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Measuring impact of climate-induced Panama Canal disruption on VLGC freight rate using Vector Error Correction Model

by

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Abstract

In late 2023, the Panama Canal experienced its worst drought since the 1950s due to climate-induced changes in weather patterns, which lowered the water level of Gatun Lake and forced the Panama Canal Authority (ACP) to limit daily transits. This disruption significantly impacted the Very Large Gas Carrier (VLGC) segment, primarily responsible for the long-range transportation of liquefied petroleum gas (LPG) from the U.S. Gulf to East Asia, leading to a sharp increase in freight rates from late 2023 to early 2024. Unlike other oil and gas commodities, LPG is unique due to its concentrated supplier base, lack of high-capacity storage facilities typical of liquefied natural gas (LNG), and its supply-push pricing structure. Despite the critical role of VLGCs in long-range LPG trade, limited literature exists on analyzing VLGC freight rates, particularly in the context of global disruptions.

This research aims to quantify the impact of sustained climate-induced transit limitations at the Panama Canal on VLGC freight rates, considering factors such as the growing U.S. dominance in LPG production, waiting times for Panama Canal transit, and price arbitrage between U.S. and Saudi-sourced LPG. A vector error correction model (VECM) is employed to analyze the statistical properties of these variables endogenously and to establish long-term relationships through co-integration. As a prerequisite to VECM, seasonal adjustment using Loess decomposition and stationarity checks with the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are conducted. Johansen's likelihood ratio tests is used to determine the co-integration rank in the estimated VECM, which includes variables such as freight rates, price ratio, U.S. Gulf LPG exports, maximum transit capacity of the Panama Canal, and VLGC waiting times at the canal. The impact of Panama Canal transit limitations is inferred from the impulse response functions of the freight rate to other variables, obtained from the level VAR conversion of the proposed VECM.

This thesis concludes that transit limitations, such as those experienced in 2023, could increase VLGC freight rates by $14,000 per day. However, further increases are anticipated due to other influencing factors, such as a rising price ratio. Consequently, a comprehensive structural analysis of variables related to Panama Canal transit is recommended for future studies.

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Chapter 1. Introduction

1.1.Research Background

Following up on COP 28 held in Doha, November 2023, it was agreed upon all participants that the progress was too slow across all climate actions, especially for increasing resilience to climate change and decarbonization effort (UNFCC, 2023). The strongest signal shown on this conference is the end of the fossil fuel era, that energy transition is the key to rectify global warming limitation target that is currently off the track from Paris Agreement. Record-breaking temperature and the increasing frequency of climate change-induced disasters is one of the main drivers to adapt and build resilience in all economic sectors. In the case of shipping industry, measures have been taken to reduce greenhouse gasses emission through legally binding regulations of MARPOL Annex VI led by International Marine Organization (IMO) (Shaw & Benz, 2024), yet impacts of extreme weather events due to climate change in shipping industry has been felt particularly on the Panama Canal operation and its users.

Panama Canal has an oversized influence on the world trade in its role as world's major shipping chokepoints especially on the trade between East Coast Americas and East Asia through Pacific Ocean. More than 13,000 transits are recorded through the canal in a typical year, however starting April 2023 Panama Canal Authority (ACP) announced transit limitation accounting to extreme dry period over Panama Canal watershed, which has recorded the lowest precipitation over 70 years (ACP, 2023). This transit limitation does not affect different sectors in shipping equally, which container being the least impacted as its transit only decrease by 9% compared to bulker that drops by 72% from 2022 figures (Holden, 2024). This drop is accounted by the booking system rules in Panama Canal which prioritizes container shipping. Re-routings are common in non-prioritized sector such as gas, and very large gas carriers (VLGC) market is significantly tightened due to combined effect of Panama Canal transit restriction and Houthi attacks on Red Sea shipping, resulting in periods of elevated freight routes (Clarksons Research, 2024).

VLGC is a major user of Panama Canal, with average VLGC transit amounting to 2.8 vessels per day in January to October 2023 owing to the prominence of US-Asia gas trade, thus disruption in Panama Canal affects this sector heavily (Stavrinidis, 2023). In addition to Panama Canal transit limitation, VLGC market is also influenced by the demand pressure from the increase of US LPG export to Japan, China, and other Asian countries due to Saudi Arabian voluntary reductions in crude oil production (EIA, 2024). Compared to other sectors, LPG transportation is unique compared to other energy transportation such as coal and crude oil that it is driven by supply push rather than demand pull, in the sense that LPG shipment volume is derived from natural gas and crude oil extraction as the alternative of flaring off petroleum gas is increasingly limited due to climate regulations (Adland et al., 2008). As LPG is increasingly seen as the “intermediate” stage to make up the deficiency of renewable energy generation during urgent decarbonization efforts, in conjunction with the need to replace biomass for home cooking purposes in parts of Africa and Asia, interplay between LPG trade and climate change merit detailed research through its indirect impact on Panama Canal.

1.2. Overview of Seaborne LPG Trade

LPG is the standard name for commercial propane and butane existing in gaseous form at standard temperature and pressure, however under sufficient pressure it liquifies and easily transported. It is a by-product extracted from crude oil refining and natural gas processing; hence it is mainly produced by countries with intensive oil-refining industry such as United States and Saudi Arabia. Other than its usage as home cooking in various parts of the world, it is also a vital feedstock for multiple products including hydrogen, ammonia, and ethylene. However, domestic sector still dominates the usage of LPG that accounts to 46% of all LPG consumption in 2021 (Kerry, 2023). Current seaborne LPG export is dominated by US Gulf following the region’s significant production expansion since 2020, with Middle East exports growth falters into second place (Clarkson’s Shipping Intelligence Network, 2024). This significant expansion of US Gulf LPG production coincides with US shale revolution, as US shale oil wells increasingly capture and export subsequent LPG by-product that by itself is not subject to crude oil export restriction (Koyama, 2013). The increase of US-East Asia LPG trade increases the ton-miles demand which starts from 2020. The impact of shale gas revolution in the LPG trade is also reflected in the production mix of LPG in the US, that saw increased portion of natural gas processing from 60% in 2007 to over 75% in 2013 (Oglend et al., 2013).

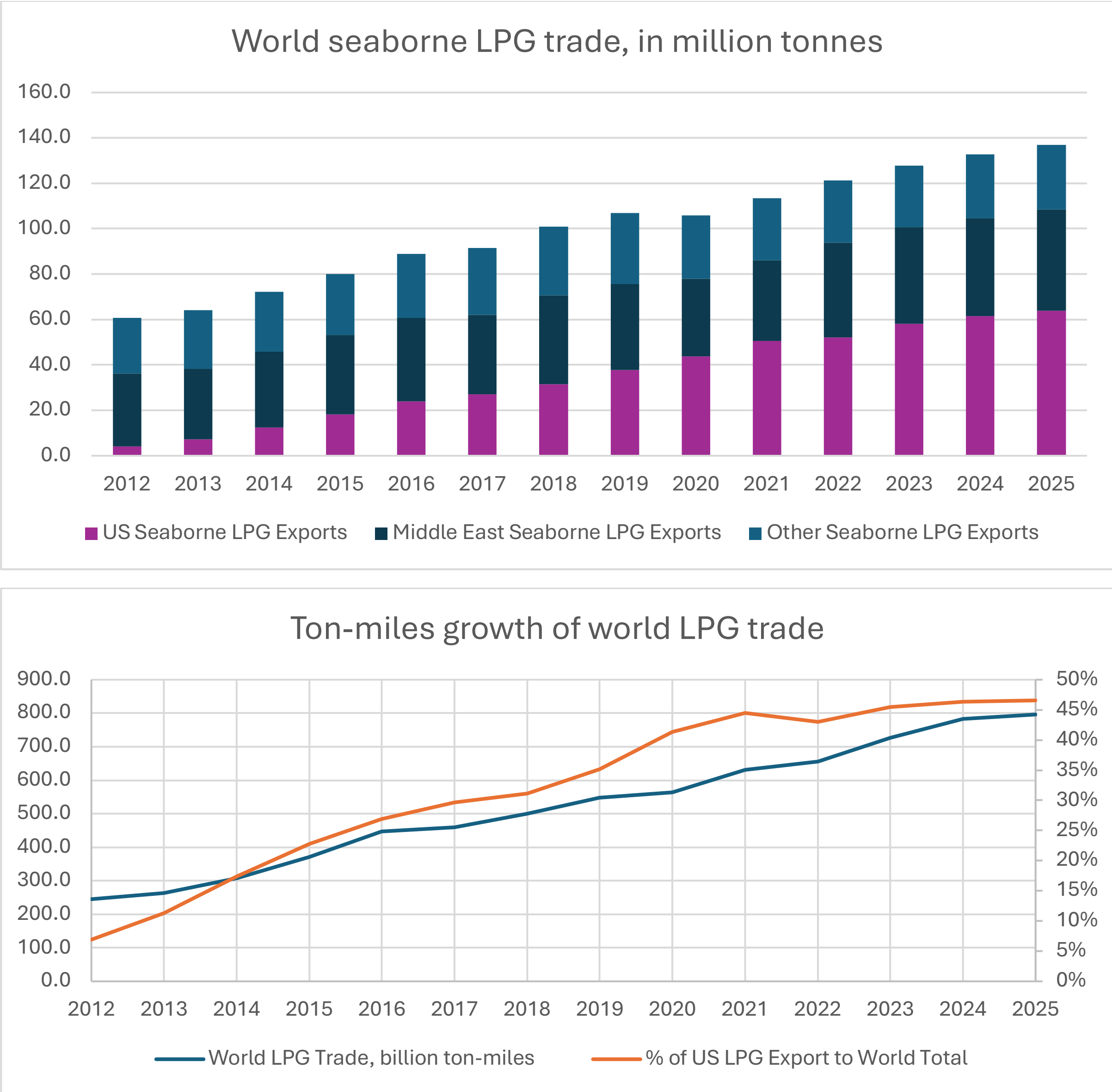

Figure 1: US LPG export and impact to LPG seaborne trade demand

Note: figures for 2024 and 2025 are forecasts, estimates are subjective and there is no guarantee that trends will continue.
Source: Author's calculation, data from Clarkson's Shipping Intelligence Network

The advantage of LPG compared to commercial methane, also known as Liquid Natural Gas (LNG) lies in the fact that LPG is easier to transport in bulk due to not needing cryogenic storage. It also does not degrade over time in storage, unlike biofuels, thus arbitrage trade is often performed from major oil refining areas to major consumers. This long-range arbitrage trade is mainly served by fully refrigerated very large gas carriers (VLGC) with the capacity of more than 70,000 cubic meters (cbm). Furthermore, arbitrage trade between Far East importers and US Gulf LPG producers is increasingly relevant to the freight rate of VLGCs as US LPG production volume increases over time (Bai & Lam, 2019a). Non-economic factors such as geopolitical considerations also play a role driving the demand of seaborne LPG trade, that the cost of spot charter rate for VLGCs is increasing during high geopolitical risk (Michail & Melas, 2022).

Shipowners are well aware of the development of US LPG export and the impact to ton-miles demand of gas carriers, thus reflected on the orderbook for VLGCs in Q2 2024 reaching historical high of 127 vessels with combined capacity in excess of 12 million cbm, operating at the latest on 2029 (Clarkson's Shipping Intelligence Network, 2024). This increasing trend is not shared with other segments of LPG carriers, however, as VLGCs offer unmatched efficiency for long-range transportation even after the fact that smaller gas carrier could also transport ammonia and other chemical derivatives. In comparison to other shipping segment, VLGC shipowners face higher risk for their decision to invest in a new vessel. Adland et al. (2008) describes that freight rate of VLGC has higher volatility compared to other oil and gas shipping market such as LNG and crude oil due to several factors. First, the high concentration of vessels to a few shipowners, comparatively small fleet in VLGCs, and low number of main trading routes suggests the presence of imperfectly competitive market. In addition to the first factor, most LPG shipments are performed under long term-contracts, creating a volatile demand in the remaining cargo requirement that operates as a quasi-spot market. Lastly, postponement of LPG shipment is effectively unheard of in this industry as LPG is a byproduct of oil refinery and gas production, thus LPG trading volume is tightly tied with crude oil and natural gas production, yet storage takes secondary precedence to those two markets.

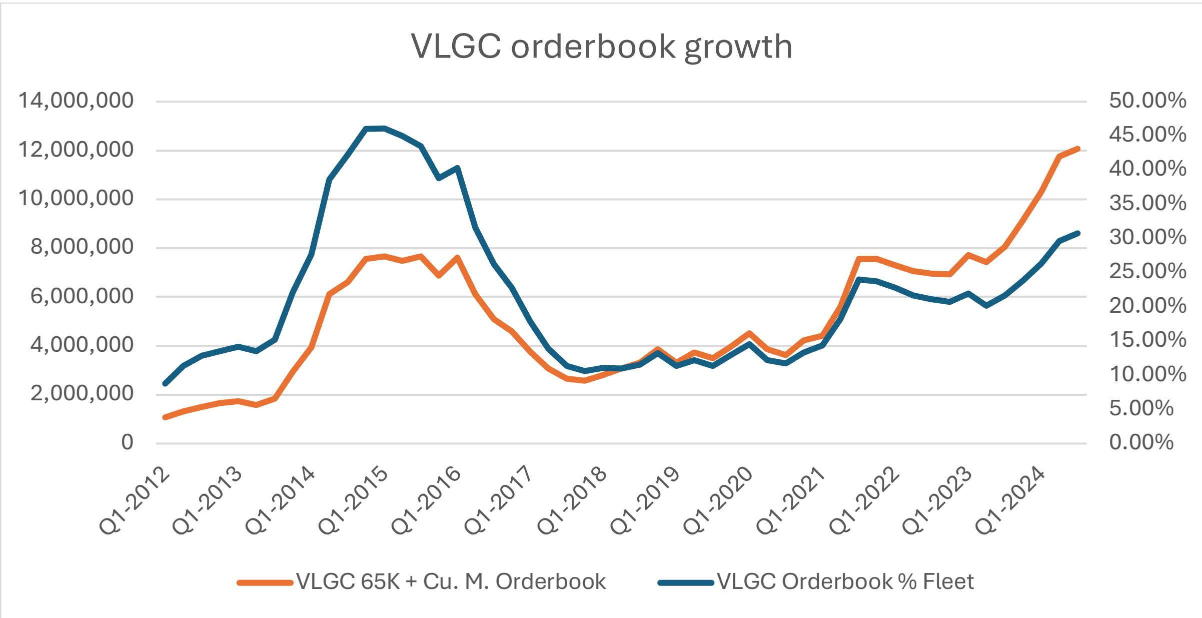

Figure 2: VLGC orderbook growth

Source: Author's calculation, data from Clarkson's Shipping Intelligence Network

1.3.Overview of Panama Canal Transit Limitation

The importance of Panama Canal to the shipping industry and specifically LPG transportation cannot be understated as 3% of world maritime traffic transit through the Canal. Particularly, US maritime trade depends on the canal with around 72.5% of all cargo transiting Panama Canal is bound or originates from the United States (ACP, 2023). Panama Canal Authority (ACP) records that the largest segment transiting Panama Canal in 2023 is container shipping, followed by bulk carriers and LPG carriers. However, 2023 figures suggest that container shipping and bulk carriers transit decreased by 1.9% and 11.8% respectively, while LPG segment transit increases by 17.4% compared to 2022 levels. The increasing LPG transit is partially attributed to the opening of Panama Canal Expansion Locks, inaugurated in 2016, that allows ships with the maximum length of 366m, width of 49m, and draft of 15m, the so-called Neo-Panamax ships (Menarguez & Flor, 2017).

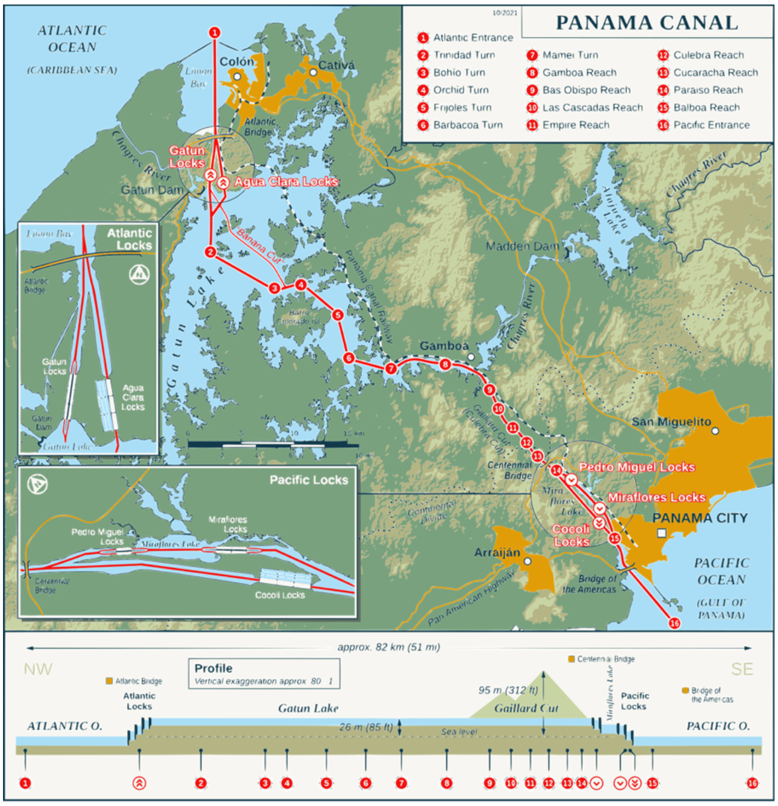

Figure 3: Map of the Panama Canal. Below: longitudinal cut out of navigable route

Source: Thomas Römer/OpenStreetMap data, free to use under CC-BY-SA 2.0 License

Panama Canal expansion has already impacted the freshwater supply of Gatun Lake that also supplies clean water to Panama City and its environs. Panama Canal has two main artificial lakes as the freshwater storage, Gatun and Alhajuela (Madden) Lake, with a water catchment area that feeds these lakes corresponds to an area of 339,649 hectares, mainly fed by rainwater during a wet season occurring from April to mid-December (Wijsman, 2013). The same report released by IMARES Wageningen in 2013 suggests that salinity concentration in Gatun Lake could increase by up to 0.7 ppt during dry season after the opening of new Panama Canal locks, and even if it is too low for marine exotic species to migrate between Pacific Ocean and Caribbean Sea, some freshwater species in Gatun Lake might be impacted by the increase of salt concentration.

The reliance of Panama Canal to rainwater put itself at a risk of changing weather pattern due to climate change. In return, studies about climate risk assessment on Panama Canal operation has been performed since the new locks was still under consideration. Risks associated during El-Nino / La Nina fluctuations that will impact the precipitation and water level of storage basins has been extensively discussed, thus draft restrictions or even disruption of operations during extreme drought event has been predicted with associated loss of revenue to the Government of Panama (Acciaro, 2016). This scenario happened during 2023 drought, which saw the reservoirs being prevented from replenishment after the last year's dry season by a climate change-amplified El-Nino, indicated by 47% less precipitation from average in the watershed thus hold as the lowest ever recorded since 1950 (Ruiz & Shintani, 2024). From climate model conducted from 1983 through 2003, future climate prediction suggests that intense precipitation will increase which heighten flooding risk yet also make drought more likely in the same cycle (Kusunoki et al., 2019).

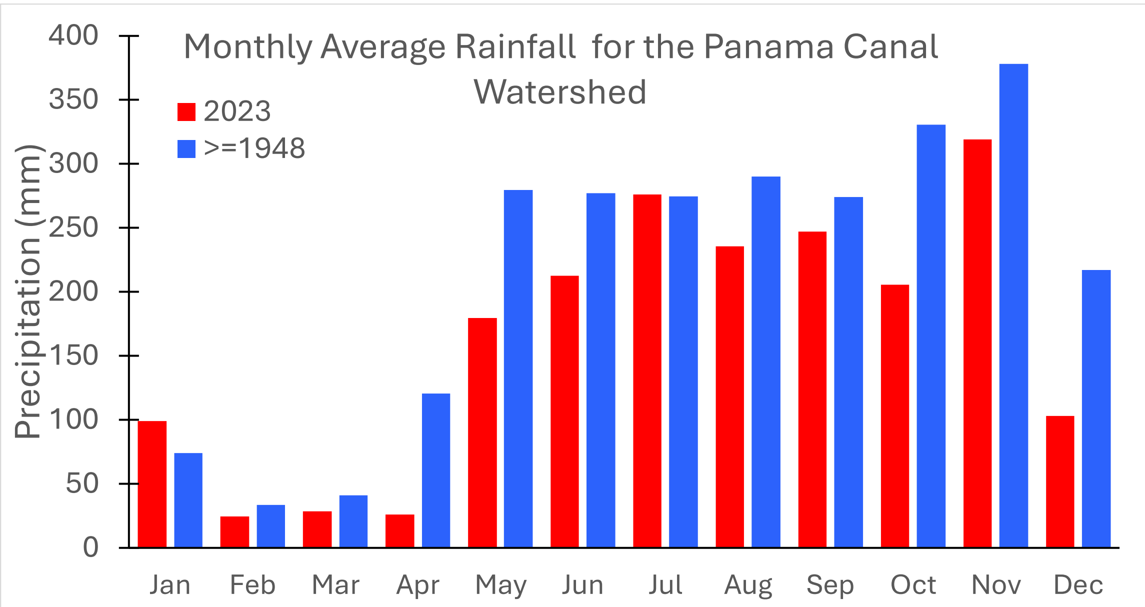

Figure 4: Precipitation anomaly in Panama Canal for 2023 dry season

Source: Paton, Steve; Panama Canal Authority (2019). Monthly Rain Dataset ACP. Smithsonian Tropical Research Institute. Free to use under CC-BY-SA 4.0 License.

1.4. Research Objective

Acknowledging the impact of Panama Canal to the world shipping and specifically LPG trade, this thesis aims to provide quantitative analysis on the impact of disruption of Panama Canal transit to the time charter equivalent (TCE) freight rate of Very Large Gas Carrier (VLGC). VLGC freight market is selected as part of LPG shipping sector due to its route predictability, comprise a major part of LPG trade volume, and the observed disruption during Panama Canal transit limitation. Therefore, the primary research question in this research is:

"**What is the magnitude of the effect of sustained Panama Canal transit limitation to the VLGC time charter freight rates?**"

To reach the conclusion of the above research question, some secondary questions will be addressed:

1. To what extent does waiting times in Panama Canal be affected by transit limitation?
2. To what extent does the freight rate of VLGCs be affected by seasonal fluctuation?
3. To what extent does LPG production trend affect the freight rate for LPG shipping?

1.5. Relevance

Panama Canal disruption due to climate change is an unprecedented black swan event yet have a profound impact to a large sector of world's economy. This research aims to provide contributions in three points:

1. Guide shipowners in anticipating transit queue spike and assessing fair charter rate of VLGC considering additional voyage cost accounting for increased transit, manpower, and fuel costs. Further analysis can also guide shipowners for investment decisions of VLGC newbuilds.
2. Identify the response of fossil fuel-related VLGC freight market from disruptions due to climate change, raising awareness to the real impact of climate change on gas transportation thus emphasizing the urgent need to decarbonize,
3. Enrich existing literature within the field of maritime transportation, especially in gas carriers which is less researched compared to containers, bulkers, and tankers.

1.6. Research Design

This thesis is designed to analyze the effect of sustained Panama Canal disruption on the time charter equivalent (TCE) freight rate of VLGCs. In this research, Panama Canal disruption is represented by waiting times of VLGC ships located in Pacific and Atlantic anchorage of Panama Canal measured in hours, based on AIS data, and the maximum transit slots offered by ACP announced regularly in Advisory on Shipping. In turn, TCE freight rate of VLGC is based on Clarkson's index of VLGC measured in $/day. Waiting times and VLGC TCE freight rate is obtained from Clarkson's Shipping Intelligence Network (SIN), while Panama Canal Advisory on Shipping is obtained from ACP website, collected from 2018 to 2024. To observe the seasonality and trend component of freight rate, we will perform data filtering by seasonal-trend decomposition using Loess (STL).

This study will start by describing and plotting all the data to obtain the first indication of structure in the data. Relationship between waiting times and transit limitation, impact of seasonality to LPG freight rate, and the general market trend due to changes in trade pattern will be described in the next step. Then, we will check the stationarity of the filtered variables using Augmented Dickey-Fuller (ADF) test and Philips-Perron (PP) test, proving the existence of unit root in the variables. Finally, we will use Vector Error Correction (VEC) model to test cointegrating relationship between waiting times and VLGC freight rate and measure the impact on freight rate using impulse response functions.

1.7. Thesis Structure

This thesis consists of 6 chapters, which are Chapter 1 – Introduction, Chapter 2 – Literature Review, Chapter 3 – Research Methodology, Chapter 4 – Results and Analysis, and Chapter 5 – Conclusion.

Chapter 1 provides the background information, objective, relevance, design, and structure of the research.

Chapter 2 conducts literature review focusing on previous methods freight rate analysis, putting a particular focus on LPG shipping market.

Chapter 3 presents research process flow and methodologies to be used in the subsequent chapters. It will introduce filtering by STL, stationarity check using Augmented Dicker Fuller (ADF) and Philips Perron (PP) tests, and multivariate analysis method using vector error correction (VEC) model approximation that is commonly used in freight rate analysis.

Chapter 4 describes the dataset used in the analysis, giving summary statistics for each data, and determine the lag period used in the multivariate model, investigates the relation between the freight rate, Panama Canal disruption, and market conditions by VEC model. Finally, response of freight rate due to shocks in various variables are calculated.

Chapter 5 summarizes this thesis' major findings and offer recommendation for future research. Limitation of this study will also be provided.

Chapter 2. Literature Review

2.1. Literature Review Approach

This chapter sought to analyze existing literature on the freight rate analysis particularly on LPG shipping segment, and the common methods used in those analysis. Due to the time constraint, a fully systematic review for all literatures related to freight rate analysis will not be performed, however this thesis will attempt to do semi-systematic review qualitatively as outlined by Snyder (2019). The following sections will describe the search strategy used, the significant papers discussed further, common methods of freight rate modelling, and finally freight rate analysis used specifically in LPG shipping market.

2.2. Search Strategy

In this thesis, we consider freight rate studies in academic journals published by reputable bodies such as Elsevier as our main source. This approach is used as journal papers have solid theoretical basis and well defined model, thus should be used as the primary source of a literature review (Rowley & Slack, 2004). We search these academic journals primarily using Google Scholar with search term “LPG freight rate analysis”, “LPG freight market” “congestion LPG freight rate”. We further refine the scope by reading the abstract and exclude common unrelated papers that discuss about LNG, port congestion in relation with container shipping, and market analysis of LPG production in various regions.

We offer a list of significant papers below that passes all our criteria as the main sources of this literature review. To further capture on the major previous works in freight rate analysis of other markets such as dry bulk or tanker, we use the cited papers in those main sources to explore papers that are not captured in the initial search. This review also references Glen (2006) and Ke et al. (2022) to summarize past quantitative modelling approaches in shipping freight rate analysis. This multi-step provided a common path that is well explored by other researchers to help understand freight rate modelling, particularly in LPG shipping.

Table 1: Significant works used as main sources of literature review

No	Year	Author	Research Subject	Significance
1	2008	Adland et.al	Price dynamics in the market for Liquid Petroleum Gas transport	The first paper to investigate the market structure of LPG shipping specifically.
2	2010	Engelen & Dullaert	Transformations in gas shipping: Market structure and efficiency	Describes the segmentation of LPG shipping market with emphasis on differentiation between VLGCs and oil product tankers. Additional notes on inelasticity of LPG shipping demand and shipowner clustering in supply side as happened with tanker market, albeit with the lack of liquidity.
3	2011	Engelen et.al	Multifractal features of spot rates in the Liquid Petroleum Gas shipping market	Confirming the stationarity of LPG shipping freight rate and disappearing memory effect in weekly observation, with remarks that there is positive autocorrelation in the freight rate, yet interrupted with sudden, large discrete movement e.g. route disruption
4	2012	Engelen & Dullaert	A Classical Partial Disequilibrium Model of the Gas Shipping Markets	The first structural model proposed for LPG shipping market, noting the strong correlation between spot freight and time charter rates in VLGC shipping and thus concluding the correlation of both types of contracts with vessel utilization.

No	Year	Author	Research Subject	Significance
5	2019	Bai & Lam	A copula-GARCH approach for analyzing dynamic conditional dependency structure between liquefied petroleum gas freight rate, product price arbitrage and crude oil price	Investigating the impact of arbitrage trade and LPG shipping, confirming that Far East and US price arbitrage become more significant over time as US shale gas production increases.
6	2019	Bai & Lam	An integrated analysis of interrelationships within the very large gas carrier (VLGC) shipping market	Emphasizes the impact of ton-mile demand volatility, with implication that longer routes should affect LPG shipping freight rate more compared to other markets.
7	2022	Bai et.al	Port congestion and the economics of LPG seaborne transportation	Confirms the causal effect of port congestion on LPG freight rate exist when supply is tight, and congestion is severe enough, where port and canal congestion can be easily compared.
8	2022	M. Shirazi	Dynamic behavioral characteristics of maritime liquefied petroleum gas freight rate	Uses VAR model to measure network connectedness based on Diebold-Yilmaz (2016) to analyze return and volatility spillover affecting Baltic LPG freight rates.
9	2022	Michail & Melas	Geopolitical Risk and the LNG-LPG Trade	Uses VEC model to analyze impact of shock in geopolitical tension to LPG freight rate, confirming the result in Engelen (2011).

2.3.Methods of Freight Rate Modelling

Freight rate model based on supply-demand balance has been proposed, adopting structural approach done by Beenstock & Vergottis (1993a) which investigates factors influencing the supply of fleet capacity and ton-mile demand of shipping in determining freight rate in various markets (Glen, 2006). This supply demand model is summarized in Stopford (2008), that shipping ton-mile demands primarily determined by world and regional economic condition combined by random shocks, while shipping capacity supply mainly determined by fleet utilization combined with orderbook deliveries, sales and purchase market, and scrapping. Another paper investigates the interrelatedness in the supply between dry cargo and tanker market, which spillover of both market are linked through the shipbuilding capacity, market switching in case of combination vessels, and scrapping which influences decommissioning earning for shipowners (Beenstock & Vergottis, 1993b). These approaches primarily consider global freight market, aggregating large amount of contract into a freight rate index of several specific shipping markets.

Other approach in determining freight rate is done by investigating each charter fixtures in microeconomic terms, assessing whether the freight rate posted is fair based on fixture and vessel characteristics in combination with market condition at the contract fix. This approach already concludes that laycan period and freight rate determine each other simultaneously, while exogenous factors influencing freight rate include vessel hull type, fixture deadweight utilization, vessel age, and voyage routes (Alizadeh & Talley, 2011a, 2011b). Other paper conclude that in addition to vessel and fixture characteristics, fixed charterer effect has a large contribution in VLCC market while charterer and match effect are large contributors in Capesize spot freight rate (Adland et al., 2016).

Approaches used by researchers are changing after Beenstock & Vergottis' work has been published, owning to the fact that structural model requires many supporting variables which are hard to find and previously proven relationship between factors (Ke et al., 2022). Modern econometric approach using statistical properties of freight rates are used, including autoregressive conditional heteroskedasticity (ARCH)-type models, vector autoregressive (VAR), and vector error correction models (VECMs) with varying accuracy. In this regard, Tsolakis et al. (2003) compared structural approach and VAR method, which concludes that while structural models is still to be preferred to evaluate policies and describe cycles simultaneously, VAR approach could forecast shipping cycle reliably.

Most of econometric methods used in freight rate analysis analyzed the impact of variables in determining freight rates using multivariate analysis, while only a third of researches in the past 20 years perform time series characteristics analysis of freight rates or forecasting using univariate models (Ke et al., 2022). For the freight rate time series characteristics, researchers are still debating on the stationarity of freight rate time series. In the same paper, it is concluded that freight rate is treated as non-stationary based on common stationarity tests. Other main characteristics concluded are seasonality and cycles in freight rates, which has different periods ranging from one year to 7-year cycle, which has impact in causality relationship between freight rate and other markets affecting it. (Ke et al., 2022)

Main application of econometrics models such as VAR, however, lies in the capability of determining the linear relation between freight rate and other factors without any distinction between exogenous and endogenous variables (Glen, 2006). Proving statistical relation at the level requires data stationarity to avoid spurious regression, in which a stationary check is commonly performed prior to VAR model approximation. In case of non-stationarity, co-integration approach is used to model long-term relation between the variables. Veenstra & Franses (1997) proves the non-stationarity and co-integration between freight rate of Capesize and Panamax bulkers in various major routes, yet first differences of those series are stationary and used in the VEC models to forecast future rates. Movement of the freight rate series using only autoregression, however, is mostly stochastic and cannot be forecasted (Veenstra & Franses, 1997). Limiting factor in this VAR method is that long-term forecast tends to return to the mean of the series. Further research using this method has been done in Veenstra (1999) that prove the co-integration of spreads, which is the difference between period and spot rate of a shipping market, thus confirming the joint behavior between those contracts.

2.4. Freight Rate Analysis in LPG Market

The first research determining price structure of LPG freight market comes from Adland et al (2008) using fully functional time series analysis, which conclude that freight rate does not show non-linearity as in oil tanker market thus could be approximately described by linear stochastic differential equation with linear drift and constant volatility. The paper also describes the unique properties of LPG shipping that it is supply driven rather than demand, as LPG export depend on LNG extraction rate and crude oil processing volume. Few trading routes between LPG transport hence are performed under term contracts, leaving small and volatile market in spot contracts of VLGCs, so that changes in spot demand might be influenced by geographical price arbitrage, supply disruptions, or increasing gas production (Adland et al., 2008).

Other methods in univariate VLGC freight rate analysis is performed by Engelen et al. (2011) using non-parametric multifractal detrended fluctuation analysis (MF-DFA) and rescaled range (R/S). Building on the segment differentiation of LPG freight market on Engelen & Dullaert (2010) and focusing on VLGC market which is the most important LPG shipping sector by volume, it confirms the stationarity of VLGC freight market as previously performed by Adland et al (2008), seasonality in VLGC freight rate, and long-range dependence. Seasonality is apparent with increased ship demand to replenish LPG stocks in August-October before winter, and significantly strengthened during the expansion of LPG markets. The paper concludes that freight rate forecasting is feasible because of the existence of 3–4-year cycles and lack of time variability over longer period and trend reinforcing behavior is dominant in determining freight rate, however it is suddenly halted with large movement recorded by stochastic event that interrupts the ongoing cycle (Engelen et al., 2011).

In the first research discussing freight rate dependence models in LPG market, Engelen & Dullaert (2012) proposes classical structural shipping model based on partial supply-demand disequilibrium. It concludes the positive relation between market utilization levels and freight rates of gas shipping, explaining the instant reflection in prices from market information. Building on the idea on term structure of freight rates, spot rate and time charter equivalent of VLGCs is particularly connected due to arbitrage smoothing out the difference (Engelen & Dullaert, 2012). In other research, the number of ships available in Ras Tanura determines the Baltic rate and the rate of the entire VLGC market that explains the volatility of the rates, putting the significance of shipping supply in determining freight rate (Engelen & Dullaert, 2010).

Factors influencing LPG freight rate is discussed further using structural equation model (SEM) in Bai & Lam (2019b). It establishes the high volatility in VLGC demand and the significant impact to corresponding freight rate. Ton-mile demand plays a more significant role compared to fleet size in determining freight rate, thus factors driving the ton-mile statistics of VLGC shipping such as changes in trade pattern could explain the trend of freight rate. Further research in the impact of port congestion in LPG freight rate is performed using System Dynamics model (SD) in Bai et al. (2022) through linear regression in a causal loop. This research is particularly important in this literature review as it explicitly uses AIS model to determine congestion and demonstrates micro-voyage level variables as a structural factor explaining VLGC freight rate.

Usage of modern econometric methods in investigating dependencies of LPG freight rate is done by Bai & Lam (2019a) using conditional copula-Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model with both time-invariant and time-varying structures. GARCH, intially used to model individual volatilities, is adapted to model dependencies using copula method to capture complex, nonlinear dependencies especially tail dependencies that is common in extreme events. It is found that price arbitrages between US-Far East and Middle East-Far East has different impact to freight rate owning to market structure of LPG production and shipping. During market downturns LPG freight rate is more correlated to Middle East-Far East arbitrage while the reverse is not apparent in US-Far East arbitrage linear correlation to freight rate thus implying the asymmetric effect of both routes to LPG freight rate (Bai & Lam, 2019a).

Another modern econometric methods in LPG freight rate dependence modelling is done using applications of VAR in Shirazi (2023) and Michail & Melas (2022). Both papers tests unit root for stationarity for the whole time series using different methods accounting to different data used, even after stationarity of LPG freight rate has been well established since Adland et al (2008). Particularly, Shirazi (2023) considers structural breaks in the date thus uses Zivot-Andrew unit root tests for examining logarithmic difference and realized volatility based on Shephard and Barndorff-Nielsen (2002), compared to ADF and PP tests used in Michail & Melas (2022) in examining level and first difference of variables. Both papers diverge in the application of VAR in determining freight rate relations to relevant factors, that Shirazi (2023) uses network connectedness measures introduced by Diebold and Yilmaz (2016) to analyze response to the shock of determinants including internal LPG pricing mechanisms and external factors such as fleet development, trade patterns, and bunker price. In turn, Michail & Melas (2022) uses VECM to explain the relation between Geopolitical Risk Index (GPR) constructed by Caldara and Iacoviello (2018) and LPG freight rate. The need to explain spillover imbalances in Shirazi (2023) necessitates the usage of network connectedness measures, while for testing co-integration relationship VECM could be used with less complexity. Shirazi (2023) proves the impact in volatility shock of arbitrage price, base LPG price, and crude oil price LPG freight rate, however the same is not apparent in difference shocks. Michail & Melas (2022) proves the co-integration between LPG freight rates and global geopolitical risk, that shows a shock in geopolitical risk increases the cost in spot charter rates of LPG carriers.

While a few research has been conducted on VLGC shipping with univariate analysis on VLGC pricing structure explained by Adland et al. (2008) and Engelen & Dullaert (2010), there is a lack of research in the impact of global disruptions on VLGC freight rates, especially related to climate risk. Previous studies examining the impact of disruptions on VLGC freight rates include geopolitical risk (Michail & Melas, 2022) and port congestions (Bai et al., 2022). As far as we know, there are no studies conducted to investigate the impact of climate-induced Panama Canal disruption to LPG shipping, while we already highlighted the vulnerability of LPG shipping to route disruptions (Bai & Lam, 2019b; Engelen et al., 2011). Thus, in this research we will test the assumption on the statistical properties of LPG freight market outlined previously to determine the stationarity of the data used in this thesis. The impact of price arbitrage shown in Bai & Lam (2019a) will be used as one of the factors affecting the freight rate that is also impacted by Panama Canal closure. Finally, we will use VECM to analyze the impact of a global disruption such as Panama Canal closure to VLGC market as it is used by Michail & Melas (2022) to model the impact of geopolitical instability on the same shipping segment.

Chapter 3. Research Methodology

3.1. Methodology Overview

This thesis starts with a literature review on general freight rate analysis and identify methods that is commonly used in tramp shipping and specifically LPG shipping. We specifically limit our scope to LPG market as LPG trade routes are constant. This phenomenon occurs as LPG is mainly produced from US and Saudi Arabian oil and gas refinery byproduct and then transported to the main markets, East Asia and Europe. From these two sources, one major route which is US Gulf to East Asia is increasingly prominent in world's LPG trade yet vulnerable to disruptions in Panama Canal operation. As we already identify that most of US Gulf to East Asia LPG trade transiting Panama Canal is served by VLGCs, we will quantify the impact of Panama Canal to LPG trade through a focused analysis on VLGC freight rates.

Data sets related to VLGC freight rate and Panama Canal disruption are first collected from accountable sources such as Clarkson's Shipping Intelligence Network (SIN), government websites, or reputable international organizations. All data are collected as posted by the source, except Panama Canal maximum transit figure that we estimate based on Advisory on Shipping announcement made by Panama Canal Authority (ACP), irregularly as disruptions are anticipated. On the next section we identify the data used, sources, and frequency of each data. We base the data frequency in weekly observations to maximize the fidelity of freight rate data, thus data with different observation will be harmonized out accordingly.

To isolate the impact of Panama Canal limitation to freight rate, we perform a data filtration using Seasonal-Trend Decomposition using LOESS (STL) method to obtain seasonal, trend cycle, and residual component of the collected timeseries. Combined with the descriptive statistics of processed data, we will perform preliminary analysis to determine the appropriate variables to be included in the VEC model. We will also check stationarity of chosen variables using commonly used tests such as Augmented Dicker Fuller (ADF) and Philips Perron (PP) tests. We will first determine the appropriate lag length in a generic VAR model; thus, this lag length is then used as the input to approximate the VECM. In the VECM we will test the co-integration rank present in the model, based on the critical values provided by Osterwald-Lenum (1992) as the default in urca package in R. As the final step, level VAR is approximated from the VECM based on co-integration rank present in the previous step, and we will quantify the impact of each combination of variables using impulse response function (IRF)

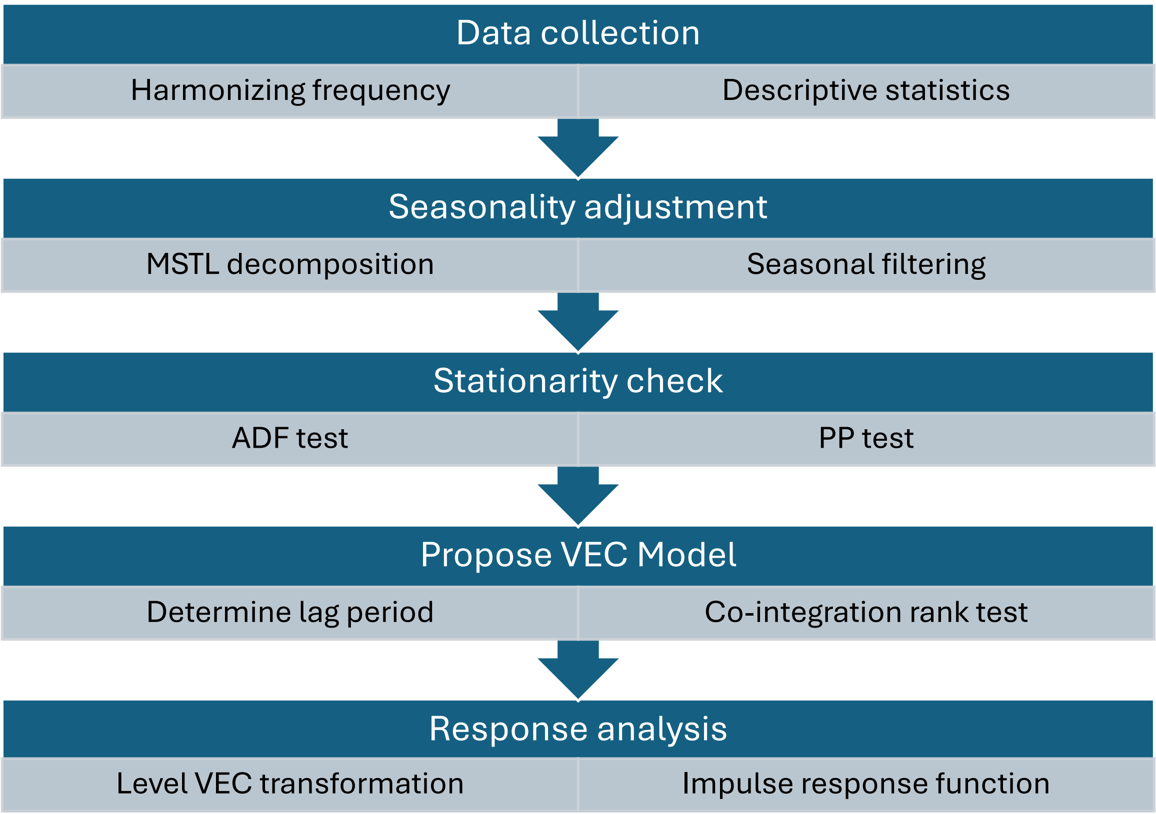

Figure 5: Proposed research flow

3.2. Variable Identification and Collection

We obtain VLGC freight rate data from Clarkson's Shipping Intelligence Network (SIN) for the Time Charter Equivalent (TCE) rate for VLGC with capacity 84,000 dwt from 2018 to 2024, quoted every Friday. We do not compare this data from another source due to the lack of access to another shipping intelligence data, for example Baltic Exchange. Regarding the period, we assume that the period is sufficient to capture the whole impact of Panama Canal disruption as the event only happened in late 2024. Variations in ton-mile demand in VLGC shipping is also modelled in the thesis through the price ratio of US Mt. Belview LPG spot price compared to Saudi Aramco Contract Price (CP), taking account for the arbitrage trade followed by traders in VLGC freight market (Bai & Lam, 2019a), and LPG export volume in Gulf of Mexico region to take account for increasing dominance of US-sourced LPG. We justify the additional variable affecting freight rate not connected to the Panama Canal disruption, as the impact of longer routes and price arbitrage could have an impact to freight rate independent to the Panama Canal condition.

We use waiting times of VLGC and the maximum transit slots offered by Panama Canal Authority as the proxy for Panama Canal disruption. Waiting times is collected daily, based on VLGCs waiting on Pacific and Atlantic anchorage measured in hours based on AIS data all collected by Clarkson's SIN as the main data representing Panama Canal transit condition. For the maximum transit slot offered by ACP, we base our figure on the Advisory on Shipping announcements made regularly from October 2018 to August 2024. We consider normal conditions to be 42 transits/day for all locks and directions as stated by ACP, unless otherwise noted in those announcements. Reduced transit occurred during regular maintenance of locks, incidents at the locks, or lower water level in the lakes.

We found that our data has different timeseries frequencies, thus harmonizing the observation is necessary before performing further analysis. As waiting times are logged daily albeit with different observation method, we convert those frequency into weekly with 2 different ways. Waiting times is a 7-day moving average, thus we only take Friday observation and discard other observations so that the weekly waiting times is represented by average waiting times in the Friday.

Table 2: Identified variable, sources, and frequency

No	Variable	Note	Source	Frequency
1	*freight.rate*	TCE daily freight rate of VLGCs collected from Clarkson's brokers estimate, for LPG ships with 84k dwt capacity from 2018-2024	Clarkson's SIN	Weekly
2	*ratio*	Calculated from the price ratio of spot Mt. Belview Texas (*bel.price)* and Saudi Aramco Contract Price *(cp.price)*. Adjustment in unit of volume is based on LPG density of 1.898 kg/m^3	Author's calculation	Weekly
3	*waiting.times*	VLGC waiting times in Panama Canal anchorage, based on hourly AIS data estimating time between arriving at designated anchorage area and defined Panama Canal location. Excluding vessels waiting for more than 4 weeks.	Clarkson's SIN	Daily
4	*bel.price*	Mt.Belview Texas spot price, in $/gallon. Quoted weekly on Friday.	US Energy Information Administration	Weekly
5	*cp.price*	LPG Saudi Aramco Contract Price (CP), in $/ton.	Clarkson's SIN	Monthly
6	*export*	US Gulf (Region 4) export of propane and propylene, unit in thousands of barrels per day.	US Energy Information Administration	Weekly
7	*max.transit*	Maximum allowable transit through Panama Canal based on offered transit slot by Panama Canal Authority, collected from series of Advisory for Shipping starting from October 2018 to August 2024.	Panama Canal Authority	Weekly

3.3. Decomposition and Seasonality Adjustment

To decompose the timeseries into trend-cycle, seasonality, and residual component, locally-weighted regression method (LOESS) is used in this analysis based on the work of Cleveland et al. (1990). Seasonal-Trend Decomposition Procedure Based on Loess (STL) consists of two recursive procedures to determine the seasonal and trend components, updated on each pass of inner loop. In return, outer loop calculates the robustness weight to reduce the influence of transient effect in the timeseries, thus making it possible to decompose timeseries with missing values. LOESS calculates the regression curve selecting the values of the closest to each observation in a neighborhood weight, based on the distance to the observations being calculated. Additive decomposition in STL method is shown in below equation:

$$X_t = \hat{S}_t + \hat{T}_t + \hat{R}_t$$

where $\hat{S}_t$ is the seasonal component, $\hat{T}_t$ trend-cycle component, and $\hat{R}_t$ the residual component in timeseries decomposition.

Multiple-STL (MSTL) developed by Bandara et al. (2021) is used in this thesis as an extension to STL which allows for separation of multiple seasonality frequency that in the normal STL, lower seasonal cycle can be absorbed by the higher cycle due to structural nesting and interlacing. Compared to normal STL, MSTL separates the seasonal pattern based on identified frequencies, sorting the frequency in an ascending order, and fit the STL decomposition for each frequency in that order to reduce overfitting of higher frequency. After all outer loop in the STL has been achieved, final iteration is used as the trend components. Decompositions in MSTL as an extension to STL method is shown in below equation:

$$X_t = \hat{S}_t^1 + \hat{S}_t^2 + \cdots \hat{S}_t^n + \hat{T}_t + \hat{R}_t$$

where n represents the number of seasonal cycles present in timeseries X_t. MSTL is also fully automated which we do not have to specify seasonal window *s.window* parameter, as the iteration sets it based on the evolution of seasonal pattern during seasonal cycle determination. Frequencies which are smaller than half of the length of the series is excluded from seasonal cycle as it cannot have any seasonal pattern. Box-Cox transformation can be set to apply automatically when $\lambda \in [0,1]$ is fulfilled.

In R, timeseries decomposition are performed through *mstl* command in the **forecast** package. Multiple seasonal periods are allowed and estimated iteratively using STL. If the iteration does not find any seasonal period, timeseries are decomposed into trend and remainder components. Before decomposition, time series may be subject to Box-Cox transformation automatically using *lambda=auto* command. Maximum iteration in *mstl* could be also explicitly stated, with the default being 2. The advantage of *mstl* is it is fully automated to determine trend and seasonal lags, thus minimizing errors in the process.

3.4. Unit Root Tests

Before applying a multivariate time series model, first stationarity must be established for all variables included. In this thesis we use 2 types of unit root tests, Augmented Dicker-Fuller (ADF) and Philips-Perron (PP) tests. Both tests are conducted at the levels and the first differences. As we assume that the timeseries we use is more complicated than modelled by simple autoregressive with 1 lag or AR(1) model, we use Augmented Dicker-Fuller test method based on the work of Said and Dickey (1984) as ADF is capable to accommodate general ARMA(p,q) model with unknown order. ADF test is based on estimating the test regression (Zivot & Wang, 2006):

$$y_t = \beta' D_t + \phi y_{t-1} + \sum_{j=1}^{p} \psi_j \Delta y_{t-j} + \varepsilon_t$$

where D_t is a vector of deterministic terms comprising of constant and terms. The lagged p difference terms Δy_{t-j} are used to approximate ARMA structure of the errors ε_t while the value of p is set such that error is serially uncorrelated and assumed to be homoscedastic. In this test, we have null hypothesis of y_t is unit-root nonstationary *I(1)* which implies that $\phi = 1$, against the alternative that it is trend stationary *I(0),* assuming that the dynamics in the date have an ARMA structure. ADF t-statistic are based on the least square estimates of the test regression and given by:

$$ADF_t = t_{\phi=1} = \frac{\phi - 1}{SE(\phi)}$$

To determine the appropriate regression model in ADF test, lag length and trend type must be determined for each variable. In R, we can automatically determine the lag length using Akaike (AIC) or Bayesian Information Criteria (BIC), as there is no practical difference in using both criteria, we will use AIC to automatically determine lag length for all variables. We will plot each variable in level and first difference to determine whether the ADF needs a constant in the test regression, exhibiting a clear trend, or none needed.

Philips-Perron (PP) tests are non-parametric in its approximation to the ARMA structure of test regression error terms in contrast to ADF tests, such that it ignores serial correlation in the test regression (Zivot & Wang, 2006). Test regression in PP test is given by:

$$y_t = \beta' D_t + \pi y_{t-1} + u_t$$

where u_t is *I(0)* and may be heteroscedastic. In this case PP test differs in how serial correlated, and error heteroscedasticity is dealt by modifying test statistics $t_{\pi=0}$ and $T\bar{\pi}$. Full explanations of modified statistics in PP test can be seen in Zivot & Wang (2006, p.123). In this test, null hypothesis is $\pi = 0$ such that there is a unit root. Also, in contrast with ADF test, we do not have to specify lag length for the PP test regression.

Both ADF and PP tests are available on R in **urca** package with the command *ur.df* and *ur.pp* for ADF and PP test, respectively. We must fit both tests with the appropriate model, which consist of constant, drift, or drift with trend. Selection of appropriate model is done from the trend-cycle strength previously concluded. Particularly in ADF test, lags should be explicitly given in the command for all variables, however in ***urca*** package lag can be automatically selected by Akaike (AIC) or Bayesian (BIC) information criteria integrated in the command.

3.5. Vector Error Correction Model

Vector Autoregression (VAR) model is an extension of univariate autoregressive model to describe dynamic interactions between independent and dependent variables. Stationary p-lag vector autoregression model is formed as the following equation (Zivot & Wang, 2006):

$$Y_t = c + \Pi_1 Y_{t-1} + \cdots + \Pi_p Y_{t-p} + \varepsilon_t$$

where Π_i are $(n \times n)$ coefficient matrices and ε_t is an $(n \times 1)$ error terms which are independent. In this stationary model, estimation matrices can be approximated using ordinary least square (OLS) method to perform the forecasts. Forecasting is possible using Granger Causality Theorem, which suggests if a variable $y_1$is found to be helpful to predict another variable y_2, then y_1 is considered to Granger-cause y_2. Testing for Granger non-causality can be performed using Wald statistics, which uses the property of lagged values coefficients between variables (Zivot & Wang, 2006, p. 403)

Co-integration, a special case of non-stationarity is used as real economic variables such as prices and freight rates are commonly non-stationary. Spurious regression is the case when all the regressors in the time series regression model are non-stationary and not cointegrated. Thus, regression with unit-root non-stationary data *I(1)* data that is commonly encountered in freight rate statistics which has a clear trend owing to the structure, only makes sense when the data is co-integrated.

This co-integration assumes the underlying long-term relationship that is explained by a linear combination of the variables that is stationary or *I(0)*. Usage of co-integration to explain long-term relationship in freight rate analysis outlined in the literature such as Veenstra & Franses (1997) and Michail & Melas (2022) will also be followed in this thesis using the work of Johansen (1991). Granger Representation Theorem first derived from Engle and Granger (1987) showed cointegration implies the existence of error correction model that allows us to determine cointegration of all variables in one step (Veenstra & Franses, 1997). Taken from Zivot & Wang (2006, p. 454), Johansen's method to model cointegration in multivariate VAR using Vector Error Correction (VEC) model are:

1. Specify and estimate VAR(p) model for Y_t
2. Construct likelihood ratio tests for the rank Π to determine the number of cointegrating vectors
3. Impose normalization and identify restrictions on cointegrating vectors if necessary
4. Estimate resulting cointegrated VECM by maximum likelihood method.

The VECM terms is shown by below equation:

$$\Delta Y_t = \Phi D_t + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + \varepsilon_t$$

where matrix Π is long-run impact matrix and Γ_k are the short run impact matrixes thus neatly divide the impact of independent variables to dependent variable in two separate terms. In VECM terms, it is considered that $0 < rank(\Pi) = r < n$, with Y_t is I(1) process having r independent cointegrating vectors and $n - r$ common stochastic trends. Further steps for likelihood ratio tests to determine the appropriate number of cointegrating vectors r through trace statistics and maximum eigenvalue is available in Zivot & Wang (2006).

Determining VEC model using Johansen's method is done in R through **urca** package by *ca.jo* command. By specifying the type of *"eigen"* or *"trace"* both trace statistics and maximum eigenvalue can be directly calculated. Lag order of the levels in VAR is determined primarily by *VARselect* command available in **vars** package, using all methods of Akaike Information Criterion (AIC), Hannan Quinn Criterion (HQ), Schwarz Criterion (SC), and Final Prediction Error (FPE) by ordinary least square equation. Co-integration rank Π will be tested against critical values provided by Osterwald-Lenum (1992), while Γ_1 matrix can be set to measure long-run or transitory effect in the equation. Centered seasonality dummy variable can be included by adding seasonality frequency in the command, while exogenous variables can be explicitly introduced by adding *dumvar* command.

3.6. Level VAR conversion and prediction

Level VAR model can be directly recovered from the VECM terms as VAR parameter Π_i is calculated by taking matrix Π and Γ_k via: (Zivot & Wang, 2006 p.452)

$$\Pi_i = \Gamma_1 + \Pi + \mathrm{I}_n$$
$$\Pi_k = \Gamma_k - \Gamma_{k-1}, k = 2, .., p$$

Further, once VAR-form has been estimated, forecasting could be made for *n* future period by the following calculation:

$$y_{T+h} = A_1 y_{T+h} + \cdots + A_p y_{T+h-p} + CD_{T+h}$$

for $h = 1, 2, \dots, n$, through *predict* command in **vars** package specifically in R. This command also can be used to model strictly exogenous variable as scenario building, by inserting a dummy variable with the same name in VECM specification. Other than predicting future values in different scenarios, impulse response function (IRF) could also be calculated to quantify the effect of endogenous variables to each other. In R, IRF is conducted through *irf* command in **vars** package, and confidence interval bands can be set in various replications. In this thesis, we will model all variables endogenously and calculate IRF mainly for all variables to freight rate.

Chapter 4. Results and Analysis

4.1. Descriptive Statistics

A summary of the data used in this thesis is shown in Table 3 below. We compare the statistics of *charter* to the result observed in Adland et al. (2008). First, the range of freight rate is explained through the difference of the data observed, although the difference is trivial as we use daily $/day while the previous research uses TCE in '000 $/month. Conversion from monthly figure to daily figure has been done automatically in SIN, thus we can assume both data refer to the same process. Skewness and kurtosis of our data are more extreme compared to Adland et al. (2008), referring to the higher volatility experienced in the LPG market during COVID-19, rush of LPG transportation happened during COVID-19 recovery period, and ultimately Panama Canal limitation. Finally, in both dataset there are clear rejection on the normal distribution of level freight rate that is not present in Adland et al. (2008). The impact various disruptions in LPG shipping market that happened one after another to the occurrence of fat tails in the distribution of new data remains to be seen, however, as the investigation of phenomenon is outside of our scope. Plot of all timeseries is available in Appendix 1.

Table 3: Descriptive statistics of all variables used

	charter	*ratio*	*export*	*waitingtime*	*max.transit*
Mean	39308	0.6824	1307	51.14	39.72
Median	35672	0.6846	1279	45.76	42.00
Max	82194	1.0043	2335	174.04	42.00
Min	20384	0.2670	607	14.11	22.00
Std. Dev	12443.13	0.121	323.28	24.04	5.39
Skewness	1.403	-0.37	0.253	1.46	-2.27
Kurtosis	5.104	3.52	2.676	6.25	6.69
Jarque-Bera (p-value)	156.89 (0.00)	10.53 (0.00)	4.615 (0.09)	244.02 (0.00)	437.77 (0.00)
Observation	306	306	306	306	306

Table 4 below shows the correlation between each variable pairs. It is expected that *max.transit* has a significant relation to the *charter* variable, as Panama Canal is one of the most important chokepoints in LPG trading. Negative yet weak correlation between *max.transit* and *waitingtime* indicates that transit policy contributes to waiting times in Panama Canal, albeit needing other variable to fully explain the decision of shipowners to wait for transit compared to using other routes. In turn, *waitingtime* are better correlated with the number of ships transiting and export volume of US LPG, confirming the importance of Panama Canal to US LPG seaborne trade. One other significant correlation is between *ratio* and *charter*, which also indicate the impact of price arbitrage affecting ton-mile demand of LPG shipping.

Table 4: Correlation matrix of all variables

	charter	*ratio*	*waitingtime*	*max.transit*	*export*
charter	1.0000	-0.3499	0.2458	-0.7160	0.6634
ratio		1.0000	0.1158	0.1706	-0.1500
waitingtime			1.0000	-0.0375	0.2381
max.transit				1.0000	-0.5521
export					1.0000

4.2.Data Filtering

Decomposition of timeseries is performed using MSTL with the decomposition plot of freight rate is shown in Figure 6 below. It is apparent that there is a clear seasonal component in the freight rate with pronounced peaks near the end of the year, that we assume coincide with the need of LPG at the winter. As we already notice that *max.transit* is a stochastic phenomenon, driven by policy arising from the needs and conditions of Panama Canal Authority, we do not include it in the decomposition process and leave it as it is on the level.

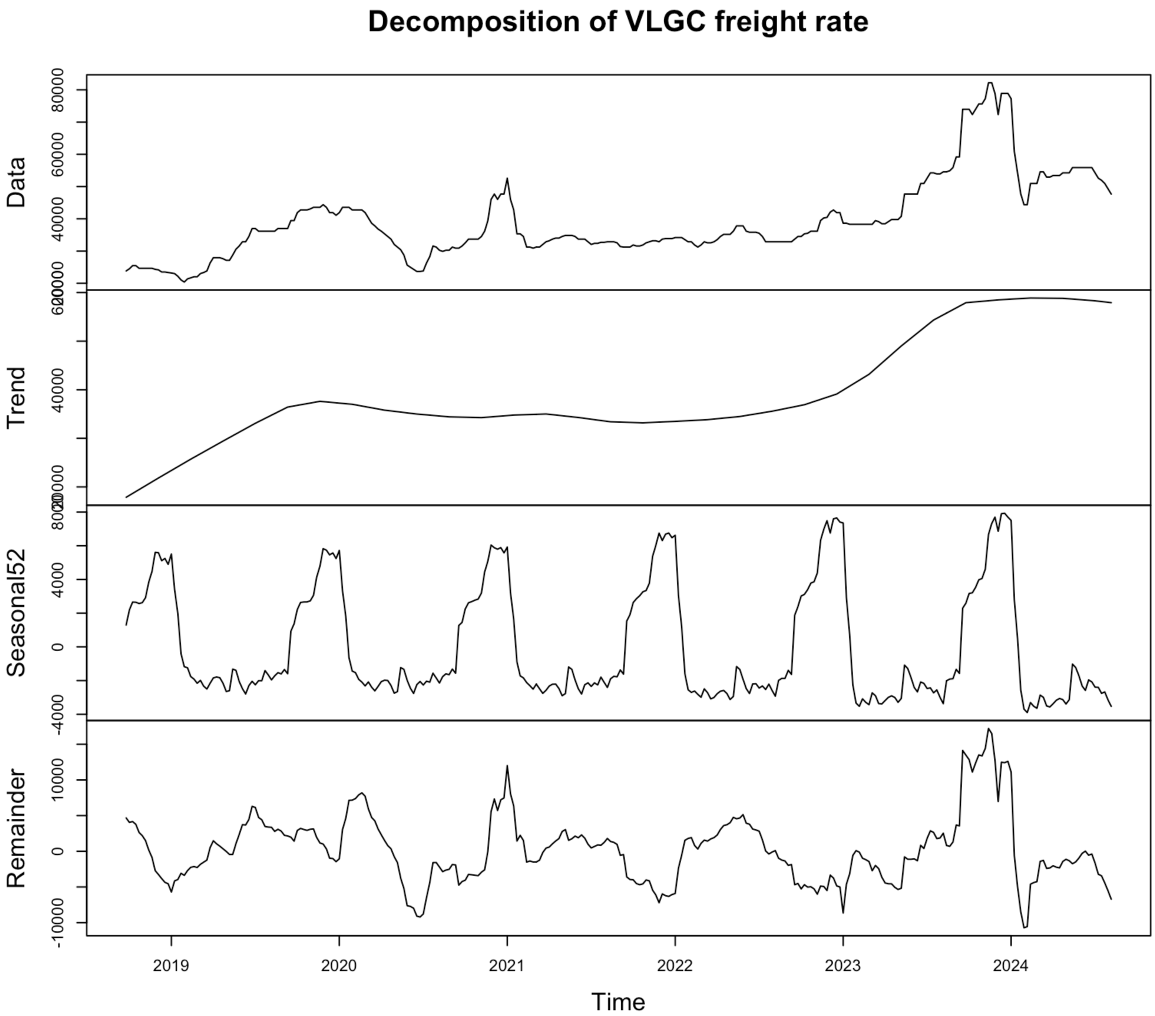

Figure 6: Decomposition of freight rate

We also notice the significant trend-cycle component of freight rate; thus, we investigate this trend compared with trending component in other variables with the correlation table shown in Table 5 below. A significant figure in correlation between charter and export proves our point that trending freight rate growth is spurred by increasingly dominant US LPG export figure that drives ton-miles demand of VLGC shipping. The clear seasonality affecting the freight rate and the clear correlation between freight rate and export justifies the filtering of freight rate to isolate the impact of Panama Canal, thus we only use the seasonally adjusted component of freight rate (*charter.adj*) and includes export variable in the model. For other variables such as price ratio and waiting times, we do not seasonally adjust those variables due to the lower power of seasonality compared to freight rate and we cannot justify what causes that seasonality.

Table 5: Correlation plot of trend-cycle components

	charter	*ratio*	*waitingtime*	*export*
charter	1.0000	-0.4134	0.3628	0.9379
ratio		1.0000	0.3727	-0.2012
waitingtime			1.0000	0.5379
export				1.0000

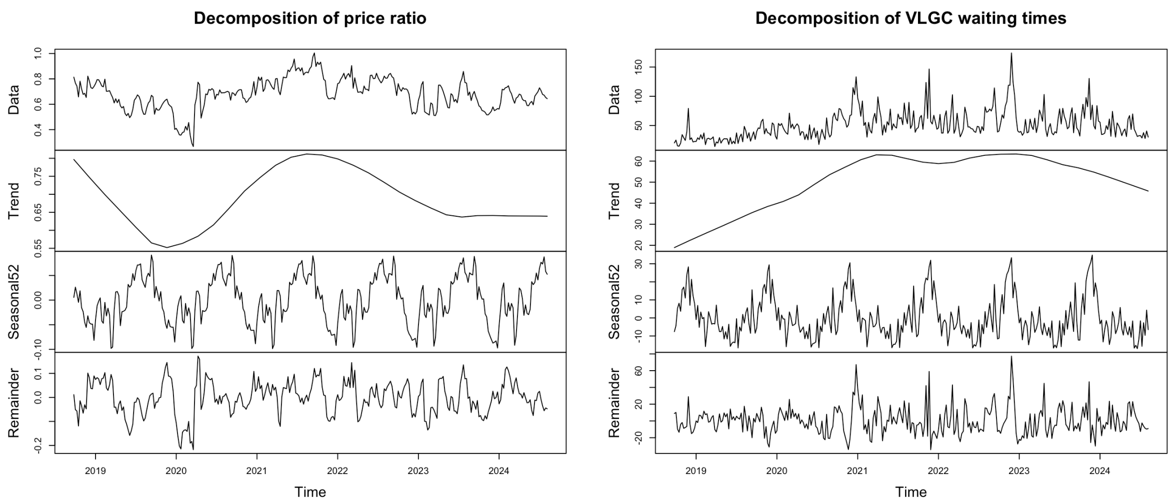

Figure 7: Decomposition of LPG price ratio and waiting times

4.3.Stationarity Tests

We test the presence of unit root of all variables used in the model using both Augmented Dicker Fuller (ADF) and Philips-Perron (PP) tests. In ADF test, lags are selected automatically using Akaike Information Criterion (AIC) to get the most suitable lags. In both ADF and PP test constant models are fitted. Critical values for 1%, 5%, and 10% for ADF and PP tests are -3.99^{*}, -3.42^{+}, -3.13 respectively. The result of both tests is presented in below table:

Table 6: Unit root testing of all variables.

	ADF test		PP test	
	Level	First Difference	Level	First Difference
charter.adj	0.23	-9.58*	1.83	-13.90*
ratio	-0.81	-12.98*	-3.96^{+}	-18.44*
waitingtime	-2.12	-17.45*	-9.04*	-30.78*

	ADF test		PP test	
	Level	First Difference	Level	First Difference
max.transit	-0.62	-16.05*	-1.65	-25.68*
export	-10.24*	-22.59*	-9.49*	-48.08*

From this tests, the main interest of this analysis mainly the freight rate of VLGCs represented by *charter.adj* and maximum transit permissible by Panama Canal Authority represented by *max.transit* which follow unit root process, where 10% confidence level is rejected in both ADF and PP tests for I(0) series yet accepted at 1% confidence level for I(1) series. For other variables such as price ratio, export, and waiting time, test results are inconclusive with different result from ADF and PP tests. As it is more prudent to assume non-stationarity even if the 1% confidence level for stationarity in is accepted in I(0), we assume that all of variables in the model is stationary only at I(1) thus all variables follow unit root process and we can proceed to build the vector error correction model.

4.4.Model Building

We continue to build the VEC model after all variables are confirmed to follow unit root model. As explained in Chapter 3, the use of VEC model to capture the long-term relationship between the variables is justified as this long-term relationship is removed in the first-difference VAR model. However, to build the VEC model we must determine the appropriate lag order. We deleted the seasonality in the freight rate through filtering, thus we do not include seasonality centered dummy variable. The result of VAR lag selection is shown in Table 7 below. As we get different results from each criterion, we choose the highest amount, thus VAR(3) is used in VECM approximation.

Table 7: Lag selection method

Lags	AIC	HQ	SC	FPE
1	26.55	26.67	26.86	3.40E+11
2	26.32	26.56	26.93	2.69E+11
3	26.27	26.64	27.20	2.57E+11
4	26.27	26.77	27.50	2.57E+11
5	26.31	26.92	27.85	2.67E+11

Table 8 and Table 9 below show the trace statistics and maximum eigenvalue of the full model obtained from Johansen LR test, where we include all variables endogenously. The result from trace statistics and maximum eigenvalue statistics indicates that the presence of 3 cointegration relations exist at 5% level. Owning to the lower power of the fourth cointegrating relations, we will assume that there are 3 cointegration relations in this model. Further, the estimated cointegrating vectors associated to the largest eigenvalue, normalized to *charter.adj* variable is shown in Table 10 below.

Table 8: Trace statistics

Hypothesis	Eigenvalues	Likelihood ratio	10%	5%	1%
r <= 4	0.0106	3.22	6.5	8.18	11.65
r <= 3	0.0509	19.04	15.66	17.95	23.52
r <= 2	0.0612	38.18	28.71	31.52	37.22
r <= 1	0.0856	65.29	45.23	48.28	55.43
r <= 0	0.2111	137.13	66.49	70.6	78.87

Table 9: Maximum eigenvalue statistics

Hypothesis	Eigenvalues	Likelihood ratio	10%	5%	1%
r <= 4	0.0106	3.22	6.5	8.18	11.65
r <= 3	0.0509	15.82	12.91	14.9	19.19
r <= 2	0.0612	19.14	18.9	21.07	25.75
r <= 1	0.0856	27.11	24.78	27.14	32.14
r <= 0	0.2111	71.84	30.84	33.32	38.78

Table 10: Cointegration relations, normalized to charter.adj

	charter.adj	*ratio*	*max.transit*	*waitingtime*	*export*
charter.adj	1.000	1.000	1.000	1.000	1.000
ratio	-7631.907	102889.163	37245.516	-126408.690	-3497.218
max.transit	-829.354	-720.390	1942.747	2023.603	-5904.666
waitingtime	481.042	-592.416	-52.698	-398.764	-401.828
export	-69.659	-55.769	4.129	-21.210	21.462

Ultimately, we calculate the coefficient matrix of lagged variables of Π in table below as the representation of the effect of cointegrating relations. Several interesting result shows. First, it is clear that the lagged value of freight rate does not contribute to other variables with a very low coefficient. Then, lagged value of price ratio is emphasized owning to the structure of the data itself, having a lower mean and variance of the price ratio. However, the coefficient of lagged price ratio to maximum transit is still very small. This trend is followed with other lagged price ratio, so we can interpret that maximum transit is a strongly exogenous variable affecting others. For the maximum transit itself, the coefficient is relatively large on freight rate but not on waiting times, so that it is not clear on the relationship between maximum transit and waiting times. Next, lagged value on waiting times has a significant coefficient to freight rate and its level value compared to others, where this is reasonable as cargo owners anticipate future waiting times thus accordingly adjust freight rate, justifying the fact. Finally, lagged export only has a significant coefficient in freight rate yet the others are negligible.

Table 11: Coefficient matrix of variables in level

	charter.adj.l3	*ratio.l3*	*max.transit.l3*	*waitingtime.l3*	*export.l3*
charter.adj.d	-4.17E-02	-9.20E+02	2.21E+01	-9.05E+00	1.76E+00
ratio.d	-8.62E-08	-1.12E-01	1.46E-04	3.33E-05	-2.71E-07
max.transit.d	-4.40E-05	-4.08E-01	-7.08E-02	-3.75E-03	5.40E-04
waitingtime.d	-7.24E-05	1.63E+01	6.20E-01	-3.70E-01	2.11E-02
export.d	6.72E-03	5.50E+01	-6.80E+00	1.20E+00	-5.32E-01

4.5. Response Analysis

We calculate the response of freight rate to various shock in maximum allowed transit, price ratio, export, and waiting times as our objective is to quantify the impact of drivers to the VLGC charter rate. Furthermore, we also calculate the impact of maximum transit to the waiting times of VLGC in the Panama Canal, as waiting times could be a good proxy to approximate the impact of transit disruption in VLGC freight rates. As our main focus, the response of freight rate is shown in figures below while the full IRF figures is shown in Appendix 2.

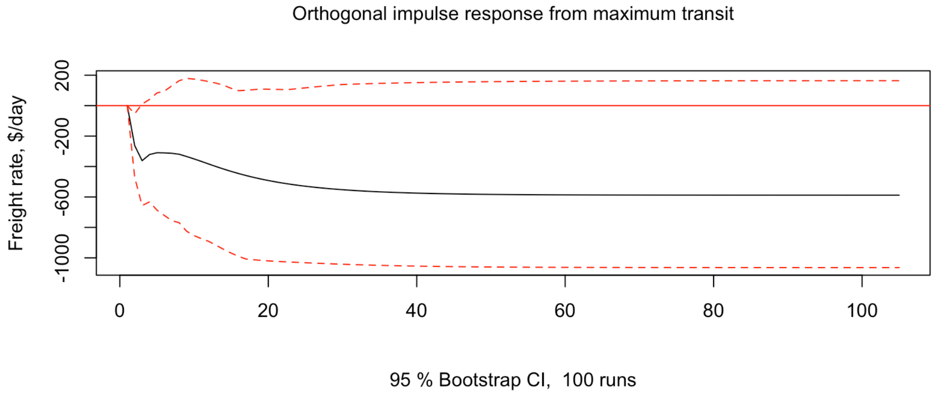

Figure 8: Response of freight rate due to shock on maximum allowable transit

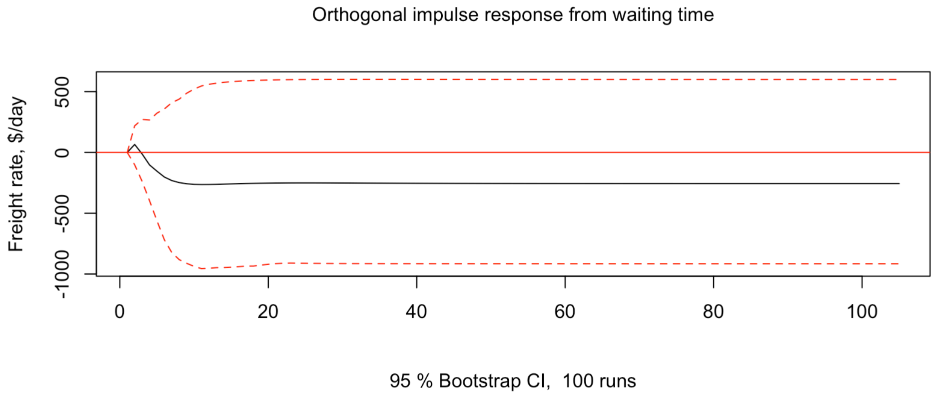

Figure 9: Response of freight rate due to shock on waiting time

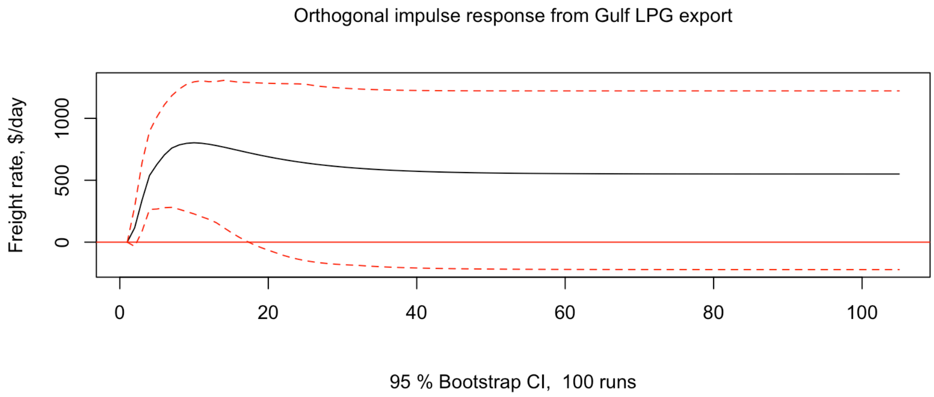

Figure 10: Response of freight rate due to shock on export

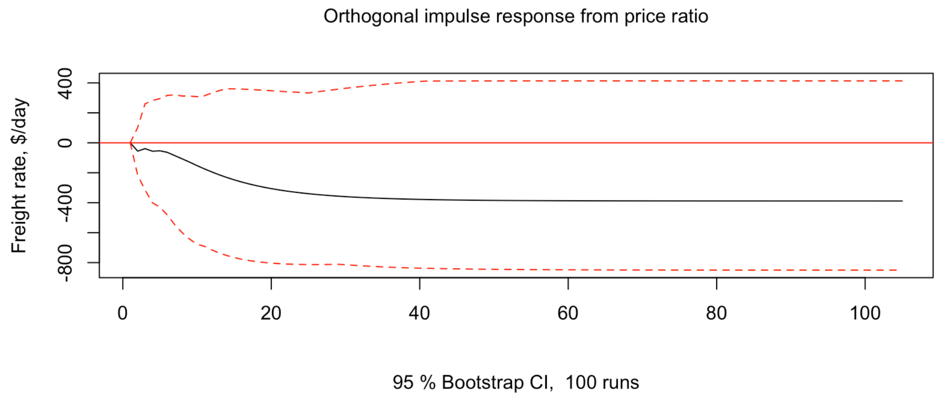

Figure 11: Response of freight rate due to shock on price ratio

The results of maximum allowable transit, price ratio, and export show a predictable pattern. First, all figures shows that a shock in other variables impacted freight rate in the long run. A shock in the transit availability of Panama Canal indicated by increased transit slot by 1 unit immediately decreases freight rate by 380 dollars, tapers down and decrease it over time by 500 dollars per unit increase. The impact of increasing price ratio means that US LPG price is strengthening, decreasing the demand in price arbitrage and encouraging Saudi LPG producers, decreasing ton-miles demand and in turn price by 300 dollars per unit percentage of price ratio. In contrast, increasing US export increases freight rate as more LPG volume being available and increases demand in LPG transportation, stabilizing at 550 dollars per thousands of barrels increase in export. An interesting result exists in waiting time, however, as an increase in waiting time results in a minor increase freight rate for a brief moment, yet in the long run it depresses freight rate. We propose that this phenomenon happen due to unpredictability in the Panama Canal transit time, which waiting time takes a large portion. In the short time, unpredictability in waiting time increases thus in turn also increase the freight rate. In longer term however, the longer waiting time is priced-in and cargo owners are less willing to pay for transport when transit time is predictable. It should be noted that we do not perform a structural analysis of variables in economic terms, and this indication is purely due to statistical properties of both variables.

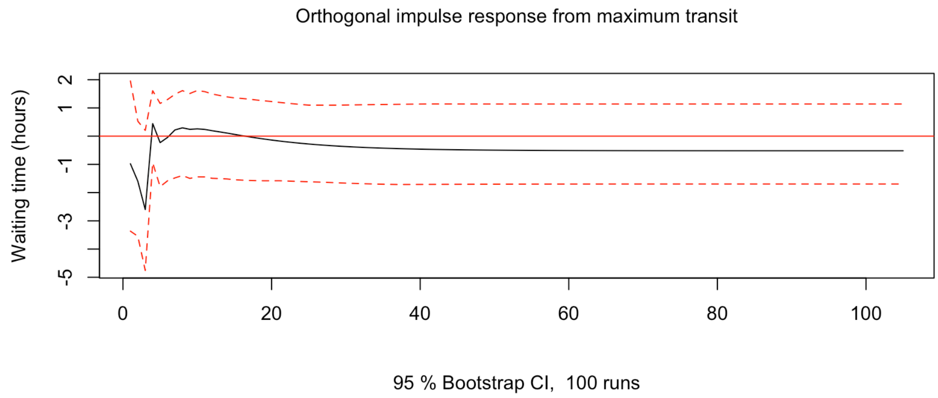

Figure 12: Response of waiting times from shock in maximum transit

As a further consideration, we also analyzes the response of waiting time from the increase of maximum transit, shown in the Figure 12 above. We notice that the response is instant, which is reasonable as the increase of Panama Canal transit booking slot immediately decreases average waiting time by 1 hour. For a short period, however, there is a positive response in waiting time that is affected by increased transit. This shock might stem from the increased amount of ships choosing to use Panama Canal for its transit while bottleneck cleared and shipowners can afford the waiting times. In the long run, the impact of increased transit decreases waiting times slightly as we expect. Ultimately, this decision-making process by shipowners in taking longer time to transit through Panama Canal or take the longer way around might be key aspect in determining the freight rate of VLGCs in case of Panama Canal that is not captured by waiting time and maximum transit figures alone.

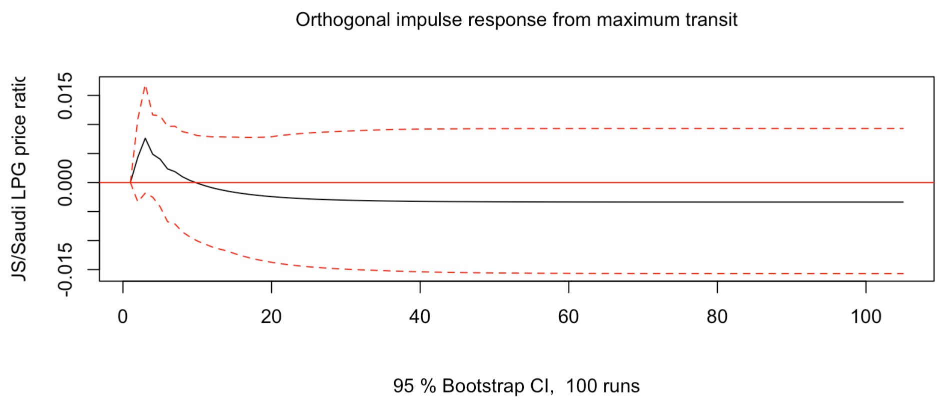

Figure 13: Response of price ratio to maximum allowed Panama Canal transit

Other significant response figure comes from the Panama Canal transit figure impact to price ratio as shown in Figure 13. As we note previously that LPG production comes from byproducts of oil refinery and gas recovery while LPG products is not commonly stored, we derive conclusions on US LPG prices assuming Saudi prices are constant. In the short term, price of US LPG soars indicated with higher ratio as the shipping supply becomes available on the increasing slot availablity to transit Panama Canal, putting pressure in limited stock of LPG available in the US while trading companies rushing in to exploit arbitrage price. However, in the long run negative response is present on US LPG price due to increased traffic. We deem this relationship reasonable, however structural analysis to determine the underlying economic process is still required.

Chapter 5. Conclusion and Recommendation

5.1. Conclusion

LPG held promise in decarbonization efforts especially for its role as feedstock for lower emission fuels. Further demand growth in LPG is driven by government-led efforts to replace biomass with containerized LPG for home-cooking purposes, which is especially prevalent in Asia and increasingly Africa. Unequal distribution of LPG and concentrated market should put the emphasis in understanding market dynamics of LPG transportation by stakeholders in this industry, however currently scarce literature is found.

Previous research such as Adland et al. (2008), Engelen et al. (2011), and Engelen & Dullaert (2012) have found significant results in the underlying properties of VLGC freight rates, while Bai & Lam (2019a), Michail & Melas (2022), Bai et al. (2022) investigates the effect of different drivers such as geopolitical stability, price arbitrage, and port congestion. However, as one of the main bottlenecks in shipping directly impacting major LPG routes which is US Gulf to East Asia, we found the impact of Panama Canal disruption has not been investigated yet. The impact of Panama Canal disruption to VLGCs is particularly important owning to the increased dominance in US-produced LPG, the threat to Panama Canal operation from unstable weather pattern stemming from climate issues, and the importance of VLGC market sector in LPG transportation due to scale economics.

This thesis addresses the literature gap on the impact of Panama Canal disruption to VLGC market by answering the stated research question and sub-research question in the following section. It should be noted that the results presented comes from statistical properties in the model used, however we are confident that we have captured a sufficiently large part of the underlying economic process. Initially we will answer the sub-research question, and at the last part the main research question will be answered to address the literature gap.

Sub-research Question 1:

To what extent does waiting times in Panama Canal be affected by transit limitation?

Answer:

Through the analysis of waiting time response from a shock in transit figures, we conclude that transit limitation presents a direct impact by increasing waiting time heavily in the short period. Assuming the IRF is symmetric, the response of waiting time due to reduction of transit slot by 1 unit in 2-month period is shown in table below:

Table 12: Response of waiting time from unit decrease in maximum transit

Week	0	1	2	3	4	5	6	7	8
Waiting time (hrs)	0.98	1.60	2.60	-0.45	0.23	0.04	-0.22	-0.29	-0.24

As the decrease in Panama Canal transit has happened gradually and only a short term lapsed during the transit limitation, the complete picture might only be accurately concluded by a queueing model. However, by statistical properties alone, we can observe the immediate increase and delayed peak of waiting time due to limitation in Panama Canal transit while the reverse occurs 8 weeks after the limitation. We propose that this behavior emerges due to adjustment in shipowners' expectation on Panama Canal condition. In the long run, waiting time will increase slightly.

Sub-research Question 2:

To what extent does the freight rate of VLGCs be affected by seasonal fluctuation?

Answer:

From the timeseries decomposition, we can clearly observe seasonality in the VLGC freight rate that coincides with the marked increase of LPG demand at the end of the year. The clear seasonality is observed in the decomposition of freight rate time series shown in Figure 6, while both plot of level and seasonally adjusted timeseries are shown below. We observe that seasonality component enhances the intensity of freight rate surges due to stochastic events, as the case in late 2020 and late 2023. This enhancing property of seasonality component in freight rate justifies our method to seasonally adjust the freight rate data in our model, using only trend-cycle and remainder component to analyze the impact of Panama Canal restriction.

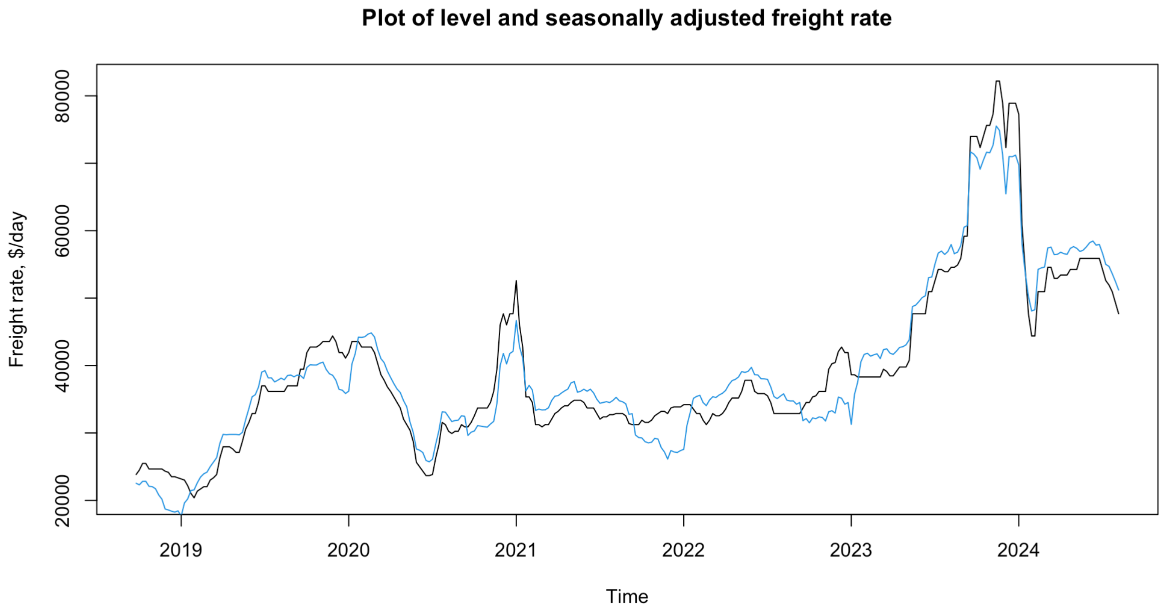

Figure 14: Plot of level and seasonally adjusted VLGC freight rate.

Note: black: level, blue: seasonally adjusted

Sub-research Question 3:

To what extent does LPG production trend affect the freight rate for LPG shipping?

Answer:

We investigate the relationship between US LPG weekly production figure and VLGC freight rate growth. We found that trend-cycle components of US LPG export and freight rate correlates significantly with the value of 0.9379. In this case, we confirm the notion that US dominance in LPG production drives the ton-miles demand of LPG shipping, which in turn drives freight rate upward. Thus, we justify the inclusion of US LPG export figure in our model to better capture this phenomenon as US Gulf to East Asia VLGC routes are one of the main users of Panama Canal.

Main Question:

What is the magnitude of the effect of sustained Panama Canal transit limitation to the VLGC time charter freight rates?

Answer:

From the impulse response function of freight rate from the shock of maximum transit, we clearly observe the delayed decrease of freight rate when transit increased. Assuming the symmetrical response, in return the transit limitation also increases freight rate in the long run. This response over time of freight rate due to the unit limitation in maximum transit is shown in table below. We found that response stabilized on 52-week mark, with the freight rate increased by 584 $/day for each reduction of Panama Canal transit slot.

Table 13: Response of freight rate in unit transit limitation

Week	0	1	2	3	4	5	6	7	26	52
Freight rate $/day	0.0	262.3	361.6	321.2	309.4	310.5	312.9	319.6	534.97	584.00

While this figure is relatively insignificant in the scale of VLGC freight rate that ranges around 20,000-80,000 $/day, climate-induced Panama Canal transit limitation as happened in 2023 could increase VLGC freight rate by 14,000 $/day assuming linear relation and transit limitation is sustained in the long run. The impact of the freight increase is not attributed only to transit limitation, however, as price ratio is also impacted by transit limitation, and we already acknowledge the effect of price arbitrage to freight rate. The full structural analysis of the VLGC freight rate dynamics pertaining to Panama Canal transit limitation affected by climate change remains to be seen.

5.2. Research Limitations

Although the results are reasonable, we acknowledge the limited ability of impulse response functions to explain the impact of Panama Canal limitation to VLGCs freight rate without building a structural VAR (SVAR). The usage of only waiting times and maximum transit as a proxy to Panama Canal transit limitation need to be further assessed, as waiting time could be better modelled by a queueing model and there could be other variables that could be included to explain the jump in VLGC freight rate. Finally, the abnormal freight rate in late 2023 coincides with both Panama Canal and Suez Canal transit limitation, we only model one part of the dynamics of LPG trading routes, thus this thesis assumes Suez Canal operating normally during Panama Canal disruption.

5.3. Recommendation for Further Research

The impact of Panama Canal limitation to VLGC freight rate could be pinpointed by building a SVAR model as the natural next step of this research. To better capture the dynamics of waiting times in Panama Canal, one could use queueing model and assess the impact of waiting times explicitly to freight rate of VLGCs waiting for transit slots in Panama Canal. Other suggestion is to model Panama Canal and Suez Canal transit limitation together, such that the surge in freight rate could be pictured as the effect of global disruption, affecting multiple routes of LPG trade.

Appendix 1: Plot of Level Timeseries

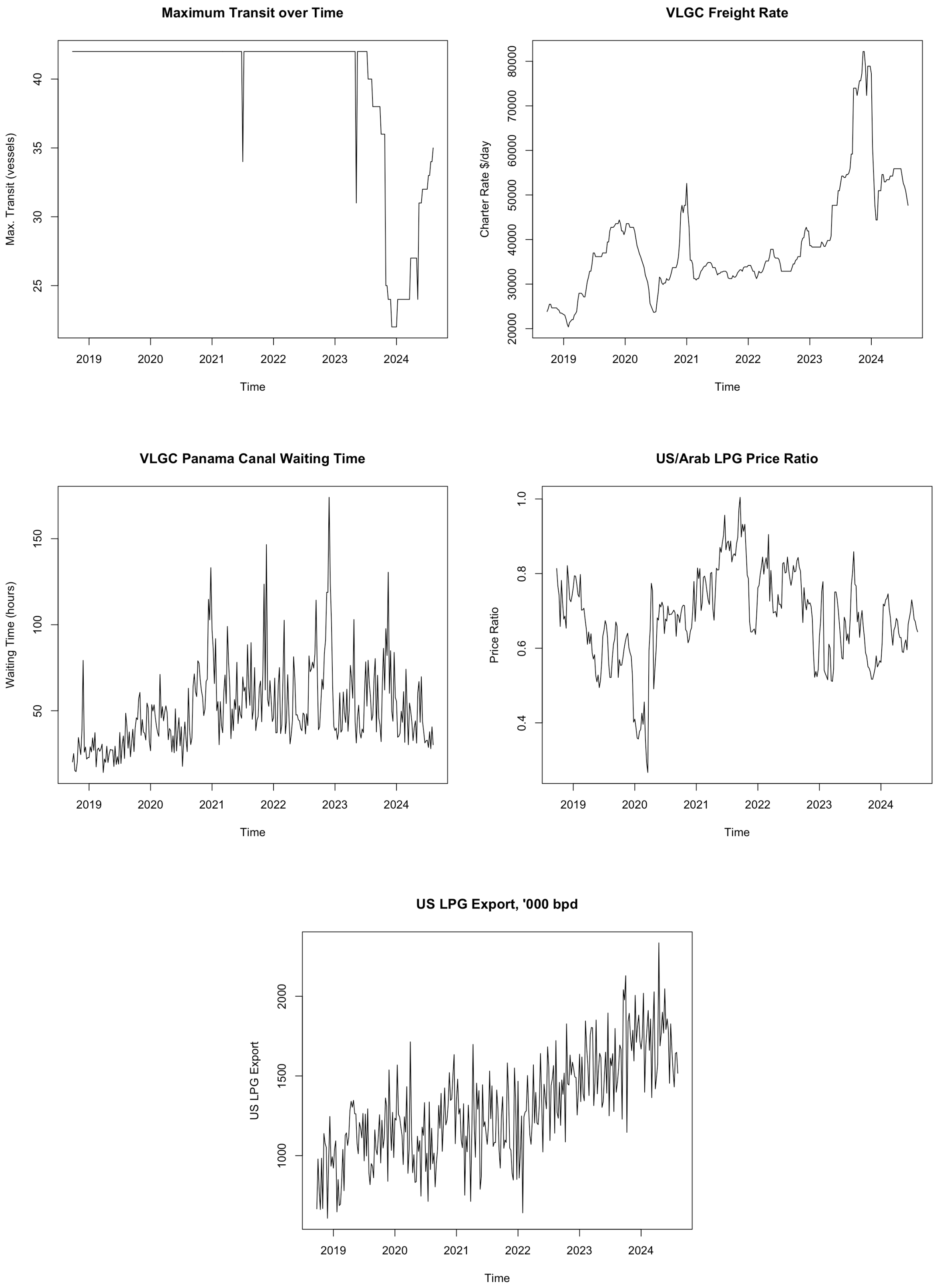

Figure 15: Plot of timeseries used in the model

Appendix 2: Impulse Response Function plots

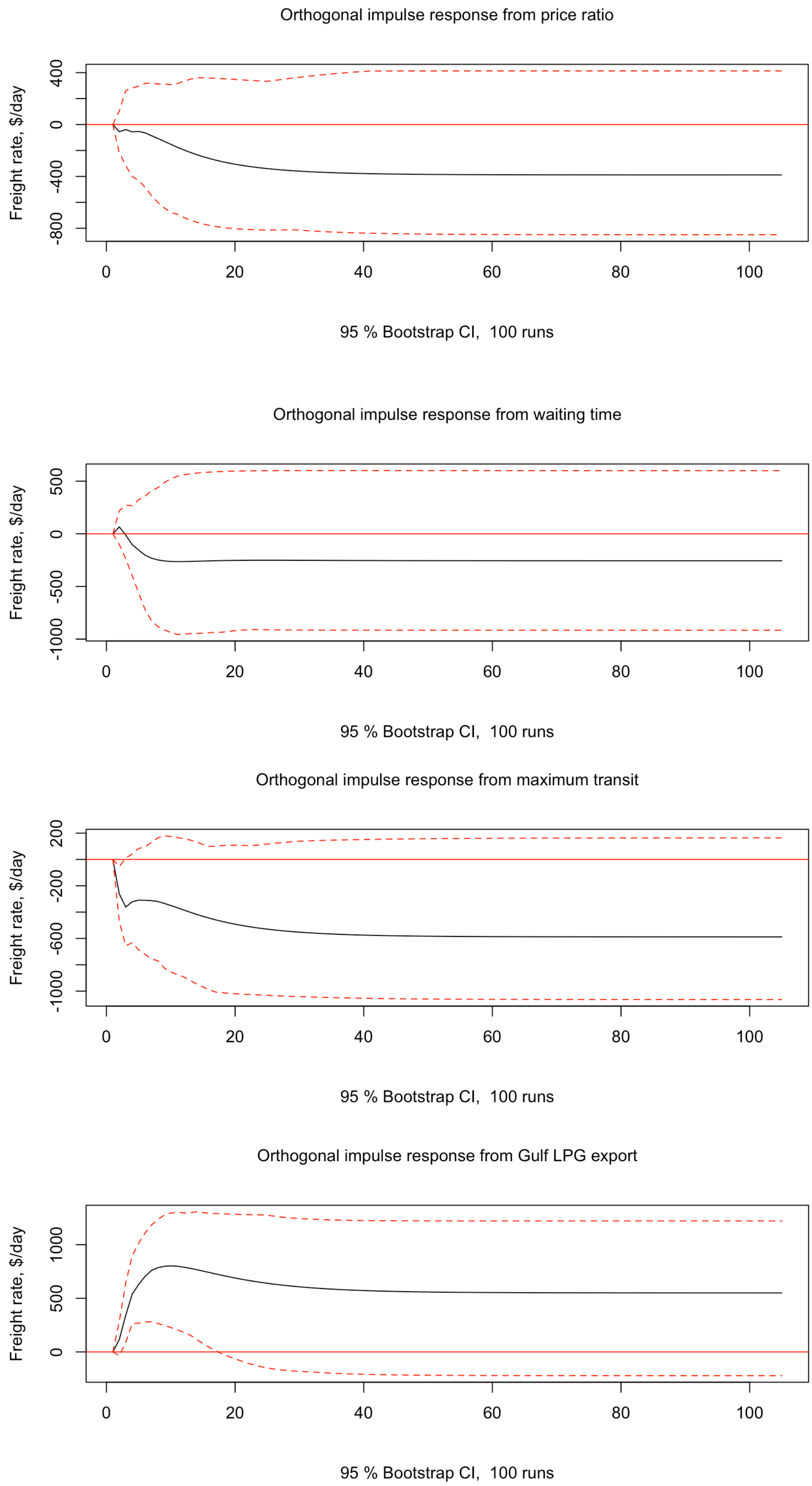

Figure 16: Freight rate response plots

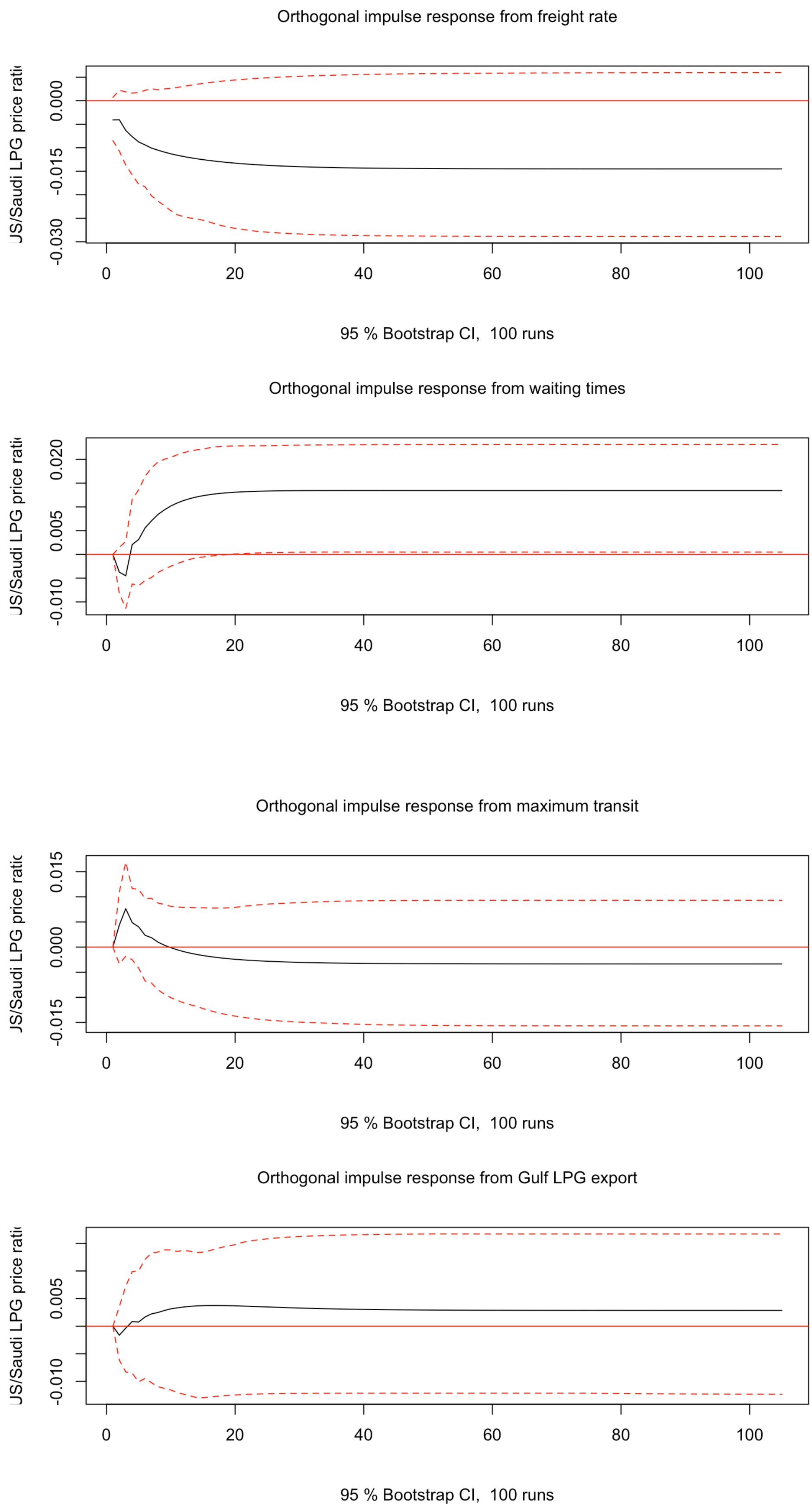

Figure 17: Price ratio response plots

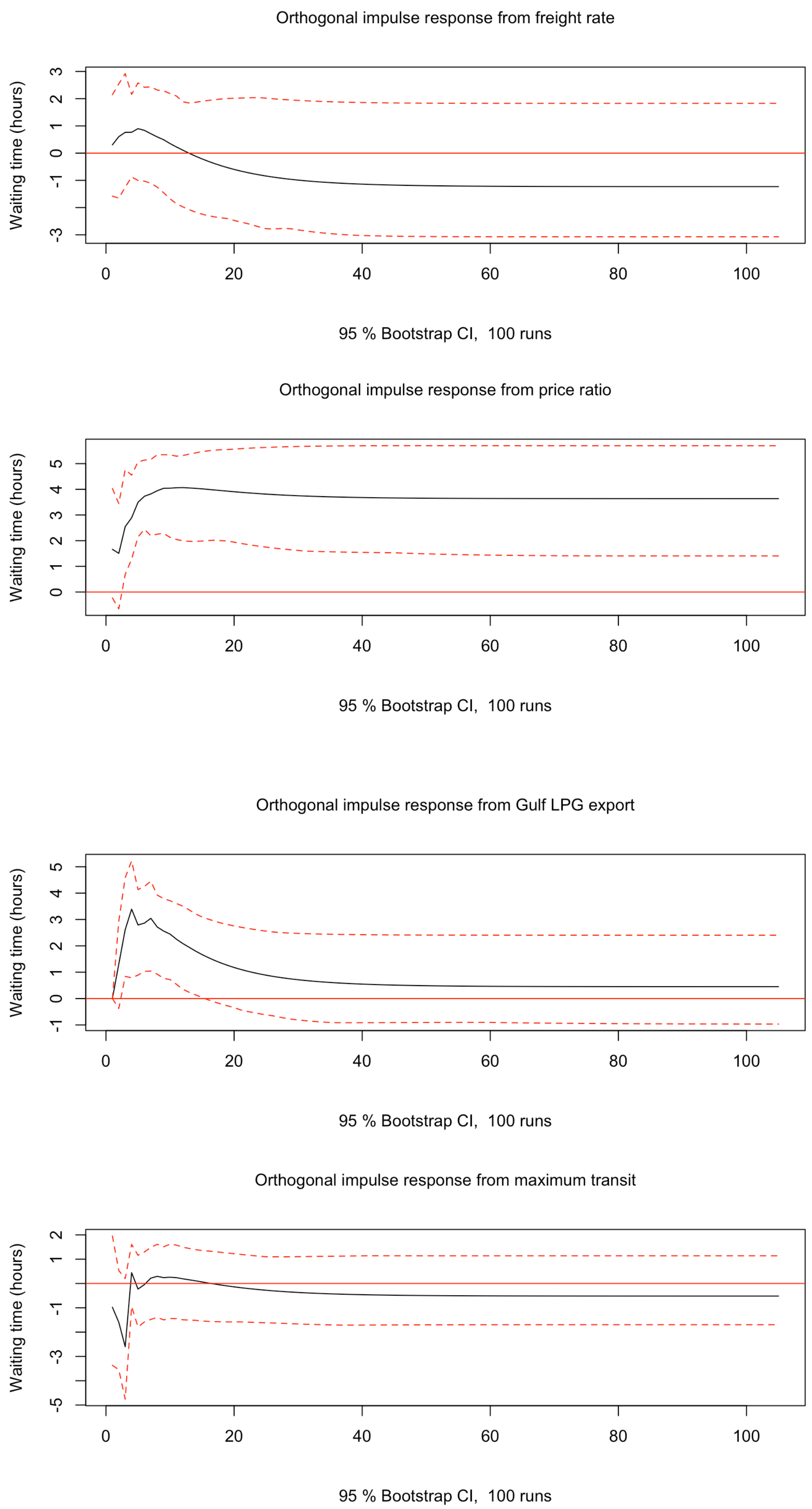

Figure 18: Waiting times response plots

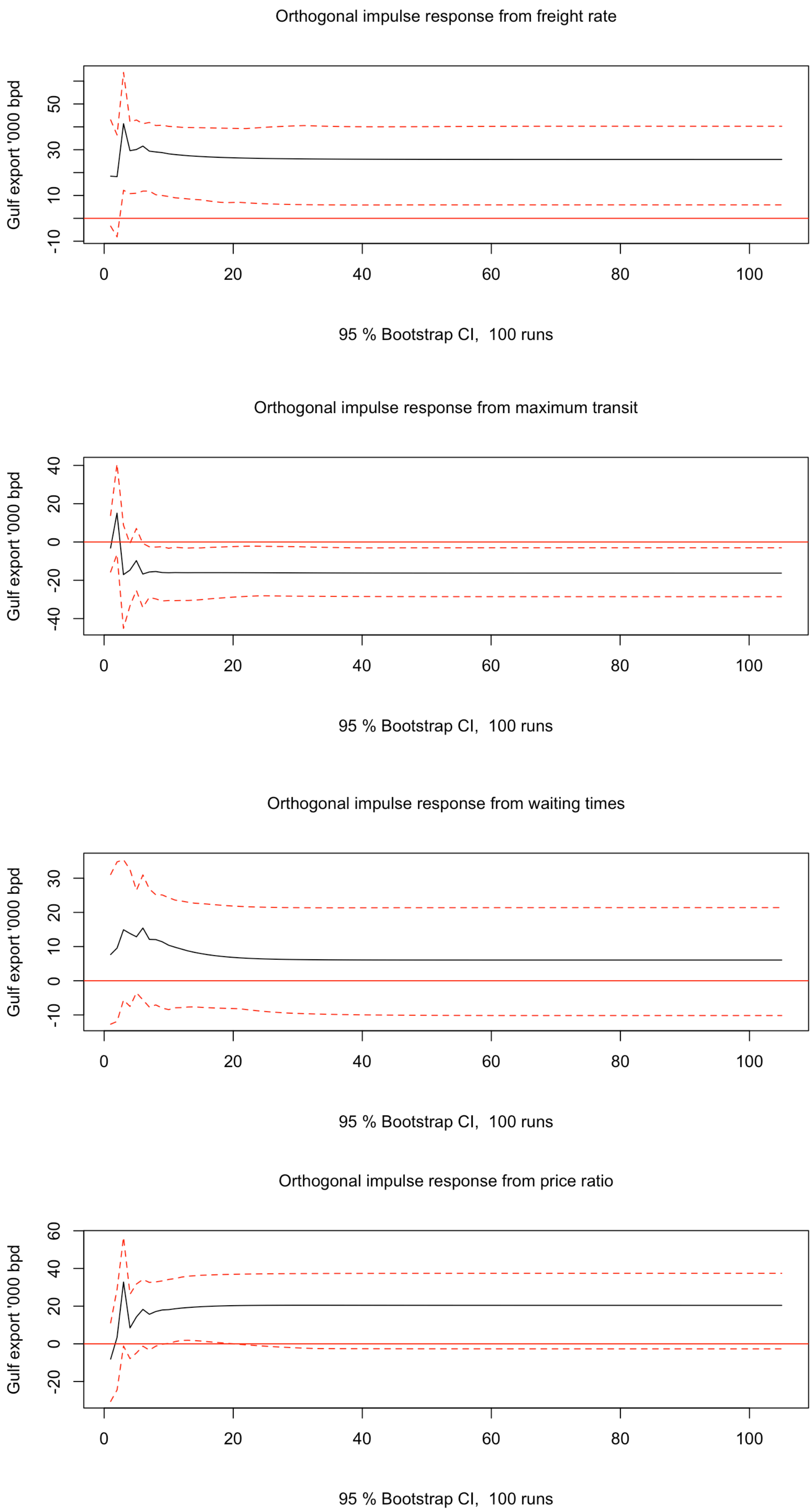

Figure 19: Export figures response plots

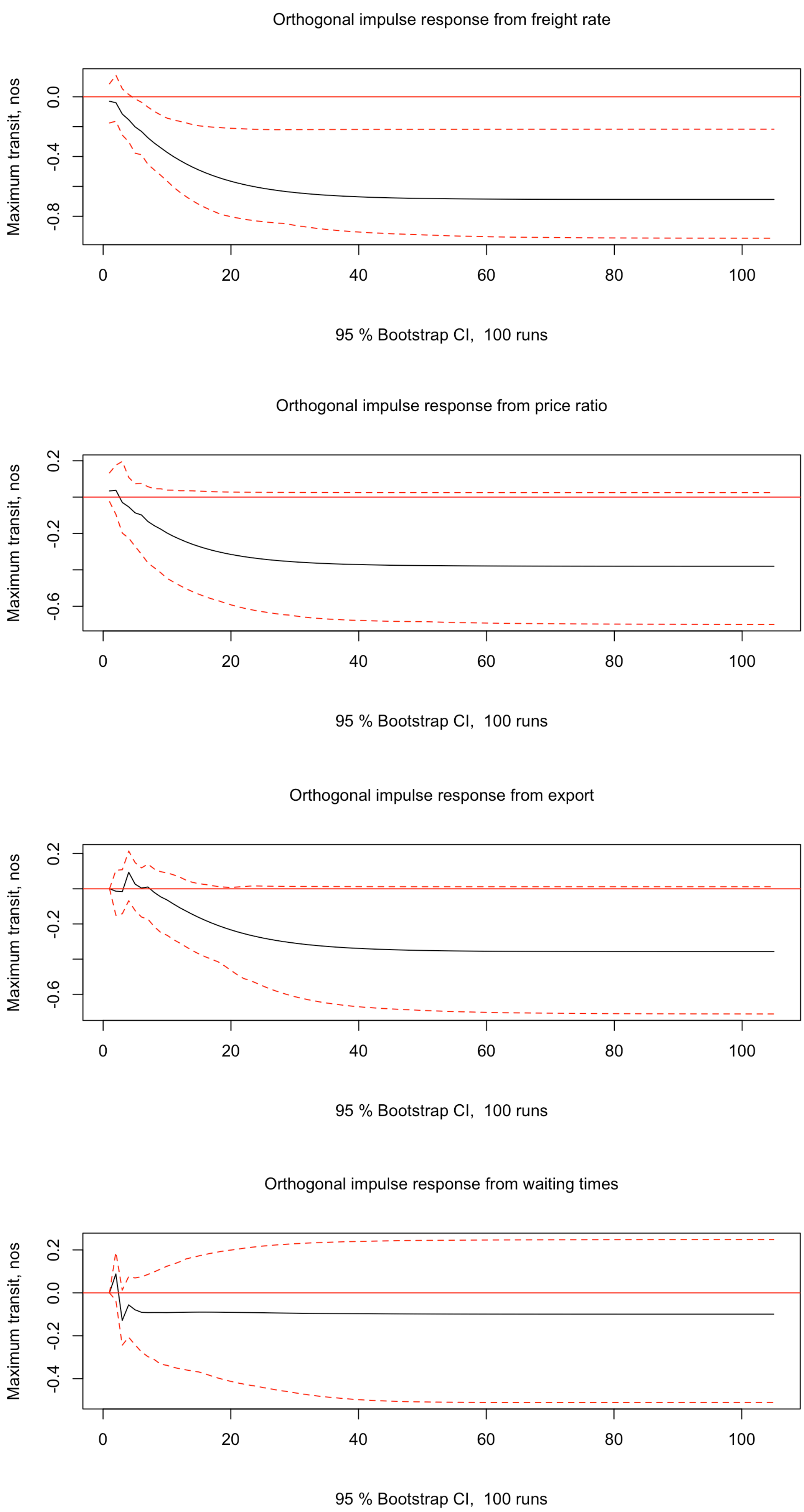

Figure 20: Maximum transit response plots

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