once the growth in demand declines. Greenwood and Hanson (2013) found that this procyclical behavior leads to depressed future earnings, which is what we would expect from an increase in supply, ceteris paribus. From figure 6, a positive supply shock does not seem to impact the freight rate immediately. Only after two months does the impulse response function indicate a decrease in freight rates. Although total tanker capacity increases instantly in our variable when a new ship is delivered, the ship might use 1-2 months relocating before it is utilized for shipments. Nevertheless, the freight rate seems to recover already in the third month after the shock has occured. Then, the IRF indicates that the effect of the shock is negative, but close to zero for some months. From the $9^{th}$ month to the $18^{th}$ month following a positive supply shock, the impulse response indicates a decreasing freight rate. The long response time of the supply side of shipping prevents shipowners from reacting to the shortage in demand (Kilian, 2006). This could help explain the long-lasting, negative impact on freight rates. Athough our results imply a somewhat negative trend, we note that the response is never significantly different from zero on the 10 percent level over the two-year adjustment path.

*Figure 6) IRF of tanker supply shock on real tanker freight rate*




Turning to aggregate demand, the development in real tanker freight rate in response to an unanticipated positive shock is shown in figure 7. In breif, the real tanker freight rate will respond with a persistent increase over the two-year adjustment path. Furthermore, the increase grows until the 10th month following the shock, indicating that the freight rate adjusts to the shock with a lag. The spare capacity and short-term flexibility of speed adjustments will reduce the initial impact of higher demand, causing the lagged effect. This positive effect is significant on the 5 percent level from the 9th to the 11th month as well as in the 22th month following the initial shock. Furthermore, a ship generally takes one to three years to deliver, and once it is built, a ship has a physical life span of between 15-30 years (Stopford, 2009). Thus, the persistency can be explained through suppliers lack of ability to respond immediately to changes in demand.

*Figure 7) IRF for aggregate demand shock on real tanker freight rate*

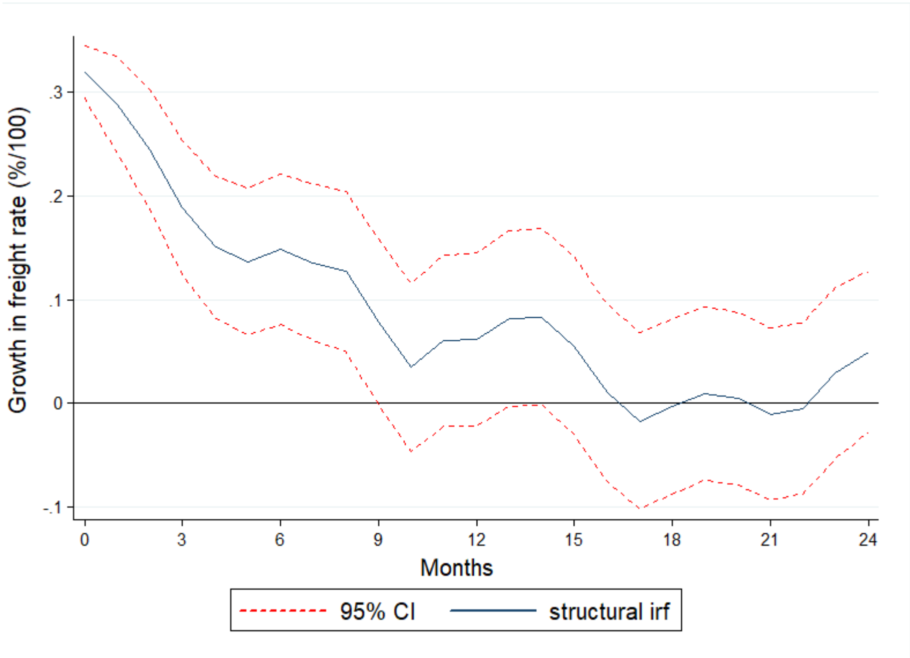



Finally, the effect from a positive tanker-specific shock on the real tanker freight rate is analyzed. The results from the IRF (see figure 8) indicates that the real tanker freight rate responds with an immediate increase. This increase reverts to zero over the next 17 months, and remains significant for the first 8 months following the shock. While the tanker-specific demand in principle could capture a broad variety of omitted factors, it is assumed that it first and foremost measures how expectations influences the demand for tanker services. The quantities supplied and demanded are a function of both current and expected prices (Zannetos, 1966). One of Zannetos' (1966) findings includes that the expectations of higher future freight rates leads to interperiod substitutions, where shippers shift their purchases from future to present periods. According to Hicks (1953), the current supply and demand for a commodity is a result of past expectations, whether right or wrong. Zannetos (1966) argues that the importance of this effect is evident in the tanker market, as can be seen from the dramatic fluctuations in the spot tanker freight rates. The great initial impact on freight rates from a tanker-specific shock seems to underpin this effect.

Furthermore, Alquist & Kilian (2007) found that increased uncertainty of future balance between supply and demand leads the real oil price to overshoot, followed by a gradual decline. If we view a shock to the tanker-specific demand as a shock to the expectations for supply and demand in the tanker market, our results for the response in freight rates seems to indicate a similar overshooting. The conclusion of Alquist & Kilian (2007) was that the overreaction in oil price is due to the assumption of predetermined inventories, which will not adjust fully to an increase in uncertainty on impact. In other words, the demand side underestimates the supply side's ability to rebalance in the short term. An obvious difference between the oil market and the tanker market, is that the oil market is assumed to be more flexible in adjusting supply. Thus, shippers would be more likely to correctly foresee the actual market balance, making the freight rate less likely to overshoot. However, the short-term flexibility of the shipowner in terms of adjusting speed and reactivating idle ships, could make it difficult for the demand side to be correct in their expectations. This could lead to an excessive increase in freight rates from expectations of increased demand as well.

Another way to rationalize how expectations influence the real tanker freight rate, is through the concept of precautionary demand. Precautionary demand for tankers implies that shippers place orders based on their expectations that it will be beneficiary to purchase sooner rather than later. When an increasing number of shippers believe this to be true, the freight rates will increase. Changes in precautionary demand could be due to strategic stock building, caused by various political and economic incentives. The overshoot in the tanker market can also be determined by how the shipowners respond to expectations of a supply shortage. Knowing that demand will increase, they will withhold their ships, leading to even higher pressure for increased freight rates before the market can rebalance.

*Figure 8) IRF for tanker-specific shock on real tanker freight rate*



In addition to the IRF analysis, we have performed a variance decomposition of the variables included in *Model 1*. This is done to determine how much of the variance can be attributed to the different variables over the adjustment path following a one-time shock. The results of the variance decomposition for *Model 1* is presented in table 1. As can be seen from the table, the short run importance of supply and aggregate demand shocks are close to negligible. Initially, less than 0.2% of the variance observed in the tanker freight rate is caused by supply and aggregate demand shocks. However, the importance of supply and aggregate demand shocks increases over the two-year period. After 24 months, the variance decomposition indicates that 4.9% of the variation in the forecast errors is explained by tanker supply shocks. Aggregate demand shocks seem to explain 15.4% of the variation at this point. The decomposition indicates that close to all variation is self-generated in the short run, while it is just below 80% after 24 months. This estimate emphasizes the importance of expectations in the determination of real tanker freight rates.

Our results show similarities to the variance decomposition of the real price of oil in a replication of the model presented in Kilian (2009). Kilian did not present a variance decomposition in his paper. However, we have performed a replication of his model and calculated the variance decomposition. A detailed presentation of variables and the variance decomposition is presented in appendix A.9. In the short run, *oil supply shocks* explain about 0,3% and *aggregate demand shocks* explain almost 1% of the variability, while the rest is explained by *oil-specific demand shocks*. After 24 months the supply shock explains almost 1% of the variability, while *aggregate demand shocks* explain about 27%, according to our replication. As we can see, the global economic activity gradually becomes more important in both markets. Further, the demand variable seems to explain much more of the variability relative to the supply variable. While it may be surprising how little of the variation is explained by aggregate demand and supply shocks in *Model 1*, our results correspond well with the findings of Zannetos (1966). He indicated that the price movements in tankship markets are too great to be explained by traditional static economic analysis. Through our dynamic analysis we find that most of the variation in freight rates is caused by shocks to the tanker-specific demand, rather than supply and aggregate demand shocks. Thus, our results strengthen the findings of Zannetos (1966).

*Table 1) Variance decomposition of Model 1 in %*

| **Horizon** | **Tanker Supply Shocks** | **Aggregate demand shocks** | **Tanker-specific demand shocks** |
|---|---|---|---|
| 1 | 0,00 | 0,19 | 99,81 |
| 6 | 0,86 | 2,46 | 96,69 |
| 12 | 0,88 | 11,33 | 87,79 |
| 18 | 3,29 | 12,71 | 84, 01 |
| 24 | 4,91 | 15,41 | 79,68 |

Lastly in the empirical analysis of *Model 1*, we assess the driving forces of the cyclical fluctuations in the tanker market by performing a historical decomposition of the variables. One advantage to the historical decomposition over the variance decomposition, is that it illustrates how much each type of shock has contributed to the business cycle at each given moment in time. A second advantage with historical decomposition is that it is directly compatible with conventional business cycle definitions (Seymen, 2008). Thus, the historical decomposition can be used to explain the importance of the shocks described in the historical evolution.

Figure 9 shows the respective cumulative contribution of shocks from each variable to the real tanker freight rate, based on a historical decomposition of our data. The plot indicates that the aggregate demand shocks causes long cycles in the real tanker freight rate, while unanticipated innovations to supply seems to mainly contribute to short-term fluctuations. Shocks to the tanker-specific demand appear to be contributing to both longer cycles and more short-term fluctuations. Further, the cumulative effect of tanker-specific demand shocks constitutes a relatively large proportion of the total change in freight rate several times over the sample period. This is as expected from the results of the variance decomposition and the findings of Zannetos (1966). The importance of each shock relative to the actual change in freight rate, is better illustrated in figure A.8.1 in the appendix.

Moreover, figure 9 indicates that the unanticipated fluctuations in supply have had smaller cumulative effect than shocks in aggregate and tanker-specific demand have had. This is particularly prominent after 2005. In isolation, it implies that changes in supply have not had the same impact on the freight rate as changes in demand have had. This could seem plausible, especially considering that China for most of this period has experienced a booming economy, with high growth and significant increase in demand for commodities (U.S. Energy Information

Administration, 2015). On the other hand, it might be that the supply effects are not properly captured in the supply variable. Since the tanker-specific variable is the residual in the model, effects not captured by the other two variables will appear as a tanker-specific demand effect. Hence, the importance of tanker-specific demand as a key driver for changes in the freight rate might be overstated in our model. This will be more thoroughly discussed in the robustness analysis in section 5.3.

From the historical evolution, we examined several events that might have influenced the real tanker freight rate. Through the historical decomposition, we can determine the relative importance of the three variables in explaining variations in the real freight rate for a given time period. The actual movements on real tanker freight rates are illustrated in figure 3. As can be seen from figure 9, the unanticipated supply shocks appear to have contributed to increased freight rates from 1995 to 2005, with peaks and troughs above zero. The relatively high fluctuations in supply over the same period corroborates the importance of the supply shortages described under the historical evolution. Furthermore, the historical decomposition indicates that since 2005, the supply side has mainly contributed to a negative pressure on real tanker freight rates. Reviewing the tanker fleet growth rate, the growth between 1995.1 and 2004.12 was 0,13% on average, while it has been 0,39 % between 2005.1 and 2017.8[6]. This supports the indication of a shift from positive to negative contributions to freight rates from lower scrapping and increased orders. However, the relative importance of tanker supply shocks in determining real tanker freight rates seems to have decreased over the same period.

The sharp rise and fall in real tanker freight rates around 2001 (see figure 3), seems to primarily be caused by changes in tanker-specific demand. From 2003 until 2005 the increase in real tanker freight rate appear to be caused by a combination of positive shocks to all three variables. Thus, the increase in demand from China seems to have had a persistent and positive effect through aggregate demand. Furthermore, the expectations of further growth appear to have had a more volatile, but still positive effect through tanker-specific demand.

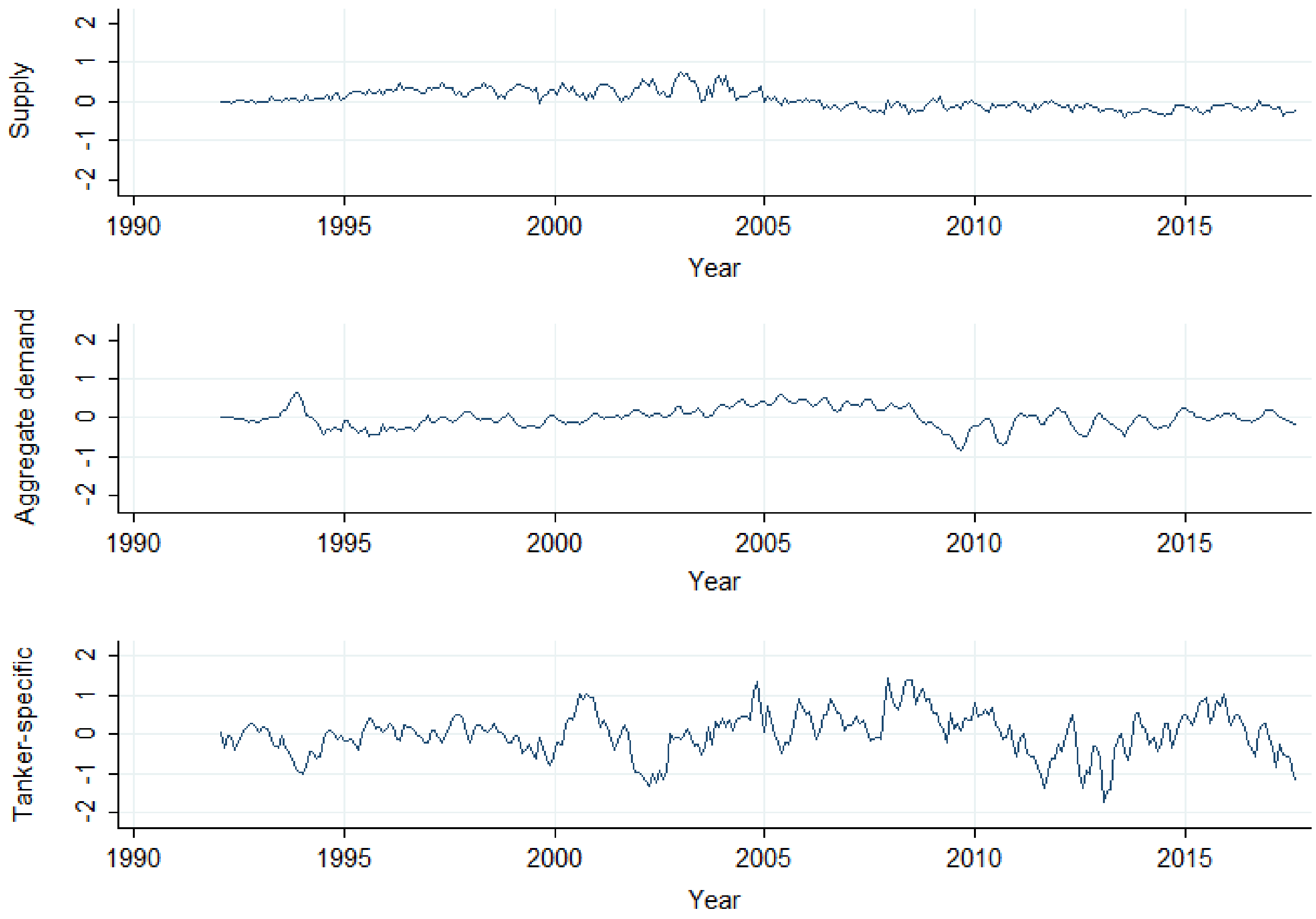
An interesting observation is that the fall in aggregate demand as a result of the financial crisis in 2007-2008, does not seem to have dragged the freight rate down with it. Instead, increased tanker-specific demand justified a high freight rate until 2009. This indicates that the effect of the financial crisis indeed hit the tanker industry with a lag. Since 2009, aggregate demand has steadily recovered from low levels, while the trend in real tanker freights rates has remained

[6] Growth rates are calculated based on time series for total tanker supply from Clarkson's SIN.

flat. The exception was for a short period leading up to 2015, when the freight rates increased temporarily due to increased tanker-specific demand. This underpins the discussion of temporary increased demand for oil from China in the historical evolution.

In summary, our results show that the residuals of the included variables capture many of the historical events influencing the tanker industry. Through the variance decomposition we find that the variables have different importance in explaining the variance in real tanker freight rates, with the tanker-specific demand being the most important. The historical decomposition further expands our understanding of the relative importance of the variables, indicating specific historical events can influence how much each variable contributes in a specific time period.

*Figure 9: Historical decomposition for the three variables in Model 1*



## 5.2 Shocks in the tanker market and total stock returns

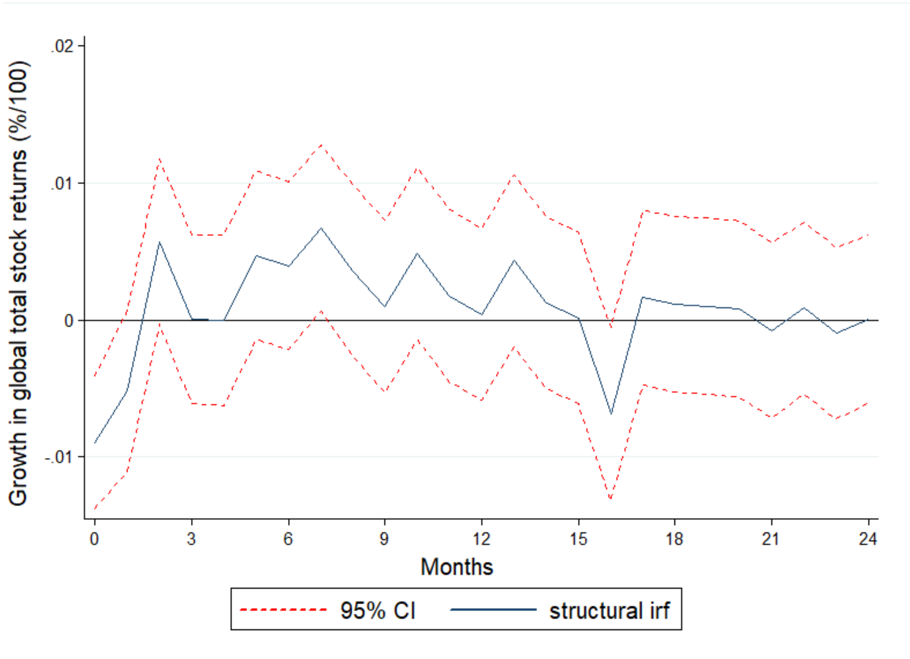
Turning to the second objective of this paper, we now present results from *Model 2*. Here we focus on the real tanker freight rate's potential as a leading indicator of global total stock returns. First, we present the analysis of how the impulse responses can be interpreted to determine the impact of demand and supply shocks on global stock market returns. Thereafter, the relative importance of the shocks in explaining variation in stock market returns are discussed. Finally, we discuss whether the true market dynamics affecting global stock returns are identified.

This paper will focus on the three relevant impulse responses of the global total stock return index in the 24-month period following a positive structural shock in *tanker supply*, *aggregate demand*, *tanker-specific demand,* and *other factors affecting the stock market*. As it lies outside the scope of this paper to consider other shocks to the stock market, this fourth type of shocks is not discussed in detail.

Looking at the IRF of a positive tanker supply shock in figure 10, the global total stock returns immediately experiences a significant drop before recovering over the next few months. However, the effect diminishes after only three months. After this, the global total stock returns seem to respond to the supply shock with a small, persistent, and positive effect beginning in the 3$^{rd}$ month and lasting until the 15$^{th}$ month after the shock. In the 16$^{th}$ month we observe a significant negative drop before it recovers in the following month. Then, the impact of the shock seemingly dies out over the remainder of the adjustment path. We note that the effects of the shock, over most of the adjustment path, are not significantly different from zero.

Assuming that the real tanker freight rate is a leading indicator, decreasing freight rates would be interpreted as a sign of a forthcoming weakening in the economy. However, disentangling the supply and demand shows that the interpretation and significance of variations in the freight rate must take the underlying factor into account. A tanker supply shock is unlikely to have an impact on the global economic activity and the global total stock returns. Since supply usually is considered a reactive variable, it does not make sense economically that a change in the capacity of tanker ships will affect the economy on a global level, at least not in the short to intermediate term. Hence, by disentangling the freight rate into different shocks, the relation between freight rates and the global stock market seems to be more complex than earlier studies have treated it.

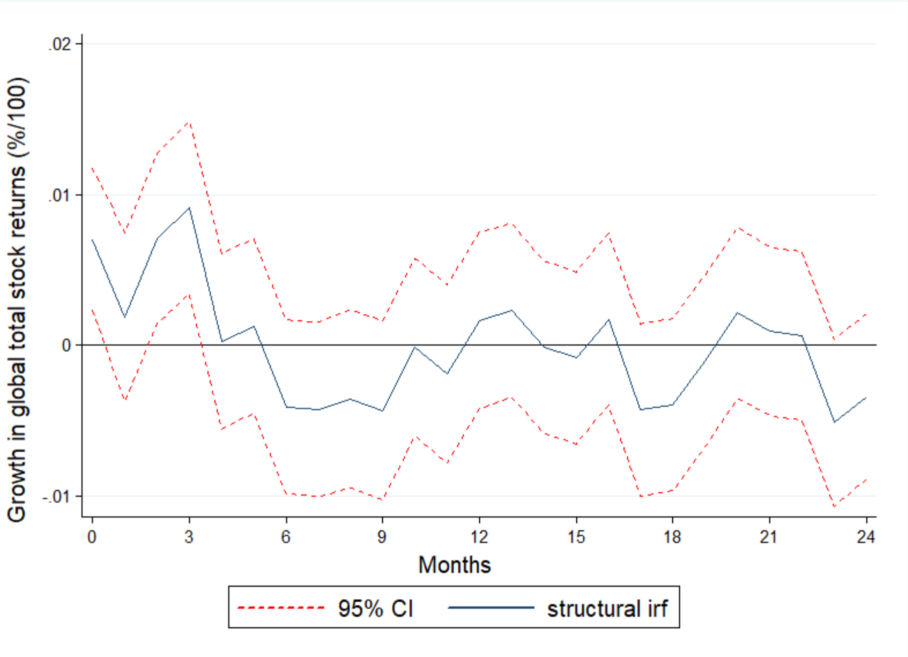
*Figure 10) IRF of tanker supply shock on total stock returns (%/100)*




Further, a positive aggregate demand shock shows that the global total stock returns experience an instant and significantly positive increase (see figure 11). This increase in returns lasts for the first three months after the initial shock. Thereafter the response does not indicate any clear trend, fluctuating around zero for the rest of the adjustment path. These high fluctuations imply low persistence in the response. Furthermore, it makes it difficult to point out any trend after the first few months.

Based on the reasoning motivating the tanker freight rate as a leading indicator for total stock market returns, an increase in real global economic activity would be reflected in increased trade. Thus, demand for shipping commodities from one port to the other increases. Further, an increase in the demand for oil would lead to increased demand for tanker ships, thus tanker freight rates increase. Using this line of thought, a change in the real global economic activity will almost immediately be reflected in the freight rate. To some extent this relation is exactly what we observe for the first few months in the IRF. Moreover, this is coherent with Kilian & Park (2009), who finds that the world economy is directly stimulated from unanticipated higher demand, and hence the world's stock markets follow. Thus, an increase in freight rate may imply a future increase in global total stock returns. However, a key takeaway is that the causal relationship might not be between the global stock market and the freight rate itself. Rather, the relationship appears to be caused by the underlying factor, global economic activity, through the demand for oil.

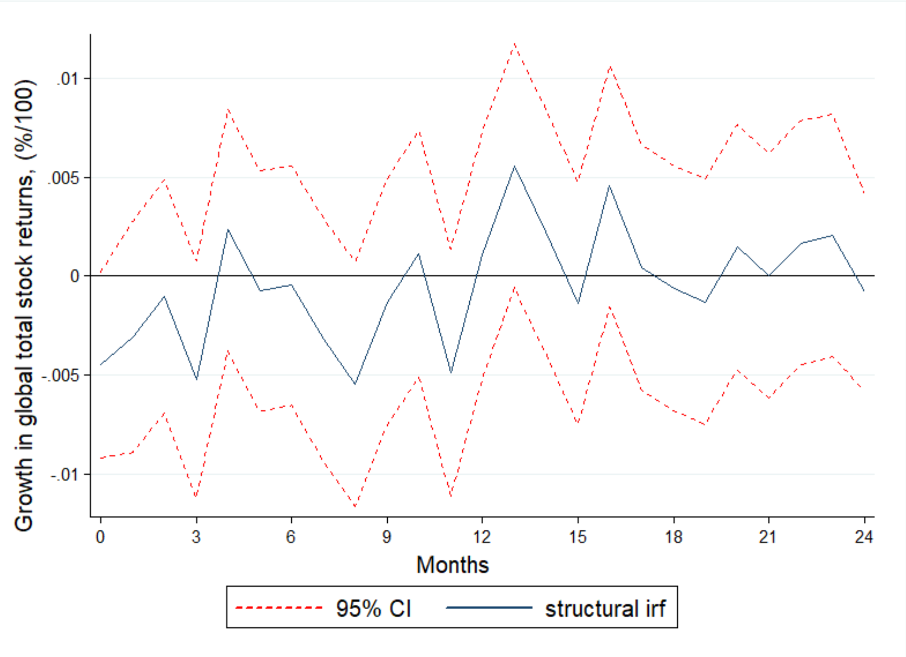
*Figure 11) IRF of aggregate demand shock on total stock returns (%/100)*




As can be seen from figure 12, the response in global total stock returns from a positive shock in the tanker-specific demand shows indications of a positive trend. For the first few months, the response of the tanker freight rate indicates that the shock has a negative effect, before it gradually increases. This could indicate that the expectations of higher demand somehow are reflected in actual increased demand with a lag, and thus an increase in global total stock returns. However, similarly to the aggregate demand shock, the impulse response in the global total stock return to a tanker specific shock fluctuates a lot.

The IRF indicates that an unanticipated tanker-specific demand shock leads to a positive change in the real tanker freight rate in *Model 1*. However, this does not materialize into a significant, positive impulse response in the global total stock return in *Model 2*. We argue that change in tanker-specific demand is mostly led by changes in the expectations of future supply and demand of oil and transport services. Thus, based on economic intuition, the change in tanker-specific demand should not be able to significantly affect the global economic activity level. In light of this, the inconclusive results from a tanker-specific shock to global total stock returns might not be that surprising. However, this makes it more difficult to argue that the tanker freight rate works well as a leading economic indicator.

*Figure 12) IRF of tanker-specific demand shock on total stock returns (%/100)*




Disentangling the shocks to the freight rate into the three supply and demand shocks, makes the complexity of the relation between cause and effect of changes in the freight rate more apparent. Alizadeh & Muradoglu (2011) found a lagged relationship between dry bulk freight rates and stock market returns. However, in our view, they did not address solutions to the problem caused by disturbance from supply and market-specific demand sufficiently. Further, they assumed the lagged effect to be caused by information diffusion between the shipping industry and the stock market. Since shipping is early in the supply chain of goods, it might reflect the temperature of the economy before the rest of the market. However, being early in the supply chain does not help if the freight rate is impacted by several other factors simultaneously.

Studying the variance composition in table 2, we quantify to what degree the disturbance caused by shocks in supply and tanker-specific demand contributes to the variation in global total stock returns. In the short run, the effect of these shocks is relatively small. On impact, the tanker-specific demand shocks account for close to 1.1% of the variation. Tanker supply shocks and aggregate demand shocks seems to be decisive for 4.2% and 2.6% of the variation in global total stock returns in the short run, respectively. This indicates that more than 92.0% of the prediction error is generated by other shocks to the world stock market.

In isolation, a low contribution from the tanker supply and tanker-specific demand would increase the freight rate's eligibility as a leading indicator. This is because both economic reasoning and the IRFs imply that their contribution to the response of global stock market return might as well be white noise rather than plausible trends. Thus, shocks that do not clarify the response of global stock market returns, like the supply and the tanker-specific demand shock, should ideally have minimal impact on the variance. Further, the aggregate demand does not contribute more than supply or tanker-specific demand, which would have been ideal since its IRF signals a clear trend in the response of global stock market returns.

As the horizon increases, the three variables' explanatory power increases. After 24 months, 12.0% of the variation is explained by tanker supply shocks, 11.9% is explained by global demand shocks, and 7.1% is explained by tanker-specific demand shocks. According to these results, the three structural shocks driving the tanker market seems to explain approximately 31% of the variability in global total stock returns. Their impact is a bit high compared to our expectations of low effects from supply and tanker-specific demand on global stock markets. Comparing this to Kilian & Park (2009) and their variance decomposition of the oil market and its effect on the U.S. real stock returns, makes us question our results. From a negligible impact the first few months, each shock's contribution to the overall variability increased to 1.5% for oil supply shocks, 2.6% for aggregate demand shocks and 6.8% for oil-specific demand shocks within the first 12 months (Kilian & Park, 2009). Further, they estimated the long-term impact to 6.4%, 5.1% and 10.5% respectively. This implies that the three supply and demand variables explaining the real oil price, accounts for about 20% of the overall variability in U.S real stock returns.

While there is a large literature confirming the importance of the oil price in the determination of stock prices, this exists to a lesser extent in shipping. Still, the variance decomposition indicates that the dynamics of the tanker market affect global stock markets extensively. Considering the viability of the results, a closer look at the robustness of the variance decomposition shows that the standard error indicates that the magnitude of the impact is quite uncertain. In addition, correlation generally tends to increase as the number of observations increases over time, even if there is no causal relationship between the variables. This might partially explain how the variance decomposition end up implying that the freight market contributes with about 31% to the variance in global total stock returns.

Intuitively the variance decomposition of *Model 2* is difficult to explain. Both tanker supply and tanker-specific demand seems to contribute significantly to the variation. Concurrently, it is difficult to determine whether their IRF's indicates white noise rather than plausible trends. This issue seems to become more evident as time passes following an initial shock. The aggregate demand, on the other hand, signals a clear positive trend. This latter effect could strengthen the freight rate's potential as a leading indicator. However, we are not able to prove that the aggregate demand variable contributes significantly more to the variation in the stock market, than the supply or tanker-specific demand.

Based on our findings, it is hard to believe that the tanker freight rate in itself could contribute significantly to global stock returns. We argue that the variables which theoretically should not be able to affect the global stock market, has a disproportionately high explanatory power in determining freight rates. Hence the importance of these variables will disturb the freight rate, making it unfit as a leading indicator for global total stock returns. However, it could be that the freight rate is affected by some of the same factors as the stock market. Hence, at some specific points in time the correlation with the global stock market might be high.

If we were to believe that the tanker freight rate is a leading indicator when it is possible to find, isolate and measure a specific underlying factor's movement, then the underlying variable would be the variable of interest. Based on this reasoning, the tanker freight rate falls short as a leading indicator.

*Table 2: Variance decomposition of Model 2 in %*

| **Horizon** | **Tanker Supply Shocks** | **Aggregate demand shocks** | **Tanker-specific demand shocks** | **Other shocks** |
|---|---|---|---|---|
| 1 | 4,2 | 2,60 | 1,06 | 92,14 |
| 6 | 7,24 | 8,44 | 2,86 | 81,46 |
| 12 | 10,42 | 10,26 | 5,19 | 74,13 |
| 18 | 12,31 | 10,67 | 7,06 | 69,96 |
| 24 | 11,95 | 11,92 | 7,14 | 68.99 |

## 5.3 Robustness of the model

Before we summarize our findings and examine potential further research, we will discuss the robustness of the models and limitations of our paper. To examine how robust the results are to changes in model specification, we alter the lag length and test both our models on two subperiods.

Since information criteria recommended a more parsimonious model, we chose to test both models with 12 lags and ran *Model 2* with 4 lags as well. Studying the IRFs, the effect on each variable have the same direction over the adjustment path as it had with 24 lags. This is applicable for both models, and makes the results presented more reliable.

A shortcoming with SVAR is the large number of estimated parameters required, even for models with few lags included. This causes a reduction of the degrees of freedom. The consequence is increased standard deviation and large confidence intervals (Brooks, 2008). Hence, fewer lags may be an advantage as long as it is economically credible. In addition, a sparse model is preferred if it does not alter the results. Regardless of lag length, the observed IRFs implies similar relationships between the impulses and the responses after an initial shock. This strengthens our belief in the model.

To ensure that the sample is not disturbed by non-recurring events, we have chosen to test the models for two separate subsamples to see whether this will alter our results. Stopford (2009) have defined the years between 1988-2002 and the years between 2003-2007 as two complete business cycles within the shipping industry. Taking this into consideration, we have chosen to test the two periods 1990-2007 and 2003-2017. The two subsamples are tested on both models with 24 lags and 12 lags. These models are presented in figures A.1.6 - A.1.9 in the appendix. For the first subperiod tested on *Model 1*, most of the results indicates similarities with the full period. However, the response to an innovation in supply is moving in the opposite direction the first few months compared to what we found using the complete sample period. Apart from this, we note that the responses fluctuate around zero and have wide confidence intervals. Shrinking a relatively small sample may be the reason why these results do not match entirely with our findings in the initial model. Turning to the results from the second subsample, they are similar to the results for the complete sample period. The confidence intervals are also wider for this subsample.

For *Model 2*, most of the shocks have similar effect on the variables regardless of sample period. However, we observe that the magnitude of the effect seems a bit lower and that the uncertainty of the estimates have increased, as implied by the wider confidence intervals. This is just as expected due to the smaller sample size. Overall, the similarity in the results across different sample periods strengthens our belief in both models.

Finally, we compare the results of the IRFs in *Model 1* with the equivalent IRFs in *Model 2*. As we can see from figure A.1.1 and A.1.3 in appendix, the comparable IRFs look quite similar. This implies that adding an additional variable at the end of the ordering does not alter the results on the initial variables. If there had been significant differences this could indicate misspecification problems, or that the identification of the shocks in *Model 1* suffered from omitted variable bias.

Based on the statistical tests of robustness we believe our results to be reliable. The robustness tests imply that the results we have obtained in this paper are not significantly altered by changing the time period nor the number of lags in the model. This strengthens our confidence in the results.

## 5.4 Reflections on limitations of our models

In a model exercise like the SVAR-model approach in this paper, one must always base analysis on necessary assumptions and simplifications compared to the complex and dynamic reality. This section will cover some of the potential issues regarding model specification and the results presented in this paper.

As discussed when presenting the methodology, the ordering is based on a priori information about the market dynamics. The analysis is not stronger than the assumptions it is based on. Thus, the robustness of our results builds on the viability of our motivation of the ordering. A consequence of an incorrectly ordering of the variables, or simply using irrelevant variables in the model, is that the relationship between the variables may not be causal even though they have high correlation (Kilian, 2011; Stock & Watson, 2001). It can be difficult to distinguishing between correlation and causality, and high correlation does not prove a causal relationship between them. Hence, rational assumptions well-founded in economic theory is vital. Moreover, the causality is not formally tested, and this represents a potential weakness.

One of the potential weaknesses with the model is how we model the supply side. As described in the data section, registered deadweight tonnage is chosen as the measurement variable for supply. Stopford (2009) underpins that he prefers fleet productivity, defined as the ton miles of cargo delivered per deadweight, as the supply variable. However, using fleet productivity would be inappropriate when disentangling the different effects in the tanker market. This is due to fleet productivity being a hybrid variable combining both supply and demand attributes.

Further, shipowners are the ones who manage supply in the short term (Stopford, 2009). An essential part of shipping supply is the shipowners' possibility to change the speed of the vessels as it suits them. Thus, they can react rapidly to changes in demand and adjust the supply accordingly. Hence, vessel speed is a latent issue measuring the supply side. In addition, the complexity of ship supply increases due to the possibility of keeping ships in lay-up. The uncertainty of how fast ships in lay-up can return to the market makes it even harder to estimate supply in the short to intermediate term. Furthermore, technological advancement and improved operational efficiency have over the sample period reduced operational costs of shipment (Greiner, 2013). However, this effect will not be captured by our supply variable. A consequence of the supply variable's incapability to capture the full supply-side effect, is that some of these effects might end up in the tanker-specific demand variable instead.

Further, we argue that the tanker-specific innovations are largely due to changes in the expectations of the future supply and demand in the tanker market. Since the tanker-specific shock is the residual, it captures all effects that are not captured by the two first shocks. Hence, the variable could consist of other main drivers in addition to expectations to future supply and demand. For instance, it may be that including a variable representing the oil price in the model had offered valuable insight. During 2014, the plunge in oil prices led to an increase in demand for tanker ships as a storage unit. Investors speculated whether it was more profitable to store oil in tanker ships for a few months rather than selling when the price had just plunged. Adding the oil price would allow for a better understanding of the effect from such events.

Drawbacks of SVAR models include the requirement of its structural innovations to be orthogonal. Furthermore, we only answer how the dynamics will respond to an unanticipated shock in the market, and not how it will react to an expected change in the variables. Thus, some might argue that the model is less relevant. However, we believe an analysis of unanticipated innovations is especially relevant due to the industry's characteristics of high uncertainty and cyclicality.

Despite its weaknesses, SVAR is nevertheless a useful analysis tool in this study because it allows us to explain, understand and forecast the relationship between the global shipping market and the stock market without being forced to treat the freight rate as an exogenous variable.

As a last remark, we note that this study is based on historical figures. What happened in the past will not necessarily repeat itself, as fundamental mechanisms in the market may change over time. Thus, the tanker freight rate and global stock market might not behave similarly to a given innovation in the future.

# 6. Conclusion

This thesis has provided original insights into the disentangling of supply and demand shocks in the tanker industry. With the analysis of supply and demand shocks to the real tanker freight rate, we have contributed to confirm much of the existing understanding of shipping market dynamics. The initial impulse response functions indicated that a positive supply shock leads to a decrease in freight rates. In addition, the decrease might occur with a lag due to the time it takes from the ship is produced until it can be utilized for the first shipment. Furthermore, the results indicated that a positive shock to aggregate demand will lead to a persistent increase in real freight rates. This positive effect seems to increase over the first months, which we expect to be caused by the flexibility of speed adjustments and the reactivation of inactive ships. The persistency is likely caused by the rigidity in supply once the short-term flexibility is maximized. Turning to tanker-specific demand-shocks, we find that a positive shock immediately increases the real freight rates, before the effect steadily decreases towards zero. Under the assumption that most of the tanker-specific demand shocks are caused by changes in expectations, the results indicate that the real freight rate tends to overshoot, and this might be a reason for the high volatility in prices. Furthermore, the variance decomposition for *Model 1* indicates that the variables have different importance in explaining the variance in real tanker freight rates. The tanker-specific demand seems to explain nearly all variation in the short-term, while tanker supply and aggregate demand becomes increasingly important over the adjustment-path. Additionally, the historical decomposition underpins that the relative importance of the different variables is subject to the market conditions of specific time periods.

In addition to the disentangling of supply and demand shocks, our thesis studies the relationship between the real tanker freight rate and global total stock returns. While some research has identified the dry bulk freight rate as a potential leading indicator for the stock market, we struggle to identify and justify such a relationship for the real tanker freight rate. Our results do not indicate any clear relationship that can be explained based on economic theory. From the variance decomposition of *Model 2*, we find a surprisingly high importance for the three supply and demand variables in tanker market. The high standard error combined with the lack of economic reasoning for why this relationship would be true, makes us suspect that the results might be indicating correlation rather than causality.

Whereas we studied the relationship between supply and demand in the tanker market, further research can assess the same framework with similar and/or additional variables. An interesting modification to *Model 1* would be to include freight futures to better disentangle expectations.

In addition, the real price of oil might be an interesting variable to include in the model. Another possibility would be to include a variable that adjusts for political regulations in the tanker industry. Furthermore, there might be procedures to model the tanker supply more accurately. By accounting for more of the factors affecting supply, the relevance of the model can potentially be improved.

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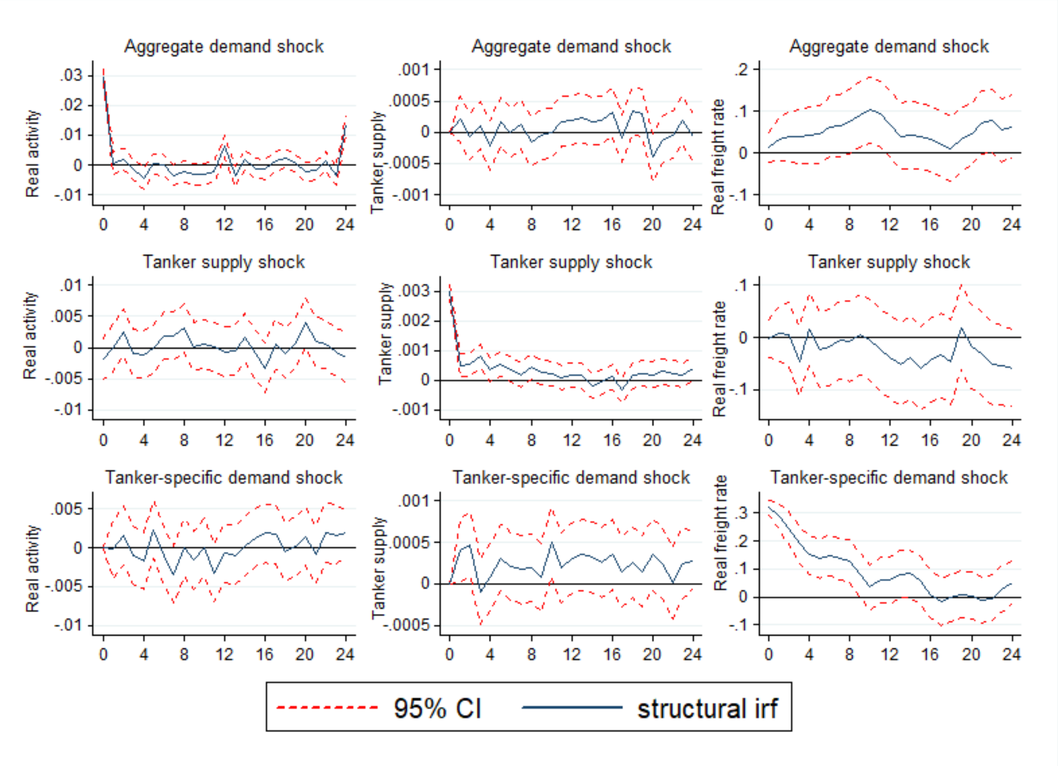
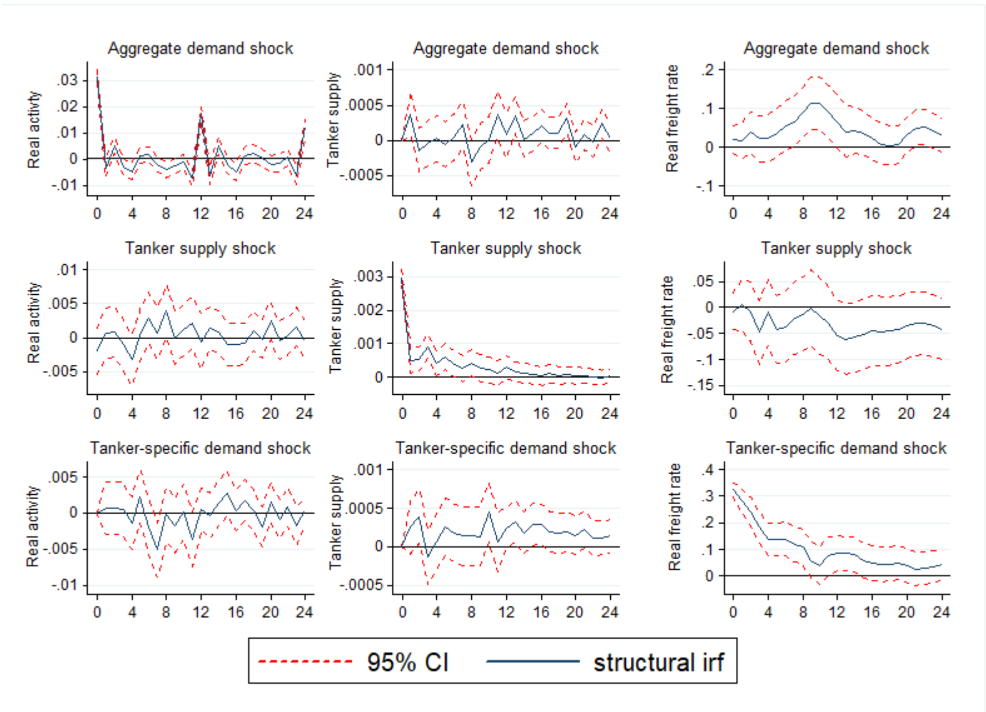
# Appendix

## A.1 Initial impulse response functions

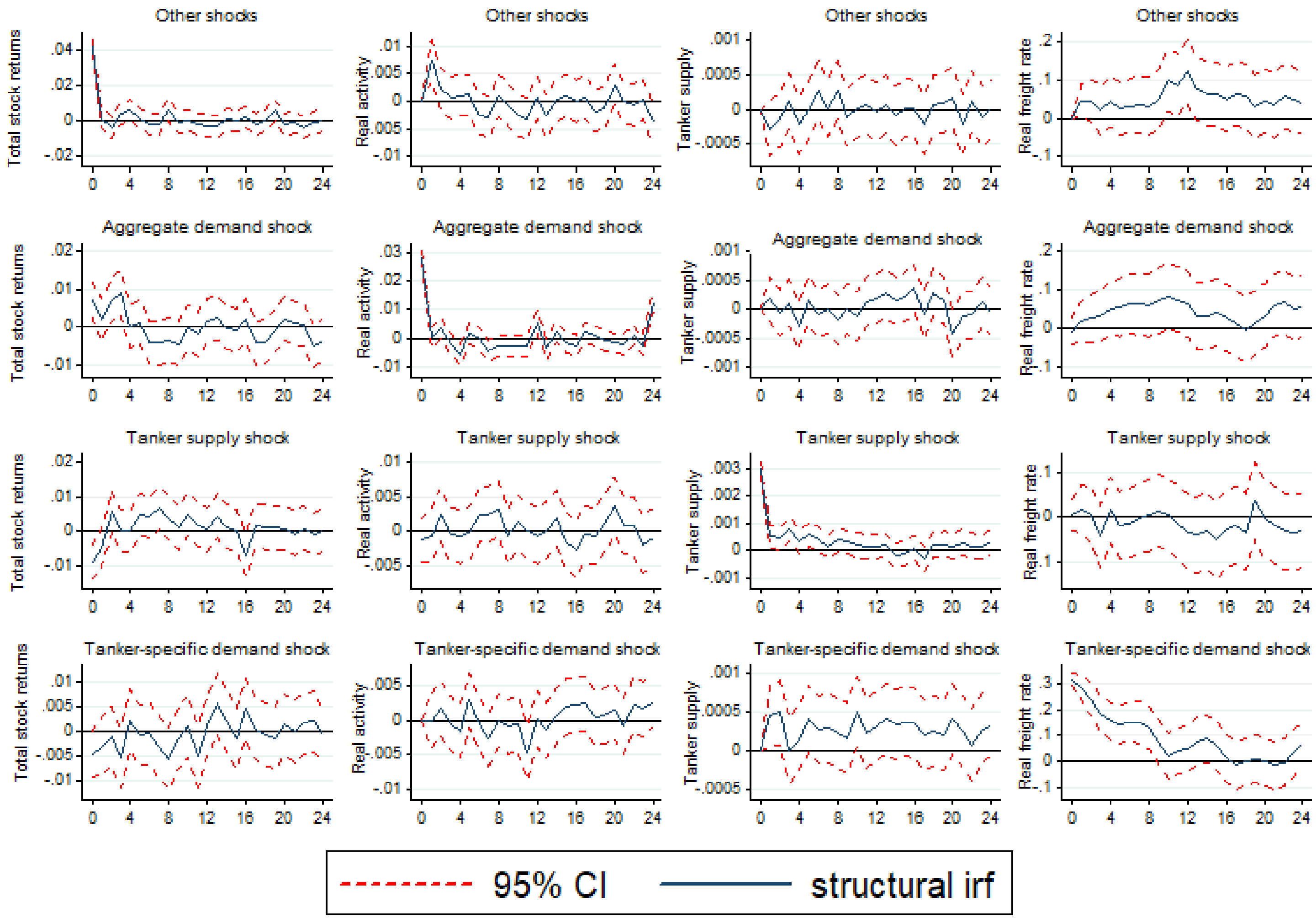
A.1.1 IRFs for *Model 1*, 24 lags



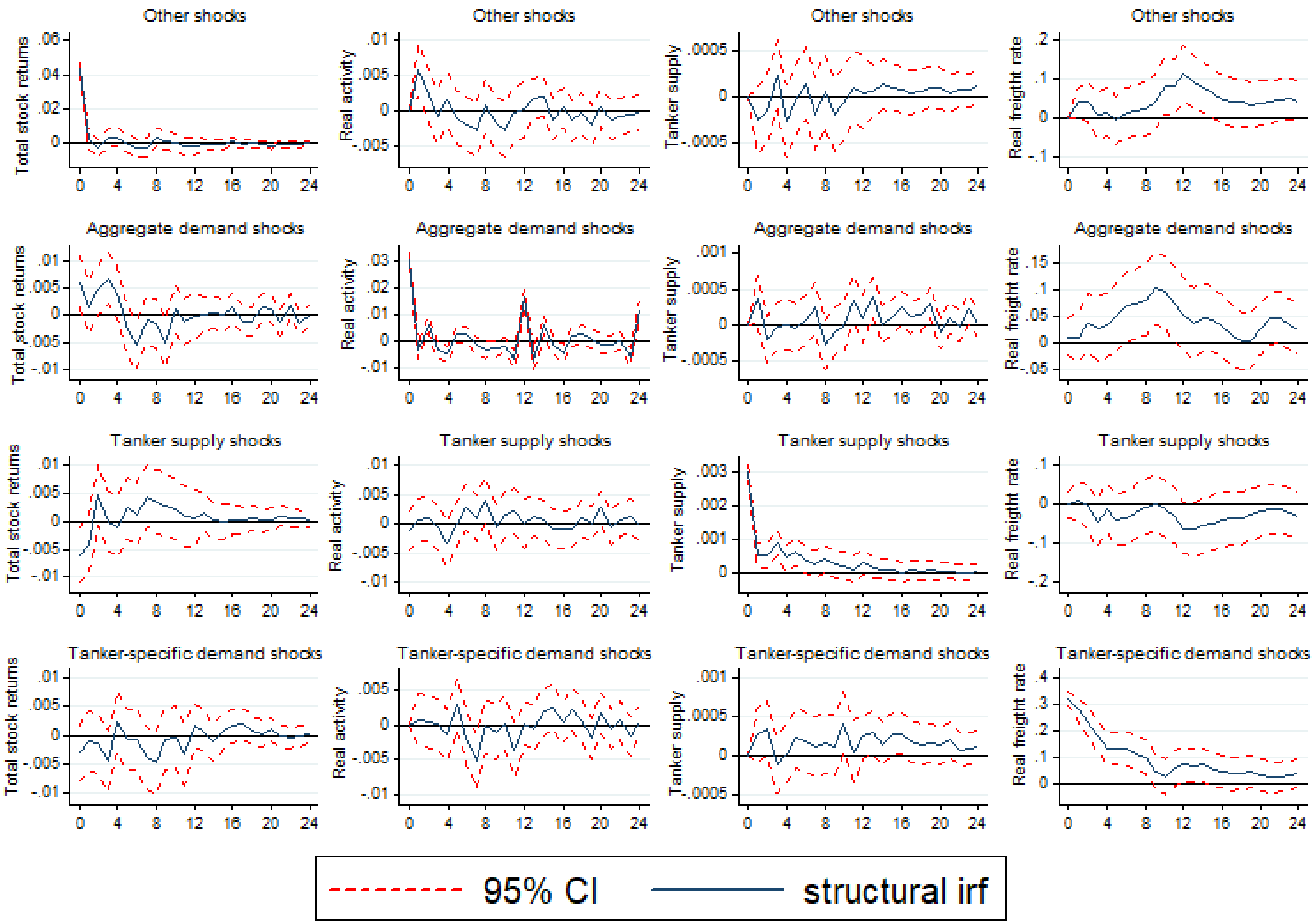

A.1.2) 12-lag IRFs for *Model 1*



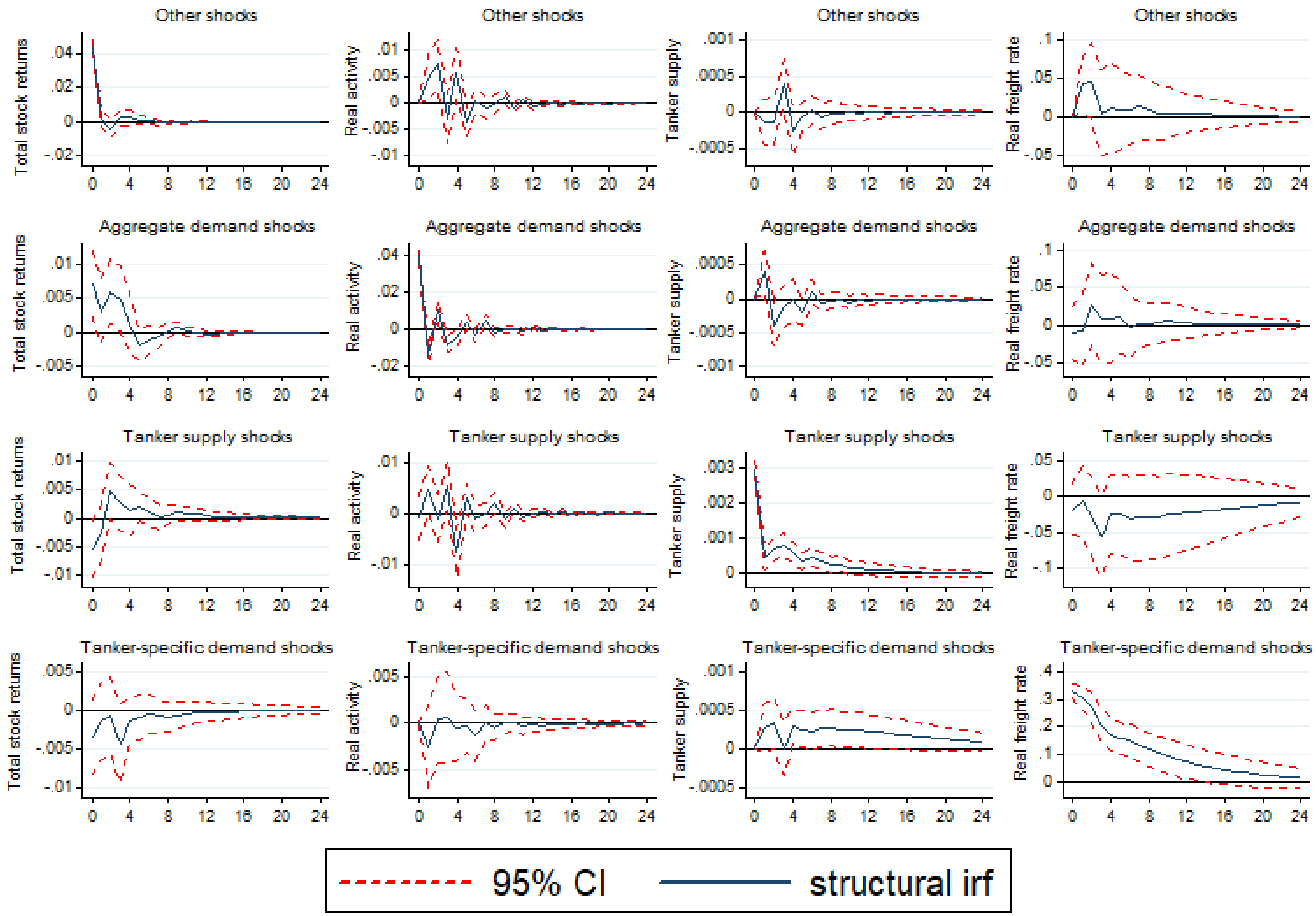
## A.1.3 IRFs for *Model 2*, 24 lags



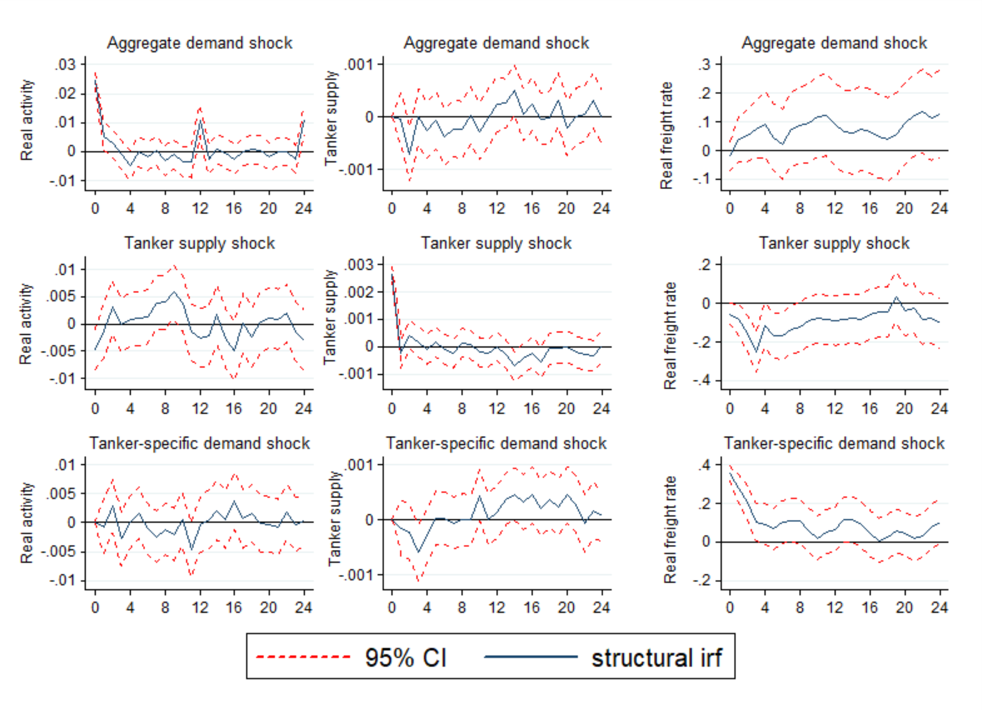
### A.1.4) 12-lag IRFs for *Model 2*



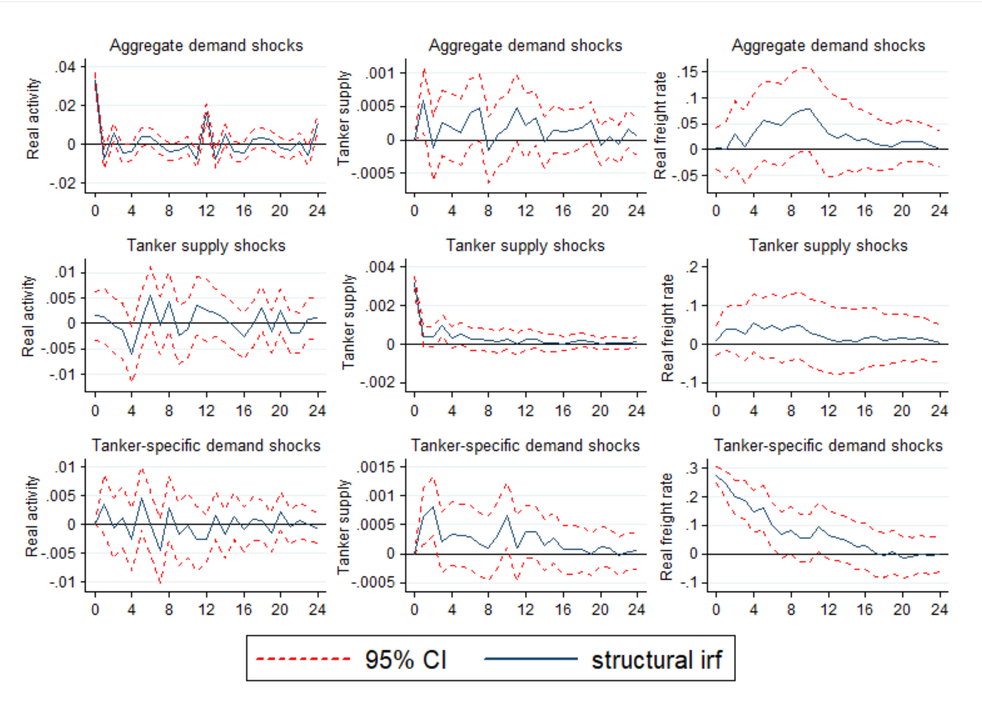
A.1.5) 4-lag IRFs for *Model 2*



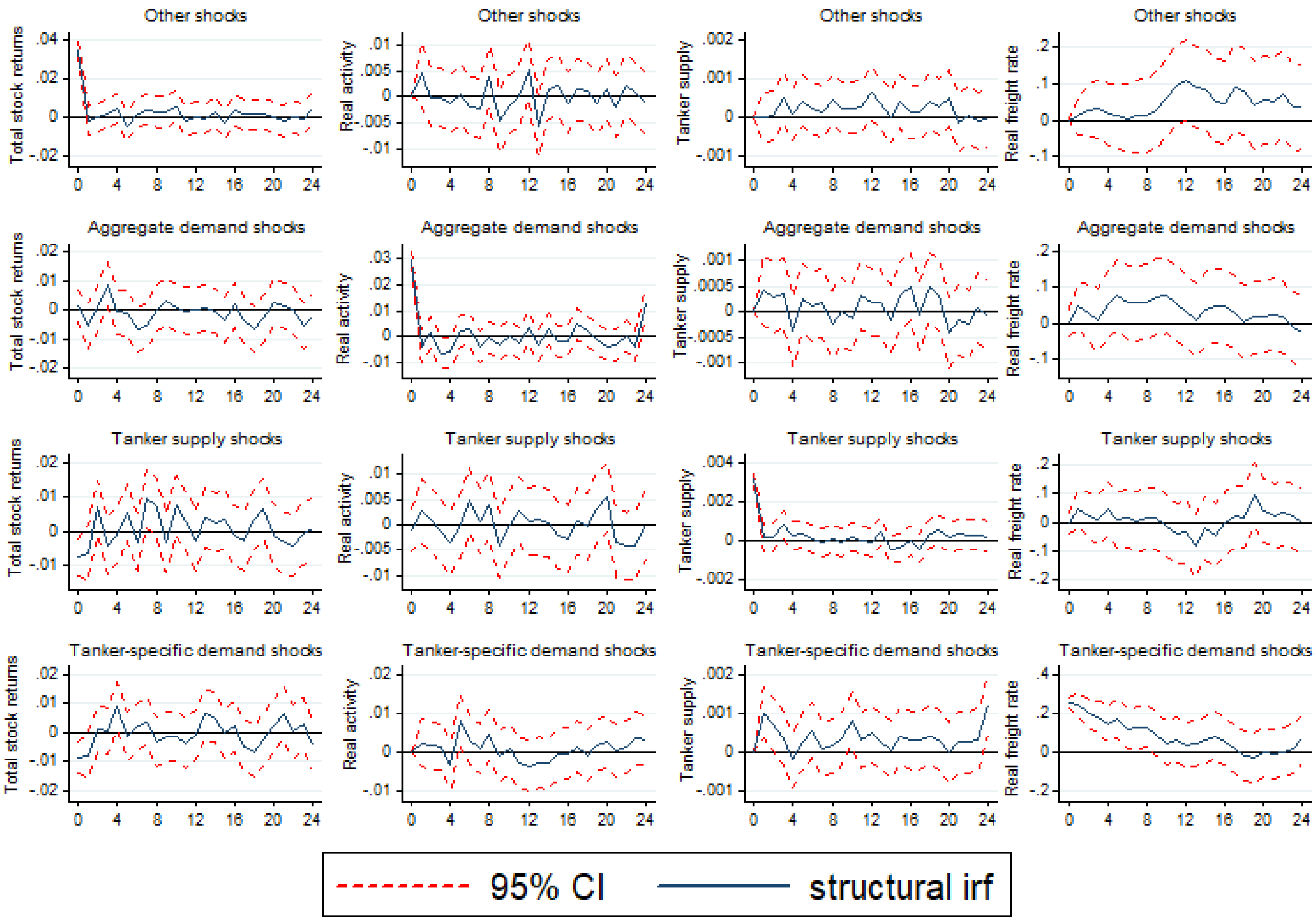
A.1.6) IRFs for *Model 1*, time period 2003.1-2017.9, 24 lags



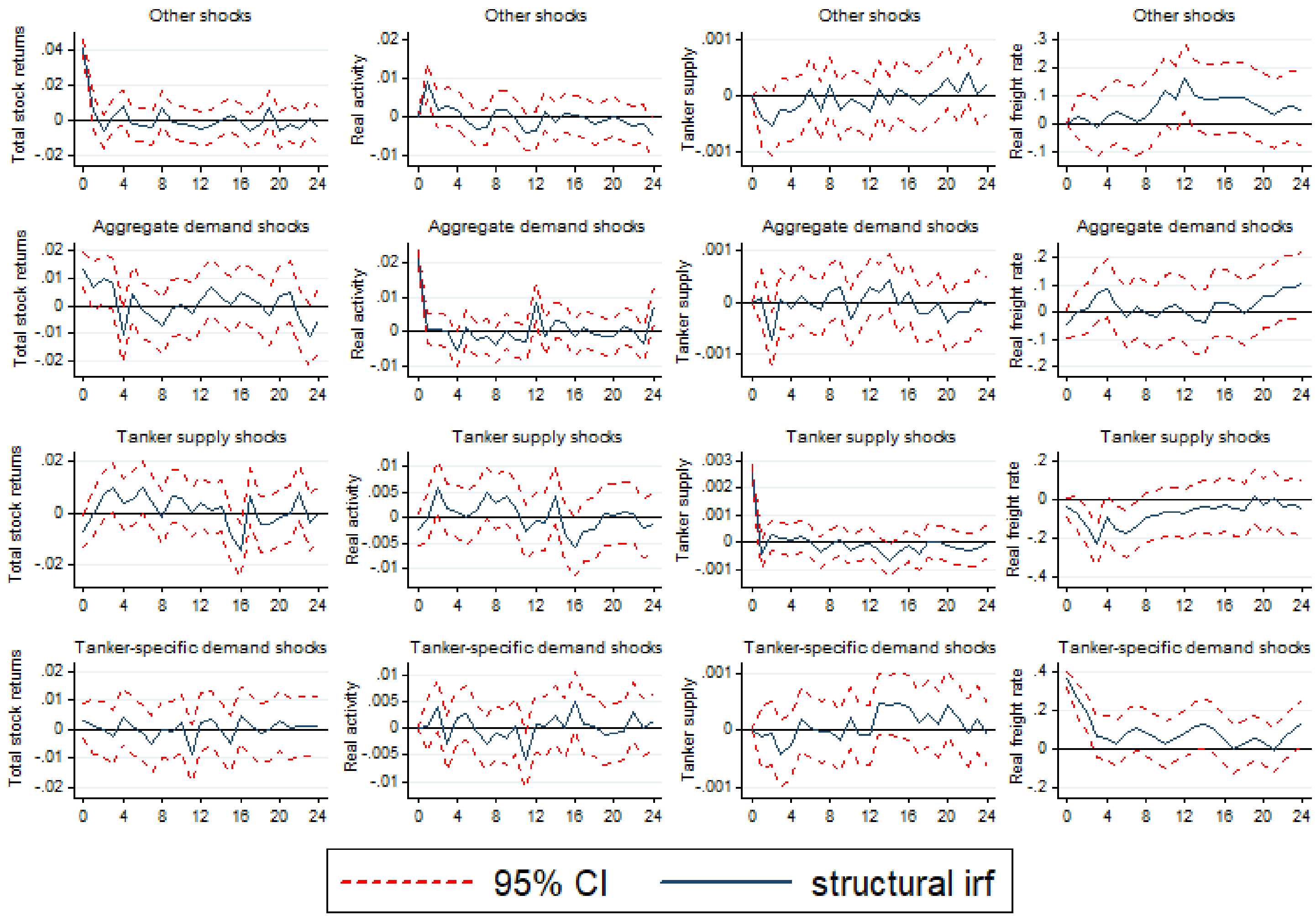

A.1.7) IRFs for *Model 1*, time period 1990.1-2007.1, 24 lags



A.1.8) *Model 2*, time period 1990.1-2007.1, 24 lags

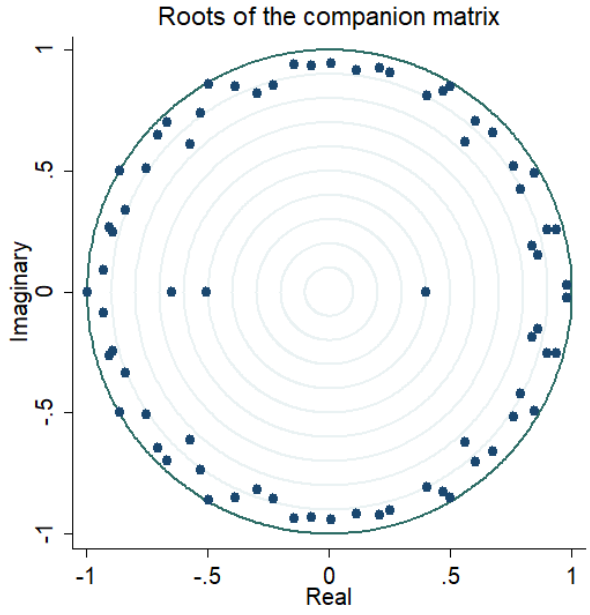


A.1.9) IRFs for *Model 2*, time period 2003.1 – 2017.9, 24 lags

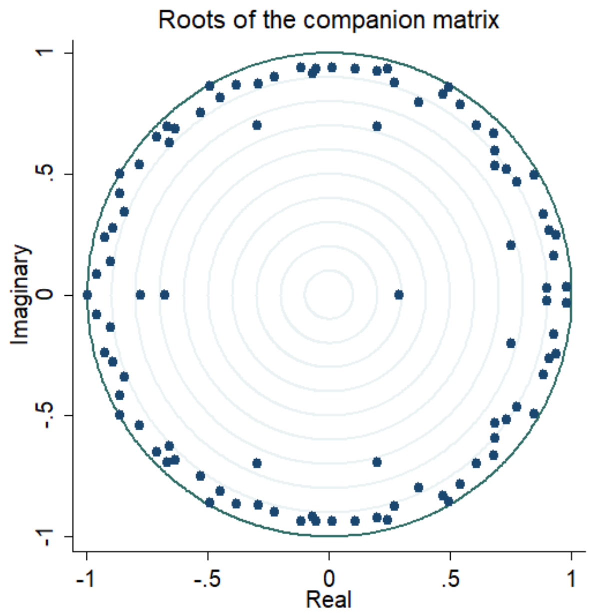


## A.2 Stability tests

A.2.1) *Model 1*, Engle Granger stability test, 24 lags

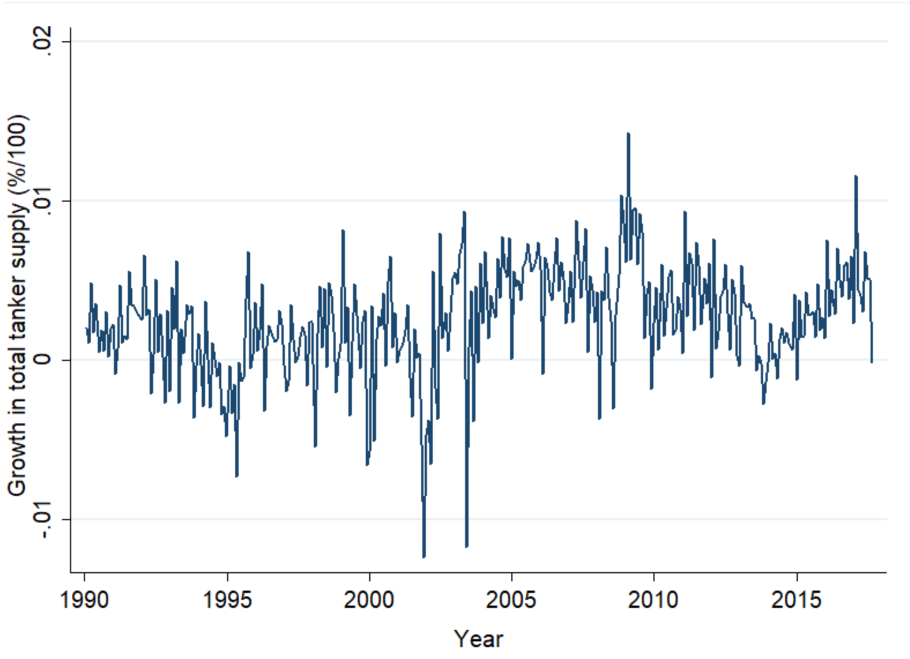



A.2.2) *Model 2*, Engle Granger stability test, 24 lags

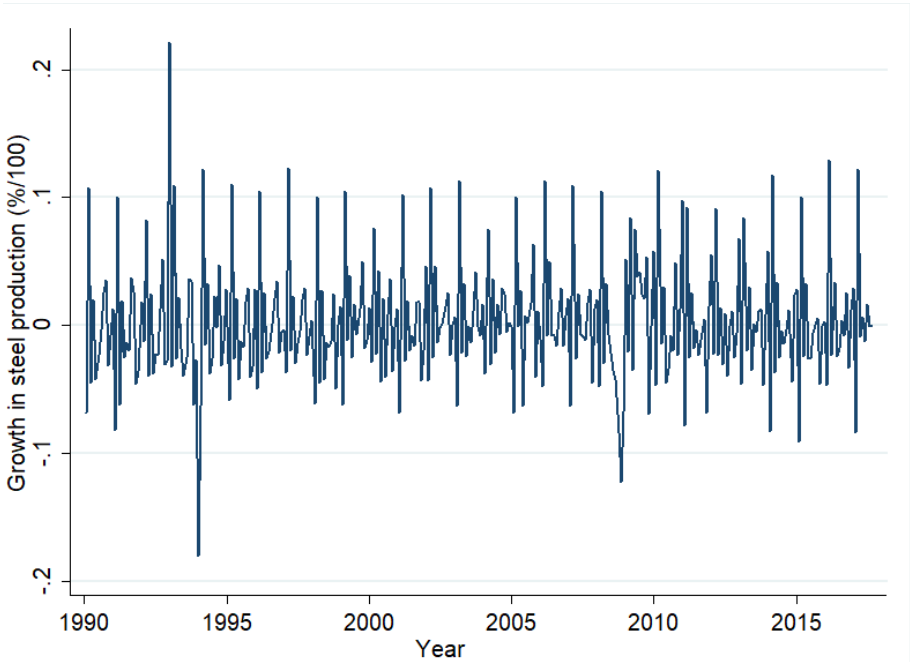


## A.3 Adjusted time series

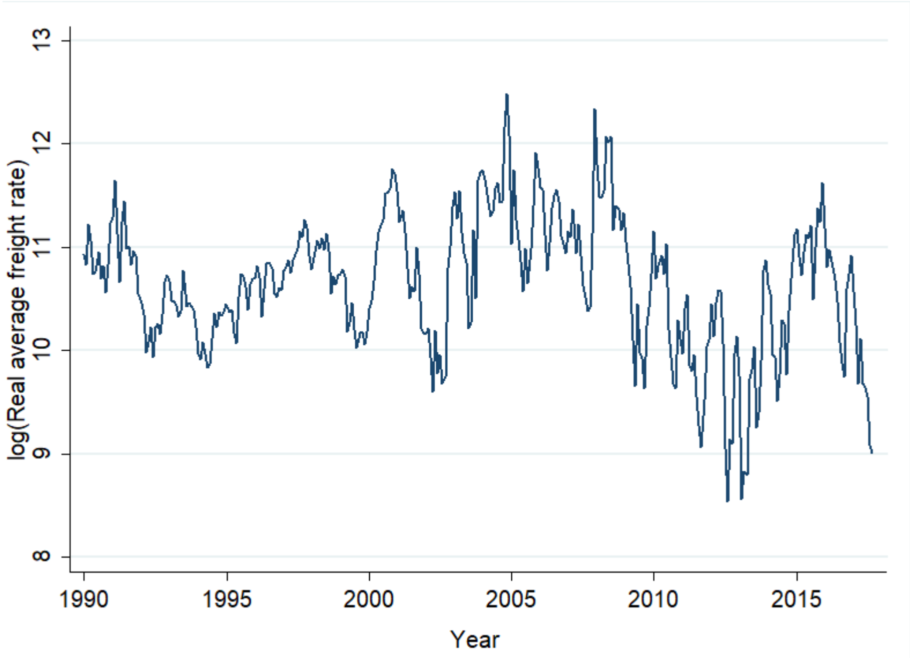
A.3.1) Log-transformed, first differenced total tanker supply



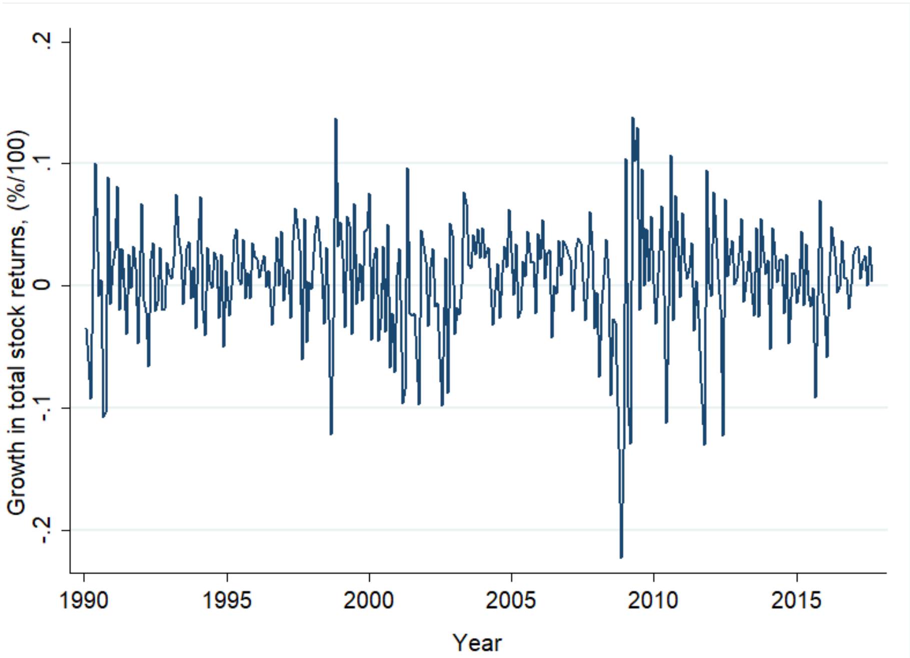

A.3.2) Log-transformed, first differenced global steel production



A.3.3) Log-transformed real average freight rate




A.3.4) Log-transformed, first differenced global total stock returns



## A.4 Stationarity tests

A.4.1) ADF & PP statistics for adjusted tanker supply times series

| | | **t-Statistic ADF** | **t-Statistic PP** | **Prob.** |
|---|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -12.959 *** | | 0.0000 |
| Phillips-Perron test statistic | | | -293.622 *** | 0.0000 |
| Test critical values | 1% level | -3.454 | -20.365 | |
| | 5% level | -2.877 | -14.000 | |
| | 10% level | -2.570 | 11.200 | |

A.4.2) ADF & PP statistics for adjusted steel production time series

| | | **t-Statistic ADF** | **t-Statistic PP** | **Prob.** |
|---|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -27.985 *** | | 0.0000 |
| Phillips-Perron test statistic | | | -467.141 *** | 0.0000 |
| Test critical values | 1% level | -3.454 | -20.365 | |
| | 5% level | -2.877 | -14.000 | |
| | 10% level | -2.570 | -11.200 | |

A.4.3) ADF & PP statistics for adjusted real tanker freight rate

| | | **t-Statistic ADF** | **t-Statistic PP** | **Prob.** |
|---|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -4.552 *** | | 0.0002 |
| Phillips-Perron test statistic | | | -39.058 *** | 0.0003 |
| Test critical values | 1% level | -3.454 | -20.365 | |
| | 5% level | -2.877 | -14.000 | |
| | 10% level | -2.570 | -11.200 | |

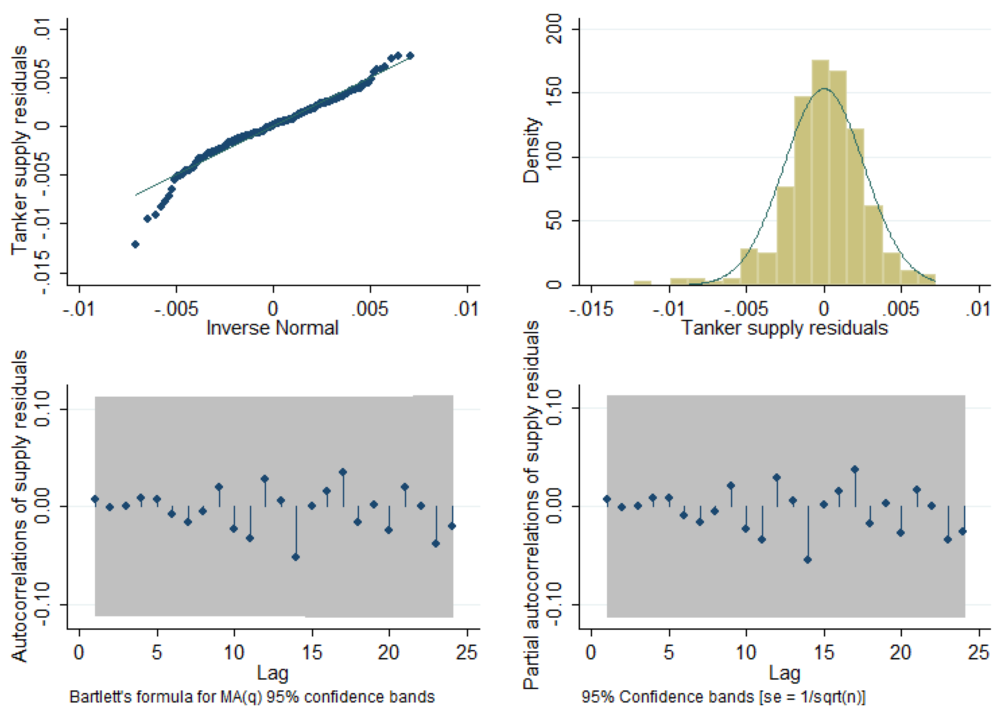
A.4.4) ADF & PP statistics for adjusted global total stock returns

| | | t-Statistic ADF | t-Statistic PP | Prob. |
|---|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -16.338 *** | | 0.0000 |
| Phillips-Perron test statistic | | | -298.665 | 0.0000 |
| Test critical values | 1% level | -3.454 | -20.365 | |
| | 5% level | -2.877 | -14.000 | |
| | 10% level | -2.570 | -11.200 | |

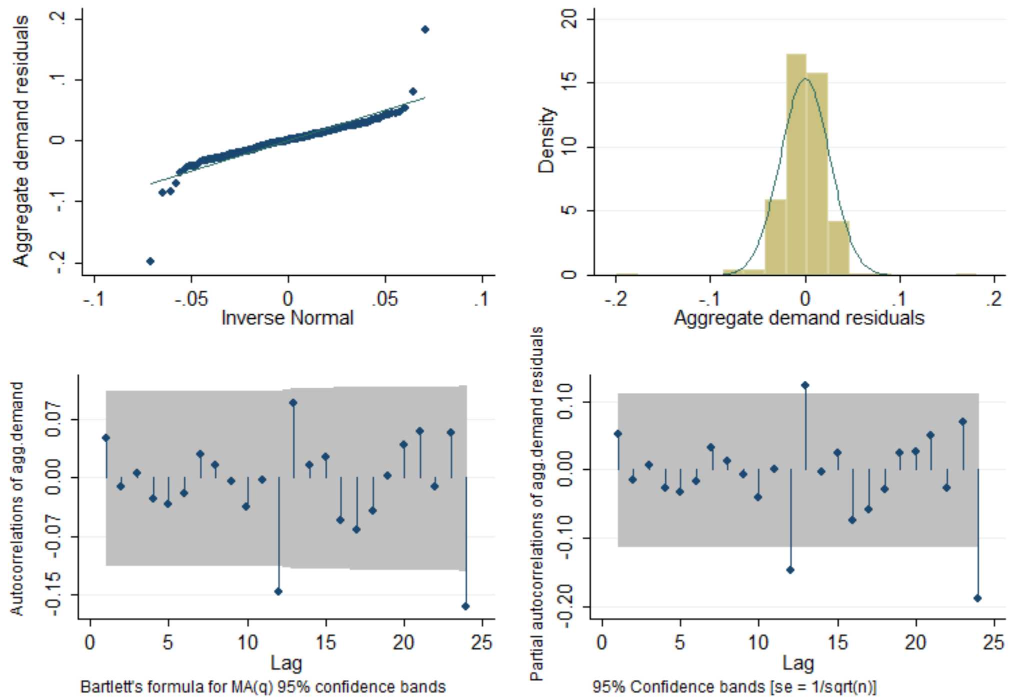
# A.5 Normality of residuals

## A.5.1 *Model 1*

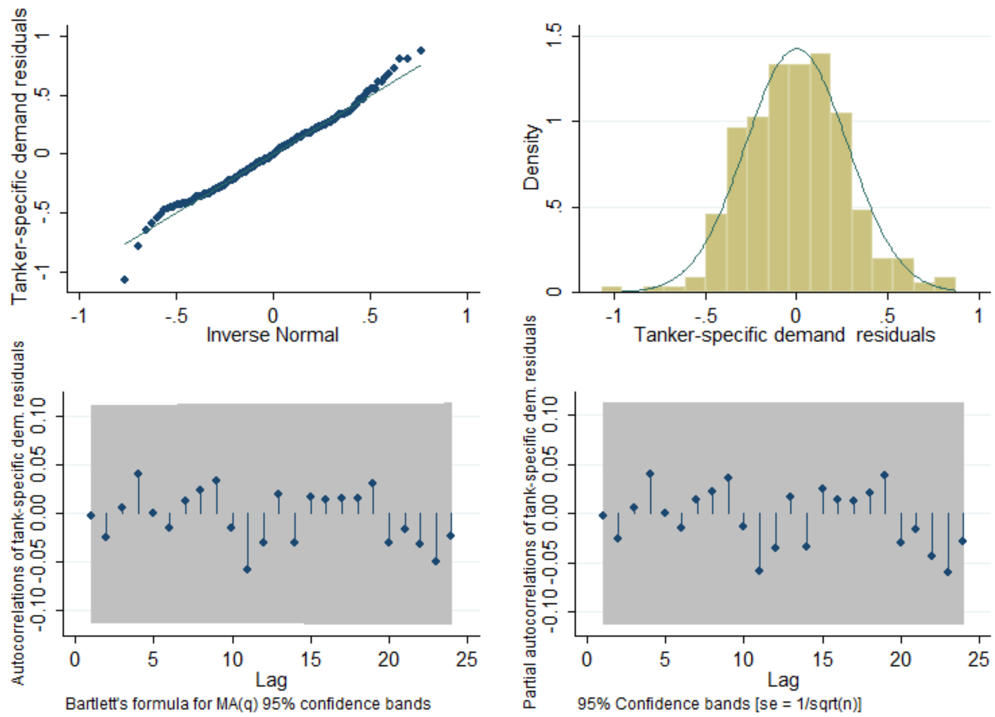
A.5.1a) Normality of residuals for the tanker supply variable in *Model 1*



A.5.1b) Normality of residuals for the aggregate demand variable in *Model 1*

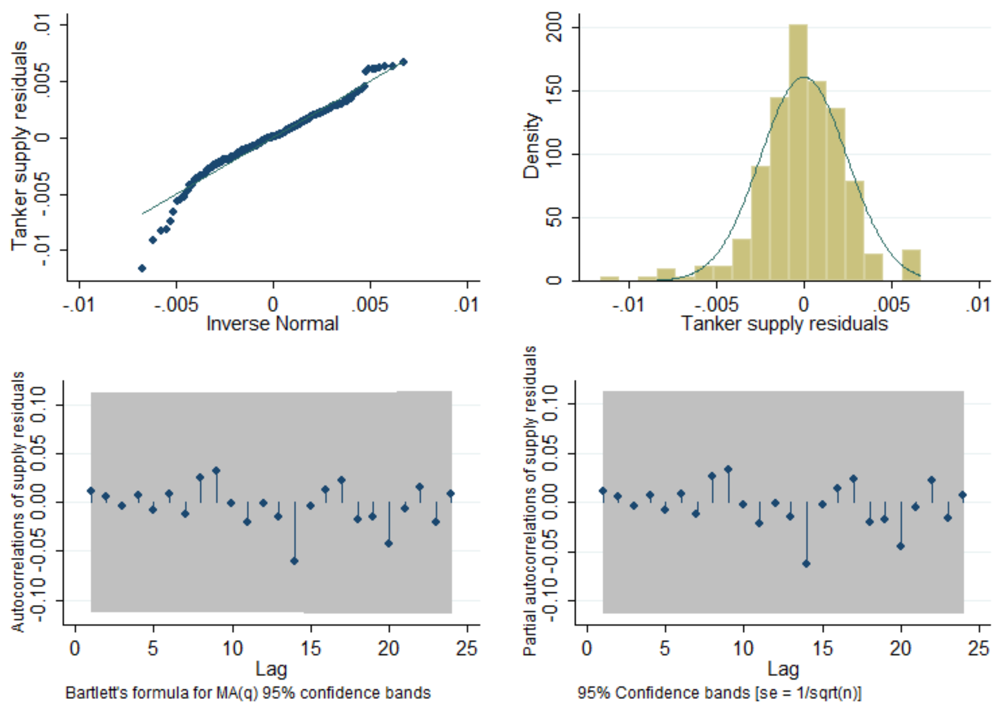



A.5.1c) Normality of the residuals for the tanker-specific demand variable in *Model 1*

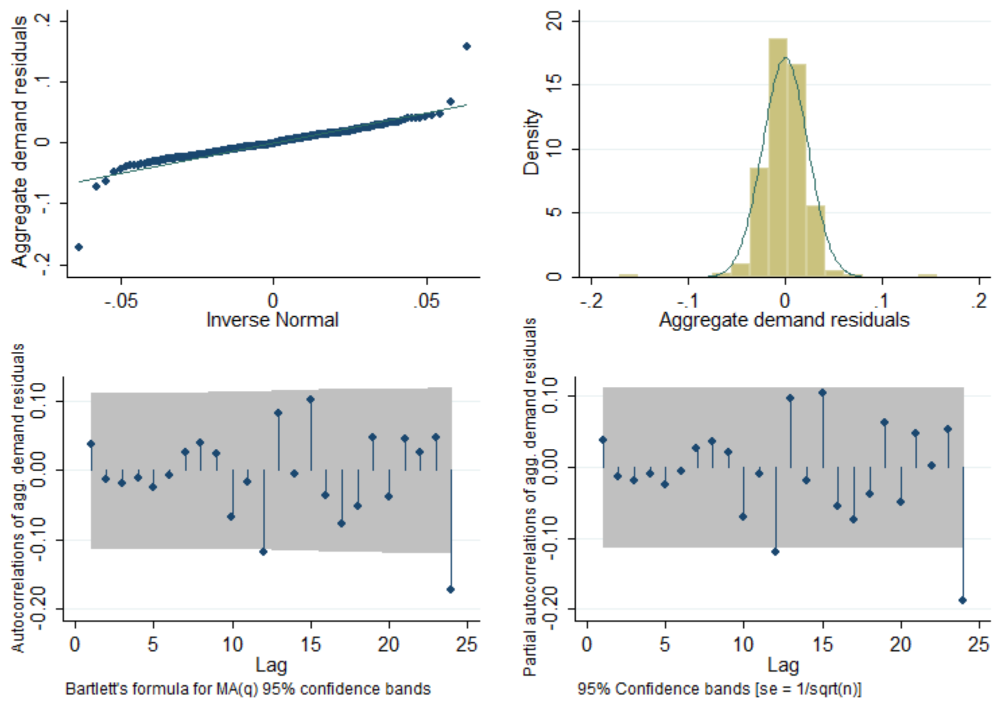


## A.5.2 *Model 2*

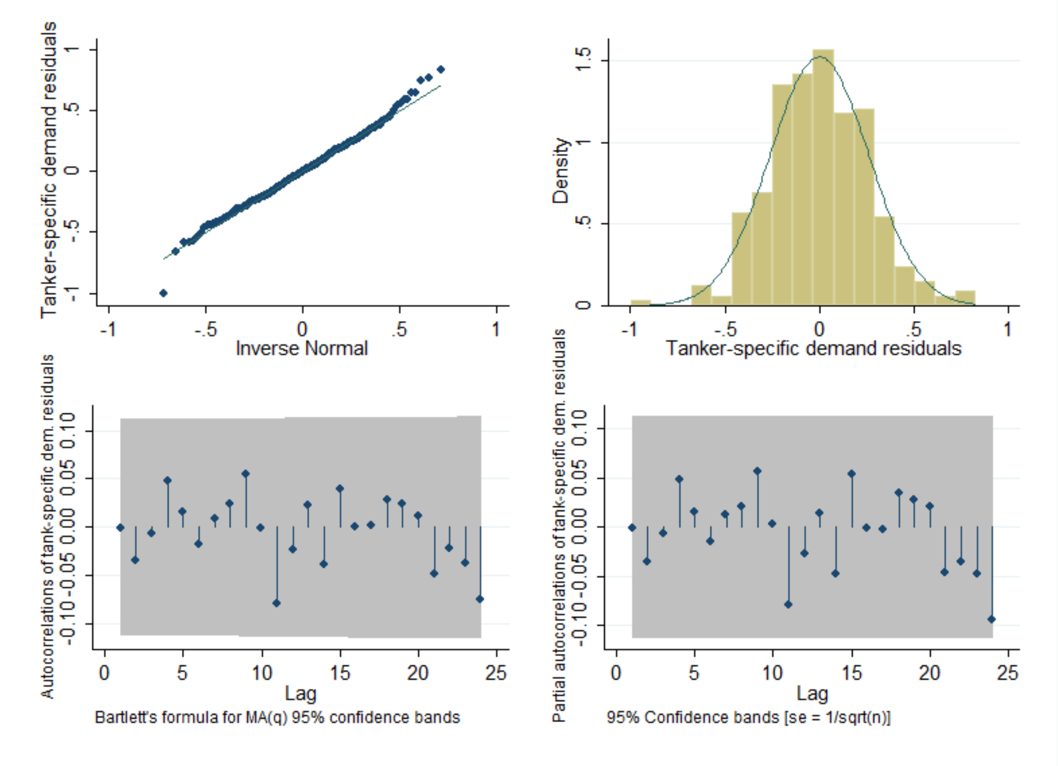
A.5.2a) Normality of the residuals for the tanker supply variable in *Model 2*



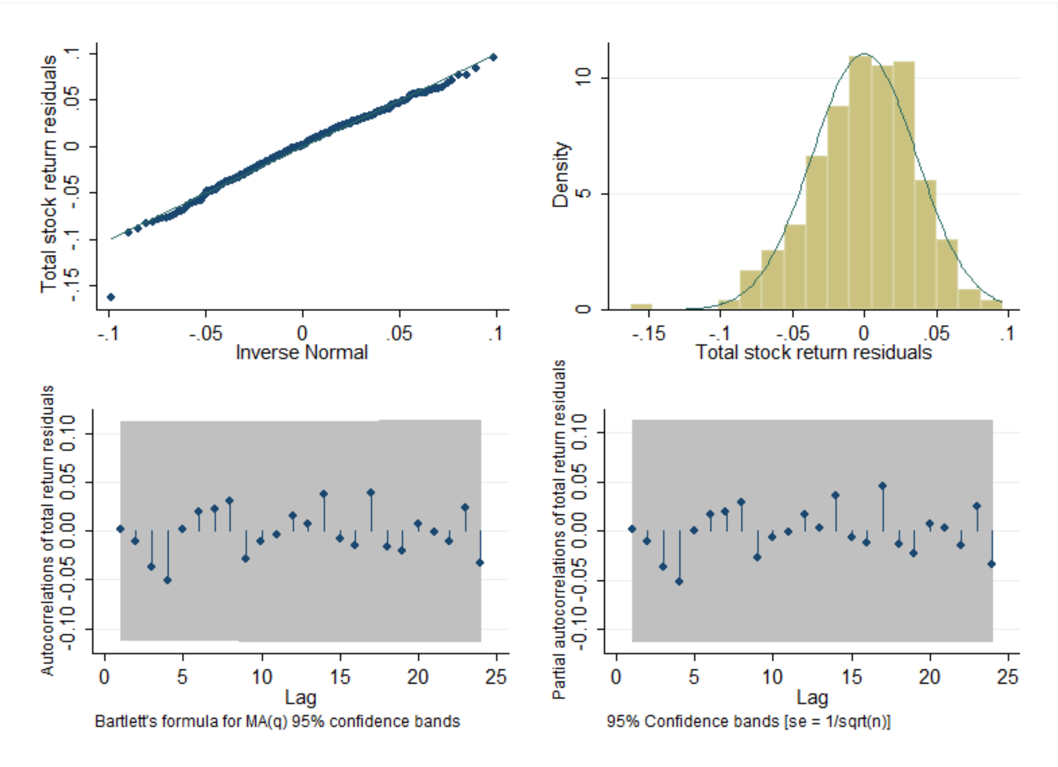

A.5.2b) Normality of residuals for the aggregate demand variable in *Model 2*



A.5.2c) Normality of residuals for the tanker-specific demand variable in *Model 2*




A.5.2d) Normality of residuals for the global total stock returns variable in *Model 2*



A.5.3) Shapiro-Wilk normality test of *Model 1*

| **Variable** | **Obs** | **W** | **V** | **z** | **Prob>z** |
|---|---|---|---|---|---|
| Supply resiudals | 308 | 0.96333 | 7.997 | 4.886 | 0.00000 |
| Aggregate demand residuals | 308 | 0.83962 | 34.976 | 8.355 | 0.00000 |
| Tanker-specific demand residuals | 308 | 0.99186 | 1.774 | 1.348 | 0.08887 |

A.5.4) Shapiro-Wilk normality test of *Model 2*

| **Variable** | **Obs** | **W** | **V** | **z** | **Prob>z** |
|---|---|---|---|---|---|
| Supply residuals | 308 | 0.96099 | 8.508 | 5.032 | 0.00000 |
| Aggregate demand residuals | 308 | 0.87066 | 28.206 | 7.849 | 0.00000 |
| Tanker-specific demand residuals | 308 | 0.99424 | 1.257 | 0.537 | 0.29556 |
| Total stock returns residuals | 308 | 0.98769 | 2.685 | 2.322 | 0.01012 |

A.5.5a) Jarque-Bera normality test for *Model 1*

| **Equation** | **chi2** | **df** | **Prob>chi2** |
|---|---|---|---|
| Tanker supply | 10.154 | 2 | 0.00624 |
| Aggregate demand | 1101.670 | 2 | 0.00000 |
| Tanker-specific demand | 10.927 | 2 | 0.00424 |
| ALL | 1122.752 | 6 | 0.00000 |

A.5.5b) Skewness test for *Model 1*

| **Equation** | **Skewness** | **chi2** | **df** | **Prob>chi2** |
|---|---|---|---|---|
| Tanker supply | -0.43314 | 9.631 | 1 | 0.00191 |
| Aggregate demand | -0.32628 | 5.465 | 1 | 0.01940 |
| Tanker-specific demand | 0.06882 | 0.243 | 1 | 0.62196 |
| ALL | | 15.339 | 3 | 0.00155 |

A.5.5c) Kurtosis test for *Model 1*

| Equation | Kurtosis | chi2 | df | Prob>chi2 |
|---|---|---|---|---|
| Tanker supply | 3.2019 | 0.523 | 1 | 0.46942 |
| Aggregate demand | 12.242 | 1096.206 | 1 | 0.00000 |
| Tanker-specific demand | 2.0876 | 10.684 | 1 | 0.00108 |
| ALL | | 1107.413 | 3 | 0.00000 |

A.5.6a) Jarqua-Berg test for *Model 2*

| **Equation** | **chi2** | **df** | **Prob>chi2** |
|---|---|---|---|
| Tanker supply | 7.928 | 2 | 0.01899 |
| Aggregate demand | 386.415 | 2 | 0.00000 |
| Tanker-specific demand | 22.765 | 2 | 0.00000 |
| Total stock returns | 29.210 | 2 | 0.00000 |
| ALL | 446.318 | 8 | 0.00000 |

A.5.6b) Skewness test for *Model 2*

| **Equation** | **Skewness** | **chi2** | **df** | **Prob>chi2** |
|---|---|---|---|---|
| Tanker supply | -0.33821 | 5.872 | 1 | 0.01538 |
| Aggregate demand | -0.18052 | 1.673 | 1 | 0.19588 |
| Tanker-specific demand | 0.05151 | 0.136 | 1 | 0.71209 |
| Total stock returns | -0.17618 | 1.593 | 1 | 0.20685 |
| ALL | | 9.274 | 4 | 0.05460 |

A.5.6c) Kurtosis test for *Model 2*

| **Equation** | **Kurtosis** | **chi2** | **df** | **Prob>chi2** |
|---|---|---|---|---|
| Tanker supply | 2.5998 | 2.056 | 1 | 0.15163 |
| Aggregate demand | 8.4754 | 384.742 | 1 | 0.00000 |
| Tanker-specific demand | 1.6721 | 22.629 | 1 | 0.00000 |
| Total stock returns | 1.533 | 27.617 | 1 | 0.00000 |
| ALL | | 437.043 | 4 | 0.00000 |

## A.6 Testing for optimal lag length

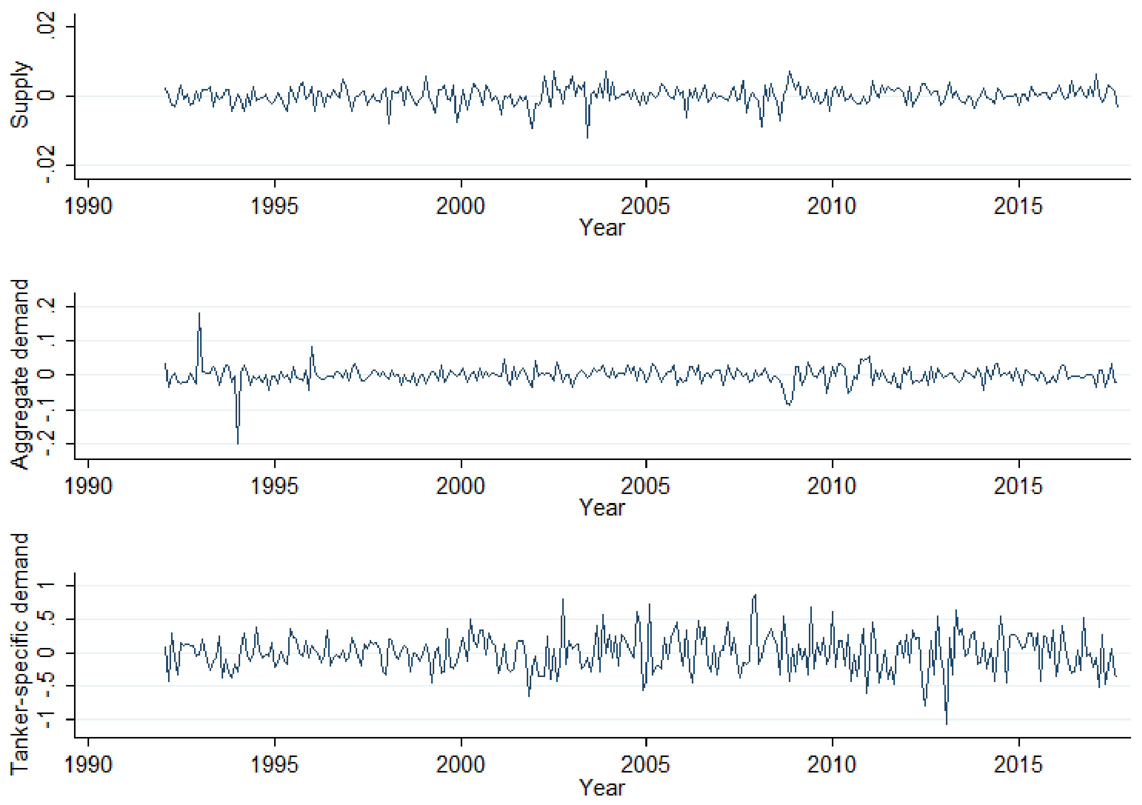
A.6.1 Information criteria statistics for *Model 1*

| **Lag** | **LR** | **AIC** | **HQIC** | **SBIC** |
|---|---|---|---|---|
| 0 | | -18.19 | -18.19 | -18.19 |
| 1 | 542.51 | -19.8929 | -19.8494 | -19.7839* |
| 2 | 27.472 | -19.9237 | -19.8365 | -19.7057 |
| 3 | 34.39 | -19.9769 | -19.8462 | -19.6499 |
| 4 | 44.564 | -20.0632 | -19.8888 | -19.6272 |
| 5 | 22.28 | -20.077 | -19.8591 | -19.5321 |
| 6 | 14.466 | -20.0656 | -19.8041 | -19.4116 |
| 7 | 6.7639 | -20.0291 | -19.724 | -19.2661 |
| 8 | 32.78 | -20.0771 | -19.7284 | -19.2051 |
| 9 | 35.095 | -20.1326 | -19.7404 | -19.1516 |
| 10 | 27.901 | -20.1647 | -19.7289 | -19.0748 |
| 11 | 60.26 | -20.3019 | -19.8225 | -19.103 |
| 12 | 63.327 | -20.4491* | -19.9261* | -19.1411 |
| 13 | 17.319 | -20.4469 | -19.8803 | -19.0299 |
| 14 | 8.6292 | -20.4165 | -19.8063 | -18.8905 |
| 15 | 8.3776 | -20.3852 | -19.7315 | -18.7503 |
| 16 | 16.553 | -20.3805 | -19.6832 | -18.6366 |
| 17 | 10.339 | -20.3557 | -19.6148 | -18.5027 |
| 18 | 9.4763 | -20.328 | -19.5435 | -18.366 |
| 19 | 15.506 | -20.3199 | -19.4918 | -18.249 |
| 20 | 30.595 | -20.3608 | -19.4891 | -18.1809 |
| 21 | 16.1 | -20.3546 | -19.4394 | -18.0657 |
| 22 | 15.219 | -20.3456 | -19.3868 | -17.9477 |
| 23 | 7.2476 | -20.3107 | -19.3083 | -17.8038 |
| 24 | 35.366* | -20.3671 | -19.3211 | -17.7511 |

A.6.2 Information criteria statistics for *Model 2*

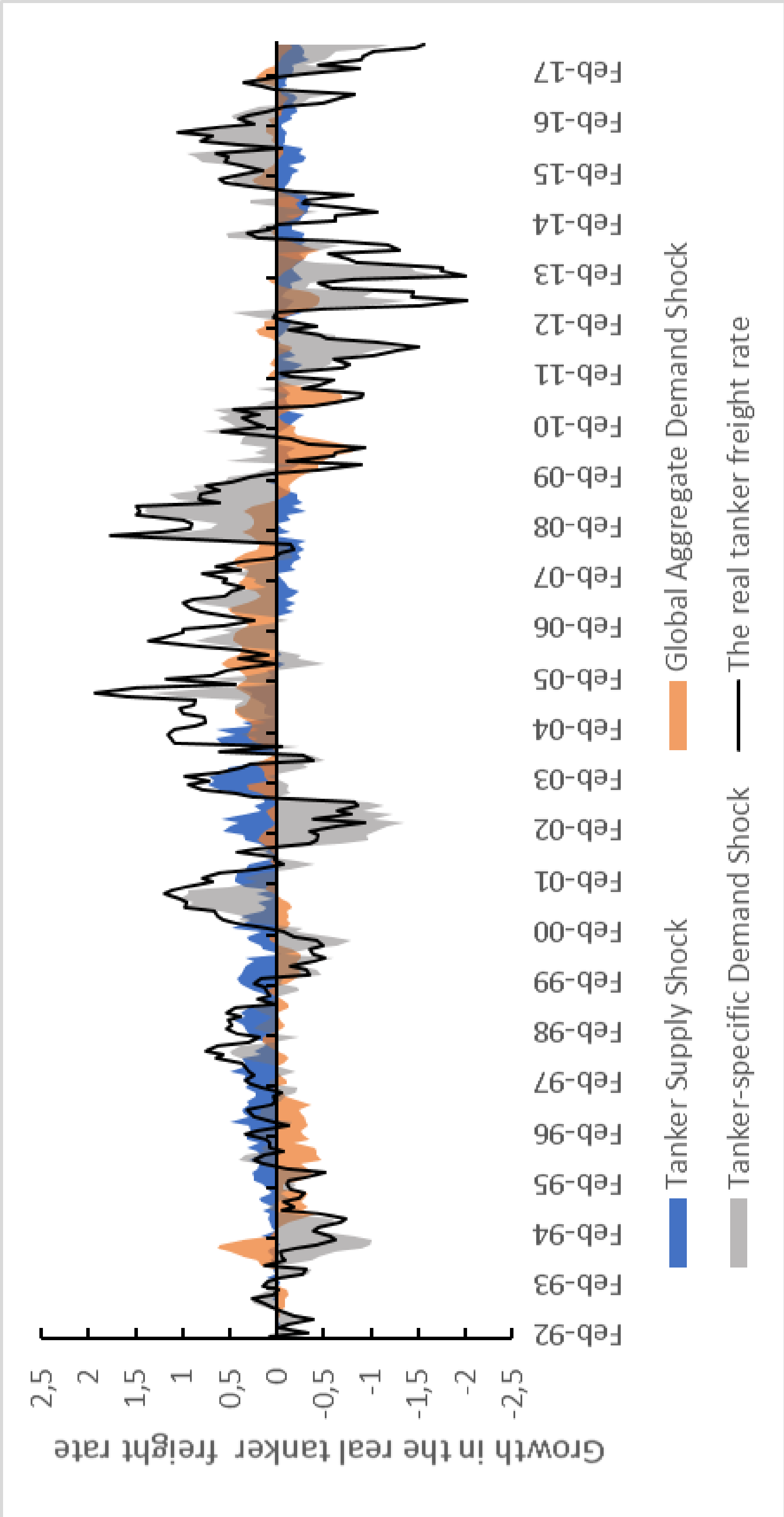
| **Lag** | **LR** | **AIC** | **HQIC** | **SBIC** |
|---|---|---|---|---|
| 0 | | -24.3894 | -24.3894 | -24.3894 |
| 1 | 560.56 | -26.1055 | -26.028 | -25.9118* |
| 2 | 50.76 | -26.1664 | -26.0115 | -25.7789 |
| 3 | 51.856 | -26.2309 | -25.9985 | -25.6496 |
| 4 | 68.536 | -26.3495 | -26.0396* | -25.5744 |
| 5 | 21.66 | -26.316 | -25.9286 | -25.3471 |
| 6 | 28.327 | -26.304 | -25.8392 | -25.1414 |
| 7 | 19.773 | -26.2643 | -25.722 | -24.9079 |
| 8 | 37.178 | -26.2811 | -25.6613 | -24.731 |
| 9 | 41.158 | -26.3109 | -25.6136 | -24.5669 |
| 10 | 42.072 | -26.3436 | -25.5688 | -24.4059 |
| 11 | 64.053 | -26.4476 | -25.5954 | -24.3162 |
| 12 | 66.984 | -26.5612 | -25.6315 | -24.236 |
| 13 | 34.758 | -26.5702* | -25.563 | -24.0512 |
| 14 | 22.514 | -26.5394 | -25.4547 | -23.8266 |
| 15 | 19.696 | -26.4994 | -25.3373 | -23.5929 |
| 16 | 25.22 | -26.4774 | -25.2378 | -23.3771 |
| 17 | 24.96 | -26.4546 | -25.1374 | -23.1605 |
| 18 | 16.709 | -26.4049 | -25.0103 | -22.917 |
| 19 | 41.07 | -26.4344 | -24.9623 | -22.7527 |
| 20 | 35.895 | -26.447 | -24.8974 | -22.5716 |
| 21 | 23.094 | -26.4181 | -24.791 | -22.3489 |
| 22 | 28.615 | -26.4071 | -24.7026 | -22.1441 |
| 23 | 20.116 | -26.3685 | -24.5865 | -21.9118 |
| 24 | 56.353* | -26.4476 | -24.5881 | -21.7971 |

A.7 Historical evolution of unanticipated shocks to the three supply and demand variables in *Model 1*, monthly data.

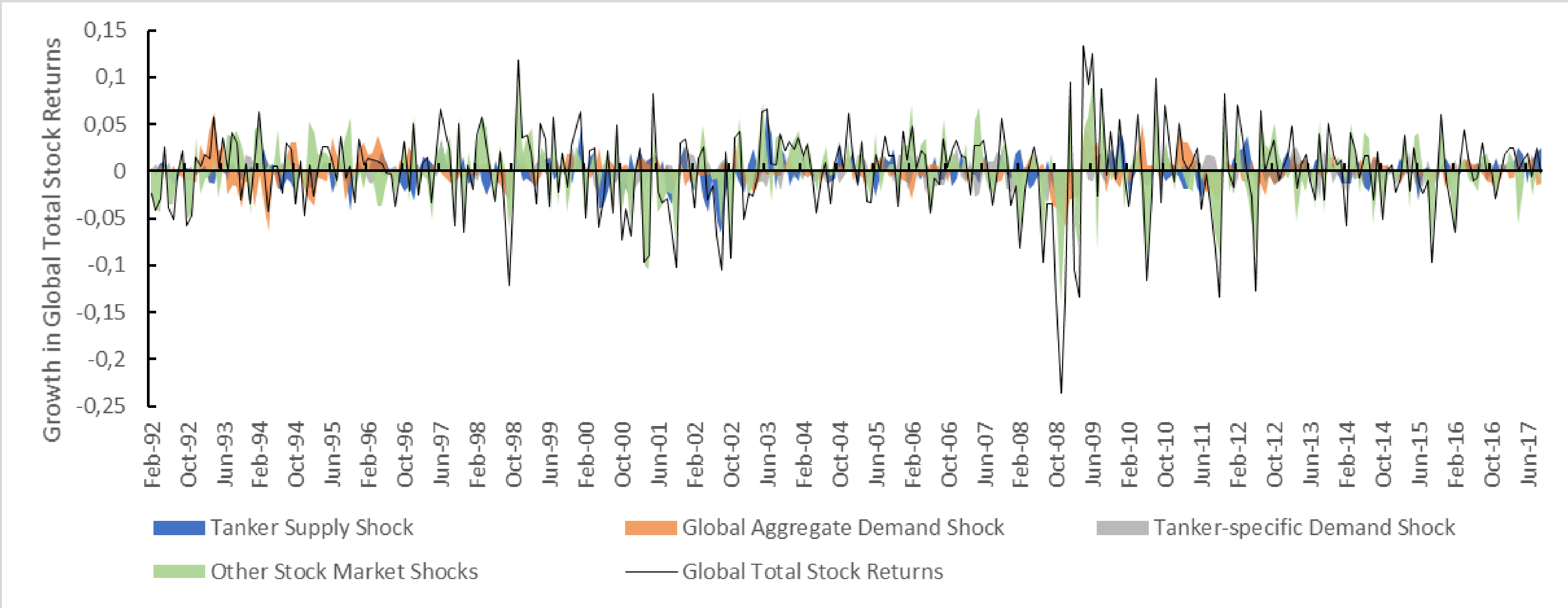


## A.8 Historical Decomposition of Model 1

A.8.1) Historical Decomposition of *Model 1*



A.8.2) Historical Decomposition of *Model 1*



## A.9 Replication of oil price model from Kilian (2009)

The dataset used to replicate the restricted model introduced by Kilian (2009), consists of three variables: oil production; Kilian's index of global real economic activity; and the real price of oil. The dataset used in this replication spans from the beginning of 1974 up to and including November 2016, hence we have extended the period with almost 10 years.

Data for global crude oil production is obtained from the U.S. Energy Information Administration. Specifically, the series shows monthly global crude oil production including lease condensate, in averaged thousands of barrels per day. This variable had to be first differenced in order to be stationary. As a proxy for real global economic activity, we used the updated version of the real economic activity (rea) index constructed and proposed by Kilian (2009). For the real price of oil (rpo), the paper uses monthly averaged imported crude oil price as reported by EIA. The lag length is 24 lags, the same as Kilian (2009) used. All variables were stationary. The model satisfied the stability condition as the modulus of each eigenvalue lies within the unit circle. Further, the residuals seem to have leptokurtic distribution. Comparing the IRFs and historical decomposition in our replication with Kilian's original ones, shows that we have practically identical results.

The model we used to replicate Kilian (2009) is expressed below

$$\begin{pmatrix} e_t^{\Delta \text{prod}} \\ e_t^{rea} \\ e_t^{rpo} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil-spesific\ demand\ shock} \end{pmatrix}$$

From this we can perform a variance decomposition. The results are presented in table 3.

*Table 3) Variance decomposition of our replication of Kilian's original model (Kilian, 2009) in %*

| **Horizon** | **Tanker Supply Shocks** | **Aggregate demand shocks** | **Tanker-specific demand shocks** |
|---|---|---|---|
| 1 | 0,28 | 0,95 | 98,78 |
| 6 | 0,57 | 5,81 | 93,62 |
| 12 | 0,69 | 17,49 | 81,83 |
| 18 | 0,80 | 21,43 | 77,77 |
| 24 | 0,71 | 27,72 | 71,57 |