MASTER OF SCIENCE (MSc) IN **INTERNATIONAL SHIPPING, FINANCE & MANAGEMENT**

CONTAINER FREIGHT RATES IN RELATION TO CONSUMERS' SENTIMENT AND PURCHASING POWER

By

KILIMANTZOS STYLIANOS & KOLLINTZA FOTEINI

A Thesis submitted
to the Secretariat of the MSc in International Shipping, Finance and Management
of the Athens University of Economics and Business
as partial fulfillment of the Requirements for the Master's Degree

Athens

31st October 2020

We approve the Thesis of Kilimantzos Stylianos and Foteini Kollintza

DIMITRIOS A. TSOUKNIDIS [SIGNATURE]

………………………………………… ……………………

MANOLIS G. KAVUSSANOS [SIGNATURE]

………………………………………… ……………………

LEONIDAS S. ROMPOLIS [SIGNATURE]

………………………………………… ....…………………

CERTIFICATION OF THESIS PREPARATION

“We hereby declare that this particular thesis has been written by us, in order to obtain the Postgraduate Degree in International Shipping, Finance and Management, and has not been submitted to or approved by any other postgraduate or undergraduate program in Greece or abroad. This thesis presents our personal views on the subject. All the sources we have used for the preparation of this particular thesis are mentioned explicitly with references being made either to their authors, or to the URL’s (if found on the internet).”

KILIMANTZOS STYLIANOS [SIGNATURE]

……………………………………………………… ………………………

KOLLINTZA FOTEINI [SIGNATURE]

……………………………………………………… ………………………

Acknowledgments

We would like to express our gratitude to our Professor and Supervisor, Mr. Dimitris A. Tsouknidis who gave us the opportunity to undertake this fascinating and innovative project on investigating “Container Freight Rates in relation to Consumers’ Sentiment and Purchasing Power”. His assist and guidance throughout the research and composition of this Thesis was of the outmost importance.

We would also like to thank the Laboratory for International Shipping, Finance and Management of the Athens University of Economics and Business for accessing its databases and collecting valuable data for our analysis.

Table of Contents

Abstract

This dissertation provides an econometric analysis of the effect of consumers' sentiment and power, as a demand factor, towards the freight rates of the containership market. It starts with a description and general information about the characteristics and the unique nature of maritime industry and especially focusing on the importance and characteristics of the container ship sector which is the topic of this thesis. What is also discussed in an introductory level is the imperative need of understanding the changes and possible fluctuations in containership freight rates. Subsequently, the thesis continues with a few words about the factors chosen to be examined as parameters possibly affecting the rates in question, and the way the model was constructed as a reasonable consequence of several econometric equations. There could not be found any previous research on models examining whether the consumers' sentiment or disposable income are related to the pattern that freight rates follow, and if affirmative, in which way, hence this intends to be an original examination. The results derived from our model and the regressions that we run, bring a turnover to what we believed would affect the development of freight rates, and give us significant indications about only a few of our variables which potentially relate to the freight rate changes. In other words, it appears that containership freight rates are rather independent from consumer's willingness to buy and consume final products; hence the formation of the rates is probably a result of more powerful factors.

Key Words: Containership Freight Rates, Consumer Sentiment, Consumer Confidence, Ordinary Least Squares (OLS), Consumption, Time series

Section 1: Introduction

Maritime transport is considered to be the backbone of globalization and a major skill game that enables international trade, a field that has significantly evolved during last decades. The volume of seaborne trade accounts for about the 80% of the total merchandise trade according to UNCTAD's latest Review of Maritime Transport and thus it can be stated without exaggeration that the economic development of the world is reflected at the freight rates.

1.1. Containerized Trade

Containerized trade is measured to be around 17-18% of the total seaborne trade and ensures the efficient flow of manufactured products from producing sites to consuming markets. Its value is more than half of the total value internationally transported through maritime industry, indicating the influence and the impact the development of containers' system has on world economy. It is a sector that appears to be continuously increasing over its short history. During the recent years, container ship market has earned a significant share in global trade which keeps growing. At the same time, statistics show that the ownership of six out of the top ten global container ports with the highest throughput is Chinese and it would be worth highlighting that all ten of the list are located in Asia. Nowadays, one of the most representative features of the port-operating landscape is the high competition among shipping companies, which is enhanced rapidly by the formation of shipping alliances who play a decisive role in the industry and can even determine the future of a container port terminal by their strategic decisions (S.Caschili and F.R. Medda, 2011). An additional characteristic is the high production of goods in Eastern Asia, which, combined with the increased demand and consumption met in Europe and North America, has led to an expansion of the trade lanes from Eastern Asia to these regions. While the geographical position of each country, as well as the distances among them are granted, liner shipping connectivity can bring them together from the perspective of meeting and matching the different needs of demand and supply. Over the years, maritime shipping tends to obtain a more regional dimension, and although in the past there was a strong relation between the basins of Europe and Asia, nowadays, as also recognized and explained in an article published in the "Global Networks" (C. Ducruet & T. Notteboom, 2012) the increase that Asian basins witness in the volume of goods shipped had as a consequence the splitting of the links between Asian and European countries, reinforcing the internal connectivity of each regional basin. Aforementioned connectivity is being enhanced not only by all the technological means that are available but also by the port operators who aim to meliorate ports' performance. Furthermore, reduction or even elimination sometimes of trade barriers and the opportunities of low-cost producers of consumer goods contributed to this development of container trade which is correlated to the aggregate movement of shipping industry. Containerization is not just a global trend but rather a technological improvement where digitalization plays a key role not only due to the need for unitization of cargoes, improvement of cargo handling efficiency and for other factors which have led to the reduction of cost of international trade and the decrease in the transportation cost, but also because it upgraded the speed and the time period required for transportation, making this way shipping of transported goods more feasible.

1.2. Freight Rates as the outcome of the demand and supply game and their relation to consumption.

It constitutes general knowledge the fact that shipping is a derived demand which means that maritime industry is driven by the forces of several demand and supply factors in a global scale. Notably, research concerning all shipping segments has evidenced that freight rates are driven by the forces of the demand and supply game which is regulated by the use of different and various economic mechanisms. While supply is mainly an endogenous factor, demand is quite exogenous and derived from the need for the transported good itself. What is more, we should bear in mind that there are many other factors affecting container shipping freight rates and which cause price fluctuations and seasonality. The existing literature has made some important steps to study and econometrically analyze the formation of container shipping freight rates and how they are constructed, yet no such effort has been made to relate them with consumers' purchasing power. Focusing on the side of the demand and specifically on the demand arising from the final receiver of the products transported, i.e. the consumers, an assumption could be shaped that factors affecting consumers' demand for products - such as their income or their confidence about the future developments of the economic scenery, finally affect the freight rates as well. Consumption which leads to import of consumer goods, is built on income and is affected also from world GDP which is by definition the spending sum of consumers. Therefore, it is worth to examine whether seaborne trade is also influenced, by extension, by the income and more specifically if this also stands for the containership market that transports such goods. One of the best ways to measure purchasing power is by comparing prices to Consumer Price Index (CPI), a price index that designates γconsumers' ability to buy, also known as Cost of the Living Index in the US and which is globally one of the most important and observed national economic statistics.

1.3. Factors that affect Consumer Behavior

Consumers' behavior can be severely affected from a lot of factors such as age, preferences, education, unemployment, expectations, general economic situation and related projections and of course, income. The latter is related to consumers' purchasing power.

Purchasing power is, as defined by Cambridge, the value of money considered as the amount of goods it will buy. It is the value of a currency described in terms of the amount of assets or services that a unit of money can purchase at a certain point of time and could be also determined as the buying power of a currency. It has an impact on every aspect of economic studies and this also includes the capability of consumers to buy assets –consumers' purchasing power. This amount of goods that could be obtained can be decreased as inflation increases. As a result, prices are increased and the value of a currency's purchasing power is reduced leading to higher cost of living, increased interest rates and to a series of factors that could create negative economic sequences. Nowadays, globalization constantly increases more and more and different currencies are highly linked and interdependent to each other. Therefore, governments' financial policies aim to control inflation and central banks to apply regulations and other mechanisms in order to protect the purchasing power of the currency as well as to maintain prices stable but can also cause loss of purchase power due to unfavorable decisions. When prices fall, consumers gain purchasing power and the opposite takes place when prices rise. Consumers may also gain purchasing power through technological innovations and containerization's evolution and its cost efficiency system is such as mentioned earlier.

Shipping magnifies the trade of the commodities, and this is also the case for containers. Since we are interested in the need for goods, and container sector transports manufactured products of extremely high value –in some cases even higher than the value of the vessel, we should also care about the capability of consumers to obtain these goods and how this is affected by seasonal, geopolitical and other factors. Despite the fact that in vessel types other than the container ships it is quite common to check the obvious relation between freight rates and the price of each respective commodity - perhaps due to the homogeneity of the dry bulk and oil segments cargo, this is not always the case for containers, as containerships carry final goods/merchandise products, not raw materials. The demand for these goods is inseparably connected with the ability of consumers to purchase them and as a result, with consumers' per capita income. This relation of the containers' freight rates to the consumers' purchasing power is an issue that has not been analyzed to a great extent, yet should be due to the constantly growing tendency of consolidation and the technology evolution which requires new products in massive numbers to be produced and transported via containers. As some changes at the dynamics of trade may occur in the near future and emerging economies could turn into key players, it is extremely important for both owners and charterers -but for producers and consumers as well- to study on the connection mentioned above, in order to visualize, plan and construct their strategic moves. Although freight rates have been connected to the GDP cycles, there is no research to advise whether container freight rates are related to consumers' purchase power. In respect of the above, the purpose of this thesis is to examine the container freight rates and how same fluctuate overtime, in relation to the purchasing power of the consumers of the countries that consist the majority of the final receivers of manufactured products.

Apart from the income itself, another factor affecting the demand, which is of utmost importance, is consumer's expectations. In the world of economics, it is widely accepted as principle that consumers' psychology and expectations about the economic developments, their individual income, the general financial situation or the possibility either of employment or unemployment, has a tremendously high impact on consumer's decision and on demand overall. Given that demand is inextricably linked with product prices, and consumers' confidence is also well linked with the demand, inferentially we could form the assumption that consumers' confidence is finally linked with the prices. In containership market, this would mean the assumption that freight rates are affected by consumer's sentiment and expectations. This interpretation will also be examined, actually as the main core of this thesis.

The analysis of subject topic could be of great interest, not only on an academic level, but also for those either intrigued by or involved in shipping. Understanding the relation (if any) between the previously mentioned factors and the freight rates - and the pattern that they follow, could contribute to forecasts on how the containership freight rates would react or adapt depending on economic changes or consumption behavior. In a more advanced level of research, such an examination could potentially help controlling freight rate fluctuations, an accomplishment which could be beneficial for traders, charterers, ship owners, and so on.

Taking all the above into consideration, we believe that subject proposal is original and quite innovative, hence really interesting to explore in-depth.

The remainder of the paper is structured as follows: Section 2 presents the relative literature review on the subject topic. Section 3 analyzes in detail our dataset, its sources and any limitations regarding the data employed. Section 4 describes extensively the methodology approach followed for our analysis and model specifics. Section 5 displays the empirical analysis, the main results of our model, as well as the validation of the results generated. In Section 6, we discuss and elaborate on the results found and in Section 7 we conclude our Thesis and recommend possible options and factors for further analysis on the topic examined. Finally, Sections 8 and 9 include the references and the appendix of plots and diagrams.

Section 2: Literature Review

The existing literature is rather poor not only as far as our topic is concerned but also for the economic modeling of the container market. As a matter of fact, the majority of the papers examining shipping freight rates do not include container freight rates and one significant reason could be the fact that container market is a non-perfect market (Sys, 2009). Researchers have not dealt specifically with the examined certain issue but are limited either to study containers' freight rates or the purchasing power of consumers separately.

Today, freight rates are commonly denominated in a single –base rate- price per container (Slack and Gouvernal, 2011) mostly determined by the origin and the destination of the cargo and not based on the value of the transported goods and which is subject to Surcharges and Bunker Adjustment Factors set by the carriers (Wang et al, 2011; Notteboom and Cariou, 2013). This basic rate can be also subject to special requirements of a particular client. In the container sector, freight rates directly influence the strategic decisions made by shipping lines and have an impact on the international trade. Container shipping market is described by a high level of concentration as a few global alliances control the biggest part of the market share reminding more an oligopoly market (Sys, 2008) yet UNCTAD supports it is closer to a monopoly and small players are quite vulnerable. According to a research conducted with respect to "The Maritime Container Shipping Industry As a Complex Adaptive System" (S.Caschili and F.R. Medda, 2011**),** freight rates and shipping company tariffs are mainly a result of such collaborations and alliances and, in addition to that, such international economic alliances are mirrored in trade agreements, processes and routes. Following the guidelines of the EC Treaty (EC Article 81, 2008), nowadays the main published on a weekly basis indices available for data are World Container Index, Ningbo Containerized Freight Index, China Containerized Freight Index and Shanghai Containerized Freight Index as China is the major container exporter and these data are more representative and convincing when Northern Europe and North America on the other side are the biggest importers (UNCTAD, 2018)

In order to analyze, examine, model and predict the shipping freight rate, first of all it is highly important to understand the shipping cycle for private business operation and public sectors as well in order to understand the state of the market. This is a really complex issue as many parts with different desires are involved in liner shipping and are distinguished between service users and service providers (Lee & Song, 2017). Martin Stopford (2009) claimed that seaborne trade is highly correlated with world GDP cycles and made an effort to describe shipping cycles that exist in the shipping industry for hundreds of years and affect it as a function with other macroeconomic factors of major economies. This is achieved through demand and supply model and therefore we should recognize the key factors that affect both of them at this early stage. Demand for shipping transportation is a derived from the need for the goods demand and it can be influenced from five factors, world economy, international maritime trade, average achieved profit, political events and transport costs while from supply's point of view we have world fleet, world fleet's productivity, shipbuilding, shipbreaking and freights (Jugovic, Komadina & Peric Hadzic, 2015). Their equilibrium point is the freight rate (Beenstock & Vergottis, 1993). From the previous factors, literature has highlighted that the world economy is the most important for the shipping demand not only due to the nature of the transported assets but also due to globalization and technology developments which introduced cyclical activities. Yet, there can be some unexpected events such as wars, political decisions or sudden changes in commodities prices that certainly are related to customers who belong to the demand side. Changes in consumption should have an impact on ship-owners as shippers reduce the quantity of cargo to be transported and their decisions should be significantly influenced by the situation of the world economy. Moreover, international maritime trade is also very important since it is essentially the outcome of demand, especially from important consumers of powerful and high economically ranked countries. International maritime trade and by extension consumption, are affected not only from indicators for development in world GDP as already mentioned but from exchange and interest rates as well. Chi (2016) evidenced that GDP -with the income to be closely related- is the major factor affecting the freight flows from China to US while Stopford (2009) supported that a strong dollar currency will increase imports for US and same for international trade as economy will be at a good state and manufactured products will be traded all over the world. As far as the supply side is concerned, Mason and Nair (2013) introduced some flexibility tactics to affect total fleet and thus influence freight rates and later, Kutin et al (2018) evidenced that world fleet has a severe negative impact on freight rates especially during economic recessions. Nevertheless, as the majority of the container vessels are at least partially debt financed due to high capital requirements, interest payments are incurred without interruption and as a result there is a lower limit to freight rates at least in the short run for which liner companies will not accept to operate containerships without covering their operating costs (Adland & Strandenes, 2007)

Many more researchers tried to econometrically forecast freight rates for other sectors but nobody did so for the container market until Meifeng Luo (M.Luo et al, 2009) – who can be characterized as a pioneer in the container sector together with Stopford- presented an in-sample model prediction to compare with the actual freight rates during that period. His purpose was to draw the attention of the decision makers to the potential risks and short-term trends in the container shipping market and confirm that container freight rates are rather flexible and negotiable. His model achieved successful predictions based on different assumptions like an exogenous demand shift such as the international trade that would change the demand of the container shipping market to the same direction even if the freight rates remained at the same levels while from the supply side, decrease in freight rates would occur from additions to the world fleet capacity. During that period of economic crisis with lower demand and consumption of manufactured goods in Europe and production in East, maritime organizations, ship-owners and even bankers could apply this model in order to stabilize freight rates and adjust their future strategy as the global container fleet's cargo capacity could not be filled.

It is easy to understand how important the capability of making accurate forecasts is as container freight rates are characterized from cyclicality and large swings of fluctuations (Nielsen et al, 2014). Container freight rates are also characterized by seasonality with the peak season for most liner companies found to be in autumn and spring as a consequence of preparation for Christmas and the recovery period of the Chinese New Year respectively (Y.Yingbo & S.Yinhao, 2018). To cover these attributes, Z.Munim & H.Schramm (2017) tried to create an amended forecasting model on weekly and monthly levels by using ARIMA model –suggested by Stopford, 2009 for the shipping industry- and ARCH model –suggested by M.Kavussanos, 1996 to examine volatile time series. Their outlined ARIMARCH combination provided a high forecast accuracy that leaves though further room for improvement.

E.Gouvernal and B.Slack (2013), made a research aiming to identify how container freight rates vary globally, regionally and over time. This was carried out by taking freight rates into consideration as a measure of economic distance which lead to the conclusion that freight rates create spatial patterns distinct from how the absolute distance of the world is arranged and that physical distance is an imperfect substitute for actual freight rates. This means that distance does not explain freight rates and the regional and temporal differences do not significantly affect the price of shipments. Their research harmonized with Stopford (2009) who stated that rising consumer spending boosted US imports from Asia and especially China and Vietnam while on the other side, limited growth in Africa and Latin America is reflected to their weak container imports but in this case, political factors should be taken into consideration.

Since the increase in the amount consumers spent caused a growth in US imports from Asia, there should be an effort to relate how consumers' purchase power is related not only with imports but with container freight rates as well. In order to do so, we should first analyze the consumers' behavior, how and from which factors their choices are affected especially in competitive markets. A customer's buying decision can be affected either by cultural, social, psychological and personal factors. The last one includes income as a personal feature of the consumer and gender that exhibits completely different behaviors between male and female consumers (Bakshi, 2012). Moreover, for decades, international marketing literature has stated brand, color and design to be such factors but for international trade we should be interested also in the country of origin since this shows the intention of the consumers (Rezvani et al, 2012). Cultural stereotypes, political systems and economic regulations of each country can also alter consumers' decisions and behavior (Teo, Mohamad & Ramayah, 2011) and this is also the case for age, education and other attributes that consists demographic characteristics. In an effort of analyzing the construction of consumer behavior, a good knowledge of the product plays a crucial role. Lin and Zhen (2005) contended that this knowledge is based on consumer's awareness, comprehension of the product and the faith in it.

Globalization gives the chance for the international trade to thrive and container market is certainly benefited by this fact. Customers' preferences for specialized and personalized products vary across business sectors and cultures (Goldsmith & Freiden, 2004) and have significant impact on their behavior (Moon et al, 2008) thus transportation is required for these products.

Section 3: Data

In order to properly decide the econometric method, we will use to examine the relationship of our variables, we have to fully understand the type and structure of our data. The data we have collected are continuous time series, meaning that they are collected at different points in time yet sequentially, with equally spaced time intervals and with a chronological order. We have selected monthly frequency in order to study the highest possible number of observations, which however include more “white noise” which needs to be removed as error term unrelated to the variables. Nevertheless, we shall also examine our variables on a quarterly basis in an attempt to include in our model and analysis two additional variables for which there are no statistical-historical data found on monthly basis. Furthermore, in order to set a common foundation for all our variables, and examine the same period, we decided to use for our sample the time period for which we had information for all of our data, i.e. 2003-2020.

3.1 Dependent Variable

Following up what we have described in the Introduction part, it is clear that the dependent variable which behavior we will try to understand in relation to various factors is the Container Freight Rate. Thus, it is essential to select the routes and the areas for the data we will examine. In order to reach such a conclusion, we downloaded from Clarkson’s database various time series regarding container throughput for different regions and ports.

3.1.1. Selection of the areas under freight rate examination

Container throughput is an expressed in TEU measure of handling activity, majorly driven by progress and growth in the global economy and demand that also includes consumption and investment assumptions. This containerized port activity is of high importance and constitutes a strategic tool during the recent years. Asian container ports dominate all other regions as 16 out of 20 of the top container ports based on UNCTAD reports are Asian while most of them are Chinese. Despite the fact that the importance of the Asian container ports is worldwide recognized, for our thesis we are interested in consumption and therefore we will focus more on the European and North American ports where manufactured goods produced and exported from various areas in Asia are imported and consumed. The most significant ports we identify to these areas and which complete the top 20 container ports globally are Rotterdam, Antwerp and Hamburg in Europe as well Los Angeles in the U.S.

About one sixth of the global container port throughput belongs to Europe and similar are the results for the port container traffic that provide us a better indication of the containers' flow from land to sea transport modes and the opposite. One of the recent developments that boosted European ports is the constantly increasing participation of the China Ocean Shipping Company, one of the major players among terminal operators, as a fundamental port investor both in South and North Europe (UNCTAD, 2019). As per Clarkson's shipping intelligence network data, apart from Rotterdam, Hamburg and Antwerp already mentioned, the ports that greatly import goods through container ships are Piraeus, Bremen, London Gateway, Valencia, Algeciras and Barcelona among others. These are also the most important ports in terms of port level liner shipping connectivity index, an index that encapsulates how well countries are connected to global shipping networks for trade facilitation and is produced for all container ports where container shipping services occur. It is essential to mention that imports from these ports can be forwarded through inland and sea transportation throughout the whole Europe.

As far as Northern America is concerned, global throughput percentage is 8%, almost half of the respective Europe's percentage yet higher than that of other regions –except for Asia's of course. This number is mainly attributed to the strong containerized port activity in the United States. UNCTAD's Review of Maritime Transport in 2019 states that the most connected ports on the West Coast of North America are in the U.S. with Los Angeles, Long Beach, Houston and Seattle to stand out. Other important ports outside the States are Manzanillo in Mexico and Vancouver in Canada. On the East Coast, U.S. ports like New York and Savannah have a primary role while Halifax in Canada and Veracruz in Mexico follow them as far as connectivity is concerned. Moreover, during last two to three years and due to the expansion of Panama Canal, East Coast is found to be more competitive comparing to the West.

As already mentioned, Europe's and especially Northern Europe's ports are some of the most prevalent and popular destination for China's containerized trade and exports. What should be pointed out though is that not only Europe countries with significant ports have demand for manufactured goods. By the time a container arrives in Europe and gets unloaded, products can be easily transported to all over the continent throughout inland transportation and as a result we are interested in examining our variables for the whole Europe and not only the countries that have ports at their disposal. Taking all the above into consideration, we have selected to examine freight rates' indices extracted from the China Containerized Freight Index (CCFI) for routes departing from China with destination in Europe, West and East Coast of America as well as a Composite Index so as to examine the effect of consumption to the total Containerized Index.

3.1.2. China Containerized Freight Index (CCFI)

The reason we have selected this specific index, is because CCFI is considered as the second influential freight index only behind Baltic Dry Bulk Freight Index and UNCTAD has preferred it for its valid statistics among others indices regarding its shipping annual reports. Over the last decade, CCFI has encapsulated the market trends and has obtained important economic and social power. It also provides reliable information that can be used by decision makers of shipping, trade and governmental sector as from a macro-economic aspect.

The basic index of 1,000 points was set on 1st January 1998. Besides the trade lanes we have selected for our model, there are twelve total lanes with a global coverage, all with a starting point in China from ten different hub ports including Shanghai, Ningbo, Qingdao and others. Finally, the information reflected to the indices is gathered from twenty-two domestic and foreign, of international status, shipping companies that established and operate the freight rate formulation committee. Some worth mentioning names among others are Maersk, COSCO, CMA-CGM, Hapag-Lloyd, EVERGREEN MARINE CORP. etc. All CCFI indices are published from the Shanghai Shipping Exchange every Friday.

The time series concerning the freight rates were located and gathered from the *Clarksons Shipping Intelligence Network*, which is the major ship-broking house database.

3.2 Independent Variables

Our independent variables, which are the factors for which their impact on the Container Freight Rates is examined, will be i) Consumer Confidence & Consumer Sentiment, ii) Disposable Personal Income, iii) Personal Consumption Expenditures and iv) Consumer Price Index. Based on the existing literature, the world economy generally and changes in consumption, as a part of the international trade, are important factors of the shipping demand. We believe that the above variables from the aspect of the consumer, will generate interesting results when testing their influence on freight rates of container ships. In order to receive more valid results with a more efficient ability to predict the future, we will use data with lags. Lagging of independent variables ensures that early instances with missing values are removed as it may take a few months to understand and feel the impact of any alteration in the economy.

3.2.1. Consumer Confidence & Consumer Sentiment Index

One of the best statistical measurements of the consumers' purchasing power is the consumer sentiment, also described as consumer confidence and these two will be our main explanatory variables. They are economic indicators that rely on consumers' feeling about their individual as well as the general financial health, both in short and long term. They have been also found to be an important ingredient of the national GDP making the behavior of the consumers a significant driver of the economic policy. Their expectations, either positive or negative, do affect the demand of final goods and therefore can be linked to the container freight rates.

Both of these indices are measured through consumer surveys that are conducted monthly from the Directorate General for Economic and Financial Affairs of the European Commission for the European Union, the Member States and the UK while for the US by the University of Michigan.

3.2.2. Consumer Confidence Index (CCI)

The consumer confidence indicator or so called as an abbreviation, the CCI, is at vast majority used and found in Europe statistics, and is created and calculated by the Conference Board, as a result of questionnaires, quantifying the answers of the consumers which concern their expectations as far as their financial state or even unemployment is concerned, their projections and intentions for savings and of course their sentiment with respect to the overall economic situation. The CCI is used as an indicator for upcoming developments of the consumption and savings of households and is based on the Consumer Confidence Survey, which is a survey of 5,000 households, and is released on the last Tuesday of every month.

The critical point for deciding whether consumers are either optimistic or pessimistic about the state and development of the general economy is the 100. An indicator above 100 signals a boost in the consumers' confidence towards the future economic situation, as a consequence of which they are less prone to save, and more inclined to spend money on major purchases in the next 12 months. Values below 100 indicate a pessimistic attitude towards future developments in the economy, possibly resulting in a tendency to save more and consume less. For example, the Consumer Confidence Index decreased in March 2020 to the level of 99.21 after declining in February 2020 from 100.65 to 100.22. It is common knowledge in the field of economic science that consumers decisions are affected by their expectations and forecasts concerning the general economic state, their personal income and probable changes to it, or possible unemployment or employment. The aforementioned decisions lead to the formation of the demand for products and result in either the increase or decrease in demand. As provided by the economic principals, a rise in the demand will lead to an increase in prices and a drop in the demand will lead to a decline to the product prices. Following the sequence described above, we can come to the conclusion that consumers decisions, since they drive the demand, are as a consequence reflected in the price, or in our case, consumers' confidence affects the freight rates. This relationship is to be examined in our models.

For such data of monthly frequency and seasonally adjusted, we visited Organization for Economic Co-operation and Development (OECD), to extract OECD's consumer confidence indicator about Euro Area (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and United Kingdom). The monthly frequency ensures that the result is representative and encapsulates several changes that may occur in the population.

3.2.3. Consumer Sentiment Index or Michigan Consumer Sentiment Index (CSI)

In a rather similar way as with the CCI, there is another indicator under the same philosophy, however now used and met in American statistical data, which is also to be under examination during this thesis, called the "Consumer Sentiment Index" or "Michigan Consumer Sentiment" (for easy reference CSI or MCSI will be used as an abbreviation). The validity and the significance of the consumer sentiment and its predictive power for variation in consumption were already mentioned in 1994 when D. Carroll, J. Fuhrer and D. Wilcox evidenced lagged consumer sentiment to have a notable explanatory power for household spending changes. Similar results were revealed by P. Howrey (2001) who proved the statistically significance of the index of consumer sentiment in forecasting personal consumption expenditure as well as the future growth rate of real GDP.

Consumer sentiment was developed as an economic statistic during the mid-20th century by the University of Michigan and operates as a barometer which tends to influence according to its results, the public and economic policy. More specifically, the MCSI is used as an economic indicator and a statistical tool for the measurement of the overall health of the economy as constructed and determined by consumer opinion. Consumer sentiment takes into account an individual's feelings (sentiment) and focuses on the way consumers view expectations for their own financial health, for the general economy over the short term, but also their perspective on the prospects for the economy over the long term.

The consumer sentiment is measured through a process called the consumer survey. This survey is almost entirely qualitative, carried out through questionnaires with only few quantitative questions. Each monthly survey contains approximately 50 core questions, each of which tracks a different aspect of consumer attitudes and expectations toward his or her current financial state, the health of the economy in the short-term and the prospects for longer-term economic growth. These questions are related to households' past and future economic situation, the general financial situation, their savings and of course their willingness to proceed to various purchases during the next twelve months. How the government is performing at the economic policy, consumers' opinion about unemployment, interest rates, prices, expectations about family income, if time is favorable for investments, real estate values are also examined through this questionnaire. The intend of the survey is to gather data through logical validation rules from households‘ spending and saving purposes, their future prospect, to check if they are informed about several changes occurred recently and to find the coefficients they believe to have an impact on their decisions. The samples for the aforementioned surveys are intended to be representative of all American households, except for households located in Alaska and Hawaii, and their results derived on a monthly basis from a minimum of five hundred interviews, which are conducted via telephone. A graph follows below, depicting the level and fluctuations of the MCSI over the last twenty-five years.

In order to measure consumers' confidence sentiment in the US, one of the biggest importers of manufactured goods; we collected monthly data from the University of Michigan's Survey of Consumers both for the whole country and regionally for West and East coasts. We should mention though that these data are not seasonally adjusted. This Survey is conducted by the University's Survey Research Center which ardently believes in the influence of the consumer spending and saving choices to the national economy. As a matter of fact, the Index of Consumer Expectations produced is found to be an important indicator of the forecast changes in the US economy and it is also published by the U.S. Department of Commerce, Bureau of Economic Analysis. The Survey is also characterized from statistical adequacy and time consistency.

3.2.4. Disposable Income (DI)

For studying the consumption of goods transported through container ships, we should be interested in the Disposable Income, an important number for the whole economy and not just individual consumers. This is the available portion of a household's income-after taxes to spend, invested or saved, according to consumer's choice as the outcome of all recent transactions before consumption and this is the reason why it is preferred to Total Income for our model. It is also known as disposable personal income (DPI). Dreger and Reimers in 2006 applied some panel cointegration techniques, providing some contradictory results about whether a long run relationship exists among disposable income and consumption in the EU countries.

For the Euro Area, we collected data for the households' disposable income from the European Central Bank, which is the central bank of the 19 European Union countries that have adopted euro as their national currency. Unfortunately, we only found historical data with quarterly frequency unlike the rest of the variables and this means that a different statistical treatment will be required in order to make all of them comparable. The statistical unit is billions of dollars. As per the latest analysis reported from the European Union concerning Households - statistics on disposable income, each member-country's data for period 2008-2018 was severely influenced from the global economic crisis with even negative rates during 2010-2013 and thus it should be taken into consideration for our further analysis. Furthermore, the disposable income per capita differs significantly throughout the members of the Union. We should also bear in mind that other factors that may have an impact on the disposable income of a country could be variation to population from year to year, either due to demographic or migration reasons.

As for the US, we found monthly and seasonally adjusted data, reported in billions of dollars from the Federal Reserve Bank of St. Louis. It is one of the twelve reserve banks that make up the US Central Bank and its main source for the time series we will use is US Bureau of Economic Analysis, an agency of the Commerce Department that produces commonly accepted and respected economic accounts.

3.2.5. Personal Consumption Expenditures (PCE)

It is the most important economic indicator that measures consumer and household spending for a certain time period. It helps us understand how much of the households' income is spent and not saved for future purchases as well as the household's buying habits. Personal Consumption Expenditures Index reports changes in prices of goods and services consumed. Especially in the US, this index drives about the 70% of domestic spending making it a key factor of GDP that secures future economic development. It is structured from different kinds of expenditures as a measure of the variation in consumption of goods and services by all households and this is why it is promoted by the Federal Reserve compared to Consumer Price Index.

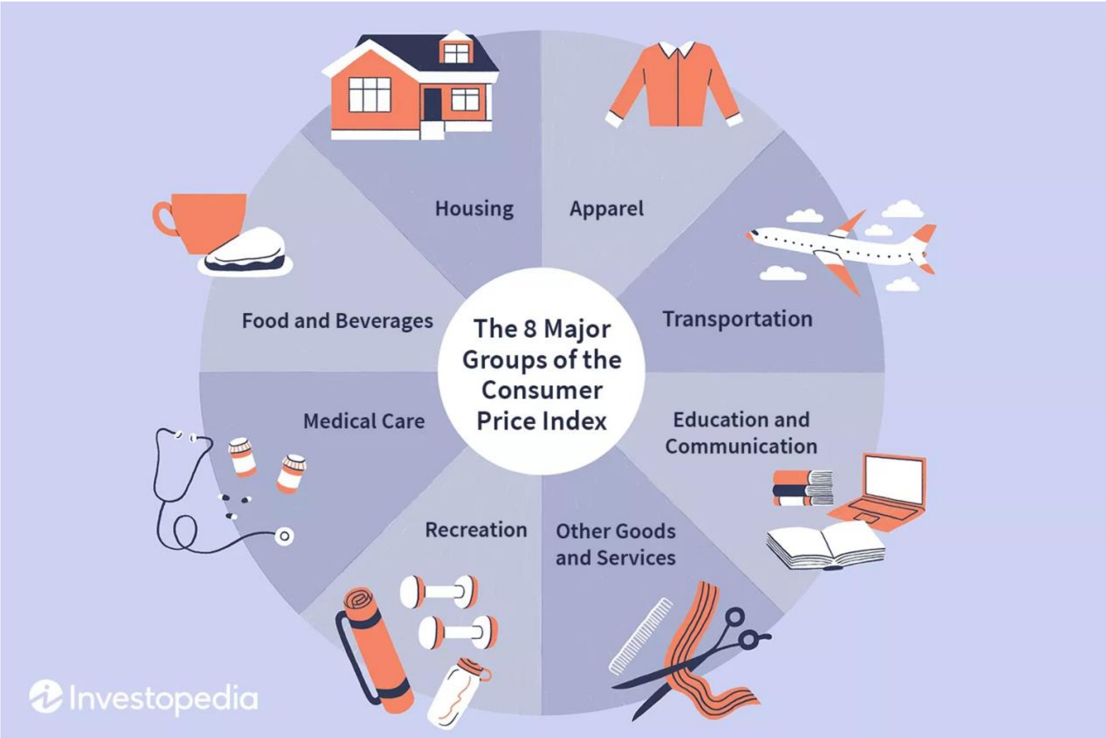
Such data for the Euro Area were obtained from the International Monetary Fund (IMF) and its statistical database for national accounts by access to Bloomberg. Again, we faced the same problem with the disposable income as the only available data are in quarterly frequency. The data are published in billions of dollars.

For the US, monthly, seasonally adjusted data valued in billions of dollars were again gathered from the US Bureau of Economic Analysis through the Federal Reserve Bank of St. Louis.

3.2.6. Consumer Price Index (CPI)

One of the best ways to measure purchasing power is by comparing prices to Consumer Price Index (CPI), a price index that designates consumers' ability to buy, also known as Cost of Living Index in the US and which is globally one of the most important and observed national economic statistics. It is a statistic measure, created back in 1913 by the U.S. Bureau of Labor Statistics that indicates the average change in household's cost of purchasing a basket of consumer goods and services between two periods. CPI is an economic indicator that points out how inflation influences consumers' purchasing power and how prices of goods and services may vary over time. A CPI 100 would mean exact match with the index average for the inflation level reported back in 1982-1984, i.e. back in the first observation range used for the calculation of this index, which was set to 100. The objective of this index is to quantify the aggregate price level in an economy, leading to informed decisions regarding the weighted average of prices by individuals, enterprises and governments. Therefore, it is an attempt to calculate the purchasing power of a nation's unit of currency. A currency's purchasing power is expected to grow when the aggregate price decreases and vice versa.

We should not neglect, however, the fact that using this index as a parameter in our model, there is the lurking risk of extracting results which lack precision since, by definition, CPI is the weighted average of the household basket which, apart from the consumer goods, includes transportation, medical and other services as well, affecting negatively the accuracy of our conclusions. Consumers' purchasing power is usually enhanced through technological innovations and containerization's evolution and its cost efficiency system is such as mentioned earlier.



While CPI has a different formula from the GDP, they are related as alternative measures of inflation as well as change in prices from various perspectives. An opinion that has also been expressed is that the CPI is linked to the maintenance of a household's standard of living at a certain level by calculating the change in its cost (Schultze, 2003) and thus we are interested in examining CPI instead of GDP – that has already mentioned before as highly correlated to the seaborne trade – about if and how it affects container freight rates. This concept of measurement weighted change of either the cost of keeping a living standard or of the goods purchased can be supported by using not only CPI as data but also indices for prices and expenditures and this comes as a consequence of the previous Consumer Sentiment and Personal Consumption Expenditures variables.

For our thesis, we used CPI monthly average price data. For the United States, we found such data from the U.S. Bureau of Labor Statistics, a fact-finding agency-department for the federal government in the field of labor, economics, and statistics which is also the Bureau that produces the CPI index. The index is available for the whole U.S. As for European Union's data, we collected - through the Federal Reserve Bank of St. Louis – monthly, not seasonally adjusted prices for the Euro Area from the statistical office of the European Union, the so called Eurostat which provides European statistics in collaboration with National Statistical Institutes, Ministries, Central Banks and other national authorities in the EU Member States.

3.3. Data Analysis & Limitations

During the preparation of this thesis, several issues arose, however the most intriguing and difficult part, was the gathering of the required information. Starting from the limited availability of data concerning the relation we aim to examine, we faced serious difficulties tracing the indexes that fitted most our model and which could best represent the measurement of consumers' power, both in terms of sentiment, and of income.

In the second place, after concluding to the indices to be used as independent variables in our model, and following excessive research, we realized that possibly due to the containership's market short history, and especially due to the fact that consumers' surveying mainly developed and started increasing not earlier than the 1990's, the time series data found were covering the recent history only.

The above, brings by return a third problem, which is the limitation in the number of observations. For our dissertation we are forced to work with variables which constitute samples consisted of a small number of observations. This means that we may be prevented from a proper estimation and modeling, given that our data cover a period of less than 17 years, leading to a number of only 209 observations per variable, referring to the monthly data collected.

It is important to state at this point that, since two of the under examination independent variables were statistically measured only in a quarterly basis, it was inevitable to work with an even smaller sample. In our attempt to deal with the problem of different frequency in which each variable was met, and to become more specific, to surmount the obstacle that whereas for the vast majority of our variables we found monthly data, the data found for two of our variables were referring to a quarterly basis, we had to find a way to bring all our data to a common ground. As a result, we needed to convert the rest of the variables from monthly to quarterly, in order to be able to run our model and analyze the relation among them. In order to deal with this issue, we calculated the average value of the observations of each quarter. This created by return an even smaller sample which again may bring debatable results. It is imperative that we gain a holistic picture and generate an effective and representative model, so as a result, the monthly variables needed to be converted in quarterly basis as well. Hence, our sample for our second approach, i.e. the quarterly basis approach, concluded to be even smaller, consisting of no more than 69 observations per variable. It is easily understood that this small sample size might have as a consequence rather misleading results, and we expect that it will be challenging to reach valid conclusions.

Further to the above, we should also take into consideration the fact that the indices used are a result of surveys conducted on a monthly basis, on a consumer sample of only about 40,000 households for Europe and 5,000 households for the United States. Compared to the actual population size of these two regions, which in total is about 1 billion people, it can easily be understood that examining such a small number of households, gives doubtful results. To translate that in numbers, only 0.00005% of Europe's population participates in the performed surveys, whereas the percentage in the United States is even less significant, mirroring barely about the 0.00001% of the U.S. total population. Therefore, the credibility of the indices we chose as variables can be questioned.

A sixth issue we had to deal with during our research was the fact that, as already mentioned, our time series contains a significantly shocking period for the global financial, economic and social state, of which starting point is the year of 2008. This year is a crucial point in economic history since it constitutes the pick of a global economic crisis. For a long period, commencing in 2008, the economy was under this "shock", which severely affected the markets, as far as both the demand and the supply sides are concerned and which up to very recently many countries were still striving to overcome. It had a huge impact on prices, freight rates, wages, and consumers' psychology, confidence and decisions. Since for a major portion of our time series, we are not dealing with what we would call as “normal circumstances”, we do not have the benefit to have a clear picture of the way our variables relate to each other and respond to each other’s changes, as we would in a world with no unexpected events where everything operates smoothly. This force majeure, i.e. the economic crisis of 2008, may be blurring the picture, leading us to false results and conclusions due to its huge impact on the under examination period, which may outweigh the actual influence of the selected independent variables on the dependent. This applies also for the period concerning the Covid-19 crisis, which is still in effect.

As a summary, it should be noted that our data were collected by valid data bases and platforms as well as globally recognized statistical organizations and surveys. Having described the most important challenges and obstacles of our research, we may carry on to the analysis and the models.

Section 4: Methodology & Model Specification

4.1. Stationarity & Unit Root Test

One of the most important tests we need to carry out is the so-called stationarity or unit root test as stationarity is a factor of a time-series that can majorly affect its properties. With the intention of running a trustworthy model and coming up with valid assumptions and results, it is really essential to ensure the elimination of non-stationarity. The non-stationarity of the under-examination variables, or else the existence of unit root, is crucial for several reasons, and it is of great importance that the non-stationary variables will be handled otherwise from the stationary ones. Unit roots are important to be tested since it is of major interest to know if "shocks" have a permanent impact or not. By the use of the term "shock", what is implied is the unexpected event affecting the pattern of a variable. To become more specific, when we are dealing with stationary variables, the duration of the impact that shocks have against such is rather modest, and the effect of the shock itself is less intense, whereas on the contrary, when the variables are non-stationary, the persistence of the shock is infinite, blurring the scenery and makes it impossible for such to be predicted or modeled. This happens because unit roots lead to spurious time series, meaning that there is a significant possibility that they indicate relationship among the variables even if same does not in fact exist. Non-stationary behaviors are met in the forms of trends, random walks, cycles or even combination of all the above.

The non-stationarity is explained through two models:

- The random walk model with a drift

$$y_t = \mu + y_{t-1} + e_t, \qquad \text{and}$$

- the trend-stationary process, which is stationary around a linear trend

$$y_t = \alpha + \beta t + e_t$$

where u_t is the "white noise".

If we re-write the random walk equation as $y_t = \mu + \varphi y_{t-1} + e_t$, we can say that, when $\varphi=1$ the "shock" is persistent and considered to last for infinity, therefore y is considered an eternal sum of its past shocks plus its starting value. This monomial which corresponds to a root equal to 1, is the so called “unit root” and it means that the concerned time series follows a systematic, persistent pattern which is unpredictable.

In a scenario in which we would be using a non-stationary time-series to our model, it would be containing more than one unit roots and it could be proved that the standard assumptions of the asymptotic analysis would be invalid and our coefficient estimators generated from the regression analysis could not be examined with hypothesis tests. In order to turn a non-stationary series to stationary we need to differentiate this random walk until it is converted to stationary. In other words, we are interested in finding the Order of Integration I( ) of our series which is the number of times a variable must be differenced so as to achieve stationarity. Freight rates, GDP, CPI and generally rates are usually non-stationary series while all returns are found to be stationary. For our thesis, we will not examine non-stationary series that can give us spurious results and we will focus only on stationary ones such as the log returns we have calculated for each variable after of course proving that they are indeed stationary. A line-plot graph of a stationary time-series has its moments constant over time while the relative correlogram “dies out” fast and lacks persistence. Those two steps constitute the so called “clinical indications” of stationarity, but we cannot be certain only by following the implications of these graphs. Therefore, we need to perform a Unit Root Test. For our model, we have selected the Augmented Dickey-Fuller (ADF) test.

Before we discuss further on the ADF, we should firstly describe the Dickey Fuller (DF) test.

The Dickey-Fuller test is testing if $\phi=0$ in the below model:

$y_t= \alpha+\beta t+\phi y_{t-1}+e_t$ (1)

If we assume that $\varphi = 1$ (variable non-stationary) then $y_t= \alpha+\beta_t+y_{t-1}+e_t$ =>

$y_t - y_{t-1}= \alpha+\beta t+e_t$

If e_t, which stands for “standard error” or “residual”, is assumed to be stationary, we can claim that we originally were dealing with the case of a “random walk” which we turned into stationary.

Model (1) can also be written as the below auxiliary model:

$\Delta y_t = y_t - y_{t-1} = \alpha + \beta t + \gamma y_{t-1} + e_t$

By this formula, we can perform a linear regression of Δy_t against t and y_{t-1}. The hypothesis test is the following:

H_0: if $\gamma = 0$ => yt ~ I(1) and Δy_t ~ I(0) => Non-Stationary Series

H_1: if $\gamma \neq 0$ => Stationary Series

Dickey-Fuller's hypothesis test can be valid only if "e_t" expresses white noise and is presumed not to be autocorrelated. If however the response variable of the regression was autocorrelated then "e_t" would be autocorrelated as well. If we deal with models like the one mentioned above, then the hypothesis test may be proved to be "oversized", indicating that the actual size of the test will be presented increased in comparison with the nominal size. In order to surpass this problem, we "augment" the model by lagging its dependent variables. We have already mentioned that for our regression analysis we will be using lagged versions of our independent variables. This way, we ensure that our results will provide robust coefficients of independent variables that are exonerated of undesired biases which could threaten the validity of our results. Furthermore, we make sure that our model fulfills the third assumption of the linear regression ($cov(u_i, u_j) = 0$) and also deal with auto-correlation effects. Lagged data allow values from recent past to be a part of the forecast by predicting future values based on what occurred to past periods. The augmented model, universally known as Augmented Dickey-Fuller (ADF), secures that the e_t is not autocorrelated, as the lags of the dependent variable imbibe any dynamic structure detected in the response variable. Consequently, the ADF is considered as a more powerful model compared to simple DF as it can undertake more complex models. In order to perform the ADF test, we need to select a lag length so as to avoid high correlation among the residuals. For our model, we have selected lag length for one period.

By including lags (Δy_{t-p}) in our model, the ADF test benefits higher order autoregressive processes:

$\Delta y_\tau = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \ldots$

Our null hypothesis remains $\gamma=0$:

H_0: if $\gamma = 0 \Rightarrow y_t \sim I(1)$ and $\Delta y_t \sim I(0) \Rightarrow$ Non-Stationary Series

H_1: if $\gamma \neq 0 \Rightarrow$ Stationary Series

We should note though that critical values may have small variations depending on the size of the sample.

4.2. Autocorrelation and Heteroscedasticity

It is essential for our model not only to control its variables and their respective coefficients but to also analyze the residuals generated as the white noise term of our model.

In models with time-series data where observations are remarked at different points in time like the one we will apply to our Thesis, we may face the issue of autocorrelation. In such models, for conventional analyses like the ordinary least squares regression, we have the assumption of the independence of the disturbance term. If this assumption is violated, we can then claim that both the values and the estimates are biased since the standard errors of the coefficients are also influenced and thus the predictions of the model may not be reliable and effective. The above problem also called as autocorrelation, may also be detected if the model is not specified properly. If for example the relationship of two variables we examine is non-linear but we perform a linear regression then the residuals of the model will be found to be autocorrelated.

The second assumption of the linear regression which states that the variance of the residuals is constant, is universally known as the assumption of homoscedasticity. If this assumption does not stand, we have to deal with the problem of heteroscedasticity, a systematic shift in the spread of the error term over the sequence of the estimated values. If this problem is ignored or uncontrolled then the model applied will still provide unbiased results yet with no minimum variance as variance contributes to the formula of the coefficient variances. While a graph plot may identify the presence of heteroscedasticity, most probably this will not give us any information about its cause.

In order to overcome the issues of autocorrelation and heteroscedasticity as described above, we will perform various validation tests to our results that will be later described so as to control residuals and specify our model in the best manner. One of the most important tests that we will carry out is the Newey–West test. The estimator generated from this test can assist to enhance the ordinary least squares regression when we have proved the residuals of the model to be autocorrelated or heteroscedastic.

Section 5: Empirical Analysis & Results

From an economical theory's point of view, before we examine any of our variables, we expect the consumer sentiment and confidence to have a positive impact on the container freight rates if they indeed have an effect over our dependent variable. As already mentioned, consumers' behavior is a considerable driver of the economic policy and their expectations react on the demand for manufactured goods. The more positive and optimistic the sentiment of a consumer is for the economy's prospect and his own financial well-being, the more willing he is to consume and the less to save. It is common knowledge that the demand in shipping is derived from the demand for the transported goods, so an increase to the consumer sentiment is expected to bring accordingly an increase in demand for goods, and subsequently, affect in a positive way the freight rates as more goods will need to be transported. A similar sign is expected for the impact of the Disposable Income (DI), the after-tax available households' income for spending, on our dependent variable. The greater the available portion of the disposable income, the most likely it is for the consumers to buy final goods. We should be assuming disposable income to be highly correlated with consumer sentiment as well as the container freight rates. Personal consumption expenditures (PCE) provide us a clearer interpretation of the amount of the disposable income which is actually spent for goods and services and therefore an increase of the personal consumption expenditures is anticipated to conduce to a rise in container freight rates. Finally, we may assume that Consumer Price Index (CPI) will also have a positive sign in relation to container freight rates. As a Cost Living Index that quantifies the aggregate price level in an economy, we have previously described CPI as an attempt to measure a nation's purchasing power that increases when the aggregate price which is expected to cause a positive change to freight rates increases as well.

5.1. Purpose and Process

The aim of the multivariate regression analysis we will apply to our variables is to provide the best possible estimate of the coefficients from the population's sample we have chosen. Such analysis will assist with comprehending the relationship among the selected variables and additionally explain to a greater extend the correlation both among the independent variables themselves and between our dependent variable and each of the independent ones. Ultimately, we want to find out and bring into light the causal effect of an independent variable's unit change on our dependent one while holding the others constant as fitting a straight line to our data. We should bear in mind though that at a multivariate model, each coefficient estimator expresses the average change in the response variable per unit change of a certain explanatory variable while the rest of the independent variables stay on their average values without changes. We have to also take into consideration the error term collected from the population as measured from the so called residuals, the estimates of the error term for each observation as the difference among the fitted line and the certain sample data that affect the dependent variable. Therefore, we will use the Ordinary Least Squares (OLS) method, best described as a fitting line that passes through our sample's data in a way that the sum of squared residuals is the least possible.

The estimation technique of OLS has certain covetable properties which are best described by the following five assumptions of linear regression which will be later on examined:

1. $E(u_t) = 0$
2. $var(u_t) = \sigma^2 < \infty$
3. $cov(u_i, u_j) = 0$
4. $cov(u_t, x_t) = 0$
5. $u_t \sim N(0, \sigma^2)$

In the quest of measuring the optimal estimate of the coefficients, it is essential to log our data and use the log returns. One major advantage of logging a time-series is that log returns are time additive and, transforming multiplicative relationships into additive, facilitates calculating compound returns resulting to better explained linear models. Furthermore, the coefficients of a regression with log returns are found to be proportional percentage changes. Small changes in the natural log of a variable are considered to be a very good approach as percentage changes. A time series consisted of log returns contributes to its detrending and secures more consistent over time seasonal variations. The latter meliorates the model's forecasting by fitting the data in a more precise manner. Logging our data ensures that we do not need to include inflation forecast into our model as its impact is quite similar while not the same to deflation by straightening a trend so as to fit in a linear model more accurately. In addition to the above, heteroscedasticity is reduced as well and more importantly we treat the stationarity problem, and to become more specific, we eliminate the possibility of unit roots and untrustworthy results and conclusions. Finally, we prefer the use of natural log as errors of logged time series that can be explicated as approximate percentage errors of the unlogged series. This means that when we apply OLS to logged time-series we minimize squared percentage error, and this is something that benefits our model significantly.

Taking all the above into consideration, we have selected to construct a multivariate regression model as an estimation technique of a single regression with multiple outcome variables. More in particular, we will examine three different models, one for the overall Composite Freight Rates Index, one for the Europe Freight Rates Index and one for the US Freight Rate Index, but all three in two frequencies, i.e. both on a monthly and a quarterly basis, so as a result we basically have six models. The basic equation for a multiple regression is the following:

$y = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + u_t$

As a dependent variable we have used the log return for each of the models examined and as an independent the first lag of the respective log return for each of the variables utilized. At the below table, all variables for all six models are presented:

Table 1. Variables, descriptions and dataset used in models

Name	Description	Dataset
CCFIALL	CCFI Composite	Monthly & Quarterly
CCFIALLlnret	CCFI Composite - Log return	Monthly & Quarterly
CCFIttlUS	CCFI Total US	Monthly & Quarterly
CCFIttlUSlnret	CCFI Total US - Log return	Monthly & Quarterly
CCFIEU	CCFI Total EU	Monthly & Quarterly
CCFIEUlnret	CCFI Total EU log return	Monthly & Quarterly

USCSI	Consulkmer Sentiment Index for US	Monthly & Quarterly
USCSIlnret	Consumer Sentiment Index for US – Log return	Monthly & Quarterly
L1_USCSIlnret	Consumer Sentiment Index for US – First lag of log return	Monthly & Quarterly
USDI	Disposable Income for US	Quarterly
USDIlnret	Disposable Income for US – Log return	Quarterly
L1_USDIlnret	Disposable Income for US – First lag of log return	Quarterly
USPCE	Personal Consumption Expenditures for US	Quarterly
USPCElnret	Personal Consumption Expenditures for US – Log return	Quarterly
L1_USPCElnret	Personal Consumption Expenditures for US – First lag of log return	Quarterly
USCPI	Consumer Price Index for US	Monthly & Quarterly
USCPIlnret	Consumer Price Index for US – Log return	Monthly & Quarterly
L1_USCPIlnret	Consumer Price Index for US – First lag of log return	Monthly & Quarterly
EUCCI	Consumer Confidence Indicator for EU	Monthly & Quarterly
EUCCIlnret	Consumer Confidence Indicator for EU – Log return	Monthly & Quarterly
L1_EUCCIlnret	Consumer Confidence Indicator for EU – First lag of log return	Monthly & Quarterly
EUCPI	Consumer Price Index for EU	Monthly & Quarterly
EUCPIlnret	Consumer Price Index for EU – Log return	Monthly & Quarterly
L1_EUCPIlnret	Consumer Price Index for EU – First lag of log return	Monthly & Quarterly

The above table lists the variables used to estimate Equation…Column "Dataset" refers to which time basis there were available data to use.

Before running any regression, we will first check our variables for possible extreme values that may alter our analysis. This can be done with the assist of Table 2 for monthly data and Table 3 for quarterly. As a next step, we will create a correlation matrix in order to have an accurate picture not only to check the relationship of the dependent variable with the explanatory ones but also to check for possible multicollinearity issues. It is essential that our independent variables are low correlated (< 0.50) otherwise we should consider dropping some of them. Extreme correlation leads to multicollinearity problem which means that independent coefficients will have high standard errors and sequentially low t-stat, wide confidence intervals and our variables can be found statistically insignificant when this may not be the case as regression analysis is more sensitive to minor changes in the specification. In a more simplistic interpretation, multicollinearity means that if a variable X1 has a very high correlation with another variable X2, then this translates to the fact that X1 can be linearly predicted by the other, so in other words there is no use in including two or more variables that are similarly explained, and which also have the same impact towards the dependent variable.

Table 2. Descriptive statistics of monthly variables used in equation.

Sample period March 2003 – March 2020

Variable	Obs	Mean	Std. Dev.	Min	Max
CCFIALL	205	994.1582	150.5862	641.504	1315.874
CCFIttlUS	205	1068.153	193.3468	650.876	1341.963
CCFIEU	205	1289.368	293.3814	635.02	1897.158
USCSI	205	84.28537	11.97045	55.3	103.8
USDI	205	12201.15	2322.426	8324.2	16831.3
USPCE	205	10991.31	1964.263	7598.4	14880.5
USCPI	205	223.1565	21.10343	183.5	258.678
EUCCI	205	99.58831	1.33446	96.4734	101.9597
EUCPI	205	94.58132	7.292866	80.93	105.44

See **Table 1** for definitions of variables. Min and max are the minimum and maximum values of the sample data respectively.

Table 3. Descriptive statistics of quarterly variables used in equation.

Sample period 2003:Q1 – 2020:Q1

Variable	Obs	Mean	Std. Dev.	Min	Max
CCFIALL	69	994.0661	148.6881	651.1538	1280.757
CCFIttlUS	69	1068.812	191.703	682.8311	1336.122
CCFIEU	69	1288.559	288.1942	678.0325	1805.944
USCSI	69	84.22077	11.64557	57.66667	98.93333
USDI	69	12163.69	2352.825	8324.2	16698.6
USPCE	69	10958.53	1991.317	7598.4	14759.2
USCPI	69	222.7801	21.43685	183.6667	258.2547
EUCCI	69	99.57728	1.330029	96.52774	101.9026
EUDI	69	1936.92	225.7861	1328.9	2495.67
EUPCE	69	1701.114	194.6176	1180.4	2090.3
EUCPI	69	94.44942	7.409108	80.93	105.3233

See **Table 1** for definitions of variables. Min and max are the minimum and maximum values of the sample data respectively.

As already mentioned earlier, in our analysis we use lagged values, both in a way of dealing with stationarity and for examining our model's ability of forecasting. Provided that our lagged time-series of log returns have been proved to be stationary, we are ready now to perform our regression analysis to all variables that do not face multicollinearity issues. Regression is actually a significance test that expresses the relationship between the independent variables with the dependent. For our thesis, we ran regressions with both monthly and quarterly data. As we have already mentioned at the "Data" part of this paper, data for Disposable Income and Personal Consumption Expenditures for Europe were found only in quarterly basis and thus they will be excluded from the monthly regression. On the other side, all our variables could be used without exclusions for the quarterly approach. In order for all variables to be comparable, we computed the average values of each quarter for all of our monthly time-series so as to bring them all to the same quarterly basis and achieve the same observations' number for our dataset. Finally, one more technique we were forced to follow and that should be also cited, was that the freight rates for the US were calculated as the average of the West and the East Coast of US, for the reason that no such Total US Index was found from China Containerized Freight Index.

After examining the significance of each independent variable to the dependent one for all of our six models, it is considered imperative to validate our results with various tests which ensure that the outcome of the regression analysis is reliable and meets the five assumptions of the linear regression. First of all, we will do the Ramsey Regression Equation Specification Error Test as an omitted variables test which is quite important for our model since it is constructed on the assumption that the explanatory variables and the error term are uncorrelated (first assumption $E(e|X)=0$). If our model meets the criteria of RESET test, then most probably there is no determinant omitted variable. To the same direction of detecting any specification errors, we will attempt to discover if further independent variables are required to our regression by regressing the response variable of the initial regression against the initial regression's prediction as well as the squared prediction. As a robustness test to the correlation matrix we will create, we will also measure the Variance Inflation Factors for every model found to have significant results. Aiming to inspect the predictive power of our model we will estimate the linear prediction from the fitted model and create a scatter plot with the dependent variable expecting an approximate 45°- degree slope for satisfying predictive results. In order to harmonize with the second assumption of the linear regression (var(u_t) = $\sigma^2 < \infty$), the so called assumption of homoscedasticity, we want the residual of our model to be constant. Consequently, we will create a scatter plot among residuals and predicted values to which we should not inspect any patter at all otherwise, heteroscedasticity may be present. Further to the previous test, in order to control heteroscedasticity, we will run only robust regressions. Separate scatter plot of the response variable with the explanatory ones that were found to be significant will be carried out, trying to detect any relationship between them. Last but not least, we will test for the fifth assumption of linear regression (ut ~ N(0,σ2)) which means that the "white noise" of our model is normally distributed otherwise no hypothesis tests can be conducted. Therefore, we will create a kernel density plot, a normal-probability and a quintile-normal plot to check if residuals follow a normal pattern comparing to a normal density, in the middle range of residuals and at their extreme values respectively.

5.2. Results

As it can be observed at **Table 2** and **Table 3**, none of our variables have any extreme values that could affect the results of our regression analysis. To deal with multicollinearity issues, we created a correlation matrix for monthly (**Table 4**) and quarterly basis (**Table 5**). While for our monthly dataset we do not track any such problem, this is not the case for our quarterly data. L1_EUDIlnret is highly correlated to L1_EUPCElnret (0.6729) and L1_EUCPIlnret (0.6198) and thus it was examined separately from the other variables for Europe. Likewise, L1_USCPIlnret was found to be correlated over the desirable levels to L1_USPCElnret (0.5978) so we decided to drop it as it was also statistically insignificant even when it was regressed alone with each dependent variable. Finally, L1_EUCPIlnret presented multicollinearity issues with L1_USCPIlnret (0.5512). The latter was also dropped alongside with EUDIlnret when we examined our Total EU & US quarterly model.

Table 4. Correlation Matrix for monthly variables

	CCFIALLInret	CCFIttlUSllnret	CCFIEUlnret	L1_USDIInret	L1_USPCElnret	L1_USCSIlnret	L1_USCPIlnret	L1_EUCPIlnret	L1_EUCCIlnret
CCFIALLInret	1								
CCFIttlUSllnret	0.6137	1							
CCFIEUlnret	0.8873	0.3697	1						
L1_USDIInret	0.0330	0.0504	0.0250	1					
L1_USPCElnret	0.1653	0.1375	0.1823	0.1763	1				
L1_USCSIlnret	0.0082	-0.0515	0.0616	0.0273	-0.0377	1			
L1_USCPIlnret	0.0605	-0.0035	0.0719	0.0310	0.4620	-0.1667	1		
L1_EUCPIlnret	-0.1267	-0.2135	-0.1182	0.1644	0.1284	-0.0638	0.3493	1	
L1_EUCCIlnret	0.1644	0.0094	0.2569	-0.0216	0.0928	0.1647	-0.0469	-0.0872	1

This table presents the pair-wise linear correlations for all the variables used in the estimated models. No pair of variables is highly correlated (>0.50) and thus they all can enter simultaneously at the regression analysis.

Table 5. Correlation Matrix for quarterly variables

	CCFIALLInret	CCFIttlUSlnret	CCFIEUlnret	L1_EUCCIlnret	L1_EUDIInret	L1_EUPCElnret	L1_EUCPIlnret	L1_USDIInret	L1_USPCElnret	L1_USCSIlnret	L1_USCPIlnret
CCFIALLInret	1										
CCFIttlUSlnret	0.6875	1									
CCFIEUlnret	0.9249	0.4912	1								
L1_EUCCIlnret	0.2232	0.0641	0.3209	1							
L1_EUDIInret	0.2272	0.1241	0.3278	0.1449	1						
L1_EUPCElnret	0.1058	-0.0897	0.1813	0.2255	0.6729	1					
L1_EUCPIlnret	0.3430	0.4103	0.3255	-0.1810	0.6198	0.0909	1				
L1_USDIInret	0.2019	0.1627	0.2147	-0.0073	0.2866	0.2391	0.2663	1			
L1_USPCElnret	0.3406	0.2126	0.2918	0.1547	0.0704	0.2210	0.2339	0.4413	1		
L1_USCSIlnret	0.3403	0.1625	0.3994	0.3600	0.0303	0.0121	-0.0893	0.0712	0.0341	1	
L1_USCPIlnret	0.2853	0.1821	0.2415	-0.0587	0.1634	0.1403	0.5512	0.2638	0.5978	-0.1211	1

This table presents the pair-wise linear correlations for all the variables used in the estimated models. L1_EUDIlnret is highly correlated to L1_EUPCElnret and L1_EUCPIlnret, the same for L1_EUCPIlnret and L1_USCPIlnret and thus they cannot enter simultaneously at the regression analysis.

The next step was to perform Augmented Dickey-Fuller test to the log returns of our dependent variables and to all lagged versions of the log returns for our independent ones. All of them provided satisfactory results and therefore all our time-series were proved to be stationary and could be used for our regression analysis.

The first analysis we carried out was for Europe, in order to identify if and how CCFI for Euro Area are affected by our explanatory variables. The main results both for monthly and quarterly basis are reported to the below table. Model 1 displays monthly results. The positive coefficient denotes that our main selected variable, L1_EUCCIlnret has significant positive relationship with the CCFIEUlnret –also expected from the positive correlation between them - which is strengthened by the t-stat (3.44) of the variable and the acceptable p-value both of the variable and of the model. Certainly, we cannot ignore the low R-squared of the model, which shows the amount of variance of response variable explained by the explanatory yet we should keep in mind that this is also a relative measure to compare with other models. Similar results were found also with quarterly data. Due to multicollinearity reasons, we performed two different regressions, one with L1_EUCCIlnret and L1_EUDIlnret as the explanatory variables and the second one with L1_EUPCElnret and L1_EUCPIlnret instead of the lagged disposable income thus we have two different outcomes. Model 2 indicates that L1_EUCCIlnret and L1_EUCPIlnret were proved to be significant factors for CCFIEUlnret which is also the case for L1_EUCCIlnret and L1_EUDIlnret as per Model 3. Nevertheless, Model 2 not only has more positive coefficients and a higher R-squared (0.2551) compared to Model's 3 (0.1838) but also has higher t-stat values (Model 2: 3.75 for Consumer Confidence and 3.95 for CPI vs. Model 3: 2.35 for Consumer Confidence and 2.79 for Disposable Income). This is something that we should highlight as t-stat demonstrates the importance of a variable at the model. P-values individually and in total for the model are acceptable for both of them. Root MSE – the standard deviation of the regression – is also lower for Model 2 which is the desired outcome. Comparing monthly to quarterly results, while there were no monthly data for Disposable Income and naturally we did not take this variable into account, this was not the case for Consumer Price Index that was found to be highly considerable at a quarterly basis. All specification error tests (see Appendix for the relevant graphs of all models) validate our results except for RAMSEY test for monthly data (Prob > F 0.0196) yet this is something we can endure as we have already mentioned the limitations for our monthly Europe dataset. The Variance Inflation errors are excellent for all three models. The predictive power for quarterly models seems better as the linear prediction from the fitted model has a clearer slope compared to the relative monthly scatter plot. By the same reasoning, the scatter plot between residuals and predicted values declares more homoscedastic variance in the residuals when the respective monthly scatter plot while it has no pattern, has more concentrated to the y line (0) observations. No outliers are detected, and residuals seem to follow a normal distribution with a small abnormality at the tails of the extreme values. Moreover, for the monthly model, kernel density distribution seems slightly higher than the normal distribution, but this may be linked with the specification error from RAMSEY test and the limitations of the monthly dataset we have already described.

VARIABLES	(Model 1) CCFIEUlnret	(Model 2) CCFIEUlnret	(Model 3) CCFIEUlnret
L1_EUCCIlnret	6.740***	7.968***	5.667**
	(1.960)	(2.123)	(2.415)
L1_EUCPIlnret		5.344***	
		(1.351)	
L1_EUDIlnret			0.583***
			(0.209)
Constant	-0.0222	-0.549**	-0.121
	(0.0663)	(0.260)	(0.223)
Observations	203	67	67
R-squared	0.066	0.255	0.184

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Our second analysis concerned the CCFI for the US and the relationship of this index with the independent variables we have selected. Results for monthly and quarterly basis are displayed at the following table. Model 4 reports the monthly results and Model 5 represents the quarterly outcome from which we had excluded L1_USCPIlnret as insignificant and highly correlated to L1_USPCElnret. What we can easily conclude is that the common denominator at both models is the statistical significance of L1_USPCElnret which also had the higher correlation with the US freight rates. The positive coefficient for both models denotes a positive effect per unit change of L1_USPCElnret. Our main explanatory variable, Consumer Sentiment was found to be insignificant for both models and actually had a negative correlation with freight rates at a monthly level. This is a fact that contradicts to Europe's models where lagged versions of log returns for Consumer Confidence were proved to be significant. L1_USCSIlnret and L1_USDIlnret were only reported to the results' table as the R-squared was further deceasing from the already low level it produced – especially for monthly data the model explained only about the 2% of the response variable. In case we performed Model 5 only with L1_USPCElnret, the Root-MSE would remain almost constant, the t-stat of the variable would be increased (3.05) and p-values of both the model and the variable would be lower (0.0033 and 0.003 respectively) yet we preferred to examine an analysis with higher R-squared. Bearing this in mind, t-stat (Model 4: 2.23 vs. Model 5: 2.05) and p-values (Model 4: 0.027 vs. Model 5: 0.045) were found to be statistically significant only for L1_USPCElnret. No specification errors were detected, and the Variance Inflation Errors were once again spotless. The predictive power of our models seemed questionable, especially for the monthly dataset as the linear prediction from the fitted model more resembles to a sphere than to a slope. Furthermore, while the scatter plot between residuals and predicted values was generated with no pattern for Model 5; there was a concentration to the y line (0) for Model 4 that warned us for possible signs of heteroscedasticity. Once again, no outliers were identified, and the residuals behaved in the same manner with Europe's models yet notably better for Model 5.

VARIABLES	(Model 4) CCFIttlUSlnret	(Model 5) CCFIttlUSlnret
L1_USPCElnret	1.984**	2.344**
	(0.891)	(1.144)
L1_USCSIlnret		0.0965
		(0.0730)
L1_USDIlnret		0.669
		(0.719)
Constant	-0.0907*	-0.405**
	(0.0536)	(0.164)
Observations	203	67
R-squared	0.019	0.074

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The third and final analysis we carried out was about our Total Europe and US model. The response variable was the Composite CCFI and the issue under question was the potential impact that all explanatory variables for both Europe and US could have on the index. The main results are presented at the table that follows and they are really interesting. Model 6 represents the upshot of the model with monthly data and Model 7 the one with quarterly observations. With a first glance, we can identify both similarities and differences between the two models. The statistical significant variables for Model 6 were L1_EUCCIlnret (positive coefficient of 2.189) and L1_USPCElnret (positive coefficient of 2.150) while for Model 7 the respective variables are L1_EUCPIlnret (positive coefficient of 2.295), L1_USPCElnret (positive coefficient of 3.874) and L1_USCSIlnret (positive coefficient of only 0.260). L1_EUCCIlnret for Model 7 was found to be marginally statistically insignificant when it was examined as the only explanatory variable, yet the p-value of that regression was not acceptable (0.0696). R-squared for Model 7 was by far higher not only from Model 6 but also from all other models we analyzed, indicating a better explanation of the Composite Index comparing to monthly dataset. L1_USPCElnret was the common explanatory variable that turned out to be important for Model 6 and Model 7 when this was also the case previously for Model 4 and Model 5. We could support that Model 7 provide us with better and more valid results, not only due to its higher R-squared but also for its higher t-stat, lower p-values for the variables and in addition lower p-value for the model

(Model 6: 0.0118 vs. Model 7: 0.0000). Only the Root-MSE is slightly better for Model 6 (Model 6: 0.53766 vs. Model 7: 0.91173) but standard deviation of the regression is so low for both models that does not have major effect. By carrying out the RESET test and by also regressing the response variable of the initial regression against the initial regression's prediction as well as the squared prediction, we ascertained that there was no specification error to any of our models. Taking this into account, we have ensured that the R-squared of Model 7 does not accrue from the higher number of variables but indeed explains the response variable in a better manner than Model 6. No multicollinearity issue was detected but again the predictive power of the models is not the desirable as the scatter plot of the estimated linear prediction from the fitted model with the log return Composite CCFI time-series did not generate a 45^0 slope for monthly data when for quarterly data despite the proper slope, the prediction was not as linear as we would like to be. The heteroscedasticity of the models is observed to be under control and also no outliers were identified. Finally, we tested that the “white noise” of the two models is normally distributed so as to validate the hypothesis tests occurred. The kernel density for both models followed a normal distribution – for Model 7 almost identically – and the normal-probability and quintile-normal plots confirmed the fifth assumption of linear regression yet with some non-normality detected at the extreme values of both of the models.

VARIABLES	(Model 6) CCFIALLlnret	(Model 7) CCFIALLlnret
L1_EUCCIlnret	2.189**	
	(1.037)	
L1_EUCPIlnret		2.295***
		(0.763)
L1_USPCElnret	2.150**	3.874***
	(0.981)	(1.026)
L1_USCSIlnret		0.260***
		(0.0922)
Constant	-0.0870	-0.652***
	(0.0538)	(0.141)
Observations	203	67
R-squared	0.050	0.317

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As discussed earlier, in order to decide whether our linear regression model is appropriate for our data, we need to examine the residual plots. The difference between the observed value of the dependent variable (y) and the predicted value (ŷ) is called the residual (e). Each data point has one residual.

Residual = Observed value - Predicted value

$e = y - \hat{y}$

Both the sum and the mean of the residuals are equal to zero. That is, $\Sigma e = 0$ and $e = 0$. The residual plot depicts the residuals on the vertical axis and the independent variable on the horizontal axis. Only if the points in a residual plot are randomly dispersed around the horizontal axis, is a linear regression model appropriate for the data. In our case, the above indeed applies for all our seven models, hence the linear regression approach we adopted is considered appropriate.

Finally, we performed the Newey-West test for all the variables that were proved to be significant for the above models. As indicated in the results of the below tables, all of the variables do not face any issue of autocorrelation and heteroscedasticity. The first table presents the results for the monthly regressions while the second the respective results for quarterly data.

Monthly Results

VARIABLES	CCFIALLlnret	CCFIEUlnret	CCFIttlUSlnret
L1_EUCCIlnret	2.189*	6.740***	
	(1.203)	(2.335)	
L1_USPCElnret	2.150**		1.984**
	(1.014)		(0.850)
Constant	-0.0870	-0.0222	-0.0907
	(0.0599)	(0.0796)	(0.0570)
Observations	203	203	203

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Quarterly Results

VARIABLES	CCFIALLlnret	CCFIttlUSlnret	CCFIEUlnret
L1_EUCPIlnret	2.295***		5.344***
	(0.637)		(1.052)
L1_USPCElnret	3.874***	2.859***	
	(1.044)	(0.930)	
L1_USCSIlnret	0.260***		
	(0.0917)		
L1_EUCCIlnret			7.968***
			(2.323)
Constant	-0.652***	-0.379**	-0.549**
	(0.151)	(0.160)	(0.256)
Observations	67	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Section 6: Discussion of the Results

Moving on, and in relation with the outcome of our models, we once more highlight the original objective of this paper which was to examine and discover if there is any relationship between container freight rates and consumers' purchasing power – as represented from the selected explanatory variables – since there was no relative literature review for containership market. Our main independent variables that were the Consumer Confidence Index for Europe and Consumer Sentiment Index for the US were proved to be significant only for Europe and to a quite notably lower level for the Total EU and US freight rates. Consumer Confidence for the EU had a major positive impact on both CCFI for Europe and the Composite Index with only the exception of the quarterly analysis for the Composite Index which was though the analysis with the higher percentage of the independent variables to explain the response one. The same analysis was also the only one that we discovered Consumer Sentiment to have a statistical significant positive relationship with freight rates and this is a fact that raised further concerns in addition to the low R-squared of the rest of our models. Our initial hypothesis of disposable income to have a prodigious effect on container freight rates, as the available income to spend for manufactured goods, had substance only for the Europe's Disposable Income and in accordance with CCFI for Europe. Changes in consumption, as expressed by the Personal Consumption Expenditures, were found out to be highly correlated to freight rates but only from the US side for both the US and Composite Index while had no outcome as far as Europe was concerned. Finally, further to the existing literature regarding GDP's connection to freight rates, our research further contributed to it by proving the positive effect of Europe's CPI to container freight rates for Europe and the Composite Index. No such relationship was detected though for the US's CPI. This research brings beneficial conclusions and information for both containership Owners and Charterers, who can use the consumers' confidence as one of the factors formatting their strategic decisions, especially for routes connected with Europe. Our findings indicate that, in the long run, consumption influences container freight rates from different perspectives and according to the destination of the routes. Both ship-owners and charterers can develop their strategy bearing in mind not only the general financial situation but also specifically the elements of consumption and attempt to forecast how container freight rates will be formulated and their fluctuations.

Also, it is easily understood that containership freight rates, are not easily affected by consumer's power or income, but instead they are quite steady and inelastic towards such. This is probably an outcome due to the formation of collaborations and alliances which create a "protective wall" around the level of freight against shocks and other events. The above results are considered extremely interesting while also leave room for further analysis based on our findings and taking into consideration certain limitations of our model.

As it becomes transparent from our results, our independent variables do not seem to have any significant impact on our dependent. This can be explained by several reasons. First of all, we understand from the start that consumers' sentiment and income could not of course affect in a direct way the freight rates of containerships. Such factors directly affect the demand for products, hence the price of the products in demand, not the transportation cost. High demand also leads to the creation of inventories, and consequently after a drop in the demand a stock is created and stored until the next rise. As a result, when the need for goods emerges again, it will be satisfied by the existing stock, so again the sea transportation of the goods and thereafter the freight rates will not be touched.

Furthermore, what is also very crucial to consider, is the process by which freight rates are constructed. More specifically, we should bear in mind that the major considerations on which the containership freight rates are built, and which influence their development, a drop or a rise, are mainly nine. Primarily, the weight of the cargo and the distance to the delivery destination are determining to calculating ocean freight rates. The longer the journey the more exorbitant the rates and vice versa. Also, the service charges levied by port authorities along with the seasonality of certain goods play a tremendous role in transportation cost. Ocean freight rates further depend on exchange rate fluctuations depending on the currency, and fines imposed at ports as well as several fees. Other factors severely affecting containership freight rates are the bunker capacity and fuel prices, the TEU capacity of the containerships and the availability of vessels. It is considered that rates tend to increase as demand increases and capacity decreases, hence it would probably be fruitful to include in our model the TEU capacity factor.

Ocean shipping rates are generally pre-set and standardized. But regular shippers take advantage of client-business relationships to avail of discounts. Although containership freight rates consist a highly unpredictable area, a lot of research has been performed lately to provide a better perception on the field and enable shippers to carry out the shipping of goods in a more efficient and simpler way.

Focusing now on the side of the flaws detected, we have already particularly described the limitations we faced regarding our data at **Section 3** of this paper and thus we will not restate them. Now we will try to highlight all weaknesses of our model as well as to propose some ideas for future research on the topic we have undertaken.

First of all, the detection of the optimal number of lags for all variables and further regression analysis with these amended time-series would probably generate more reliable results, for which we should mention though that they may not contradict to our findings. Especially for the US where the R-squared of our models was notably low, optimal lags could be a valuable addition to our research. Furthermore, it would be extremely interesting to inspect for seasonality effects. Demand and consumption for manufactured products transported through container ships can be severely affected and vary from period to period due to Christmas and Easter Holidays, commencement of school year, summer vacation etc. Another possible extension to our analysis would be the addition of variables from the supply side with the expectation though not to have significant impact on consumption. Last but not least, the same regression analysis we performed could be carried out again with the application of Mixed Data Sampling (MIDAS) models that can analyze simultaneously data of different frequency among the dependent and the independent variables in order to overcome the conversion of monthly data to average quarterly so as to be comparable with the other variables examined.

Section 7: Conclusions

This paper has amplified the existing literature since there is no other reported attempt to measure the effect of the consumption to container freight rates. Our first finding was that in addition to world economy and international maritime trade, consumption does indeed have an effect to container freight rates from the demand side. Nevertheless, the coefficients that have an impact on freight rates vary as we proved that freight rates for routes from China to Europe and US were not affected by the same factors when consumption enters the equation.

Consumer Sentiment as the main explanatory variable of how consumption affects CCFI was proved to be significant only from Europe's side while US Consumer Sentiment slightly influences the Composite Index. Moreover, the results revealed that Personal Consumption Expenditures of US households have a major impact both on the US and the Composite Index pointing out the importance of the US inhabitants for the maritime trade of manufactured goods. The only other variables that were found statistical important were the Europe's CPI and Disposable Income, the latter with a minor impact on CCFI for Europe while CPI was a key driver for the Composite Index as well. This comes as a consequence to the existing literature of how GDP and income affect the international trade but also contradict their impact on freight flows from China to US for other shipping segments.

Section 8: References

- Adland, R., Strandenes, S.P. (2007), "A discrete time stochastic partial equilibrium model of the spot freight market." *Journal of Transport Economics and Policy* 41(2): pp 189-218
- Bakshi, S. (2012), "Impact of gender on consumer purchase behavior." *National monthly refereed journal of research in commerce & management* 1(9): pp 1-8
- Beenstock, M. and Vergottis, A. (1993), "Econometric modeling of World Shipping." London: Chapman & Hall
- Brooks, C. (2012), "Introductory econometrics for Finance", second edition, Reading, England
- Carroll, C., Fuhrer, J. and Wilcox, D. (1994), "Does Consumer Sentiment Forecast Household Spending? If So, Why?" *The American Economic Review* 84(5): pp. 1397-1408
- Chi, J. (2016), "Exchange rate and transport cost sensitivities of bilateral freight flows between the US and China." *Transportation Research Part A: Policy and Practice* 89: pp 1-13
- Dreger, C., Reimers, H.E. (2006), "Consumption and disposable income in the EU countries: the role of wealth effects." *Empirica, Springer; Austrian Institute for Economic Research; Austrian Economic Association* 33(4): pp 245-254
- Ducruet, C.,and Notteboom, T. (2012), "The worldwide maritime network of container shipping: spatial structure and regional dynamics",Golbal Networks:pp 395-423
- European Commission (2008), "Guidelines on the application of Article 81 of the EC Treaty to maritime transport services." *European Commission Brussels* 2008/C 245/02
- Goldsmith, R.E., Freiden, J.B. (2004), "Have it your way: consumer attitudes toward personalized marketing." *Marketing Intelligence and Planning* 22(2): pp 228–39
- Howrey, P. (2001), "The Predictive Power of the Index of Consumer Sentiment." *Brookings Papers on Economic Activity* 32(1): pp 175-207

- Jingbo, Y. and Jinhao S. (2018), “Seasonality patterns in the container shipping freight rate market.” *Maritime Policy & Management* 45(2): pp 159-173
- Jugovic, A., Komadina, N. and Peric, Hadzic, A., (2015), “Factors Influencing the formation of freight rates on maritime shipping markets.” *Scientific Journal of Maritime research* 29: pp 23-29
- Kutin, N., Moussa, Z., and Vallée, T. (2018), "Factors behind the Freight Rates in the Liner Shipping Industry." *Working Papers halshs*-01828633, HAL.
- Lee, C.Y. and Song, D.P. (2017), “Ocean container transport in global supply chains: Overview and research opportunities.” *Transportation Research Part B: Methodological* 95: pp 442-474
- Luo, M., Fan, L., & Liu, L. (2009), “An econometric analysis for container shipping market.” *Maritime Policy & Management* 36(6): pp 507-523.
- Mason, R. and Nair, R. (2013), “Supply-side strategic flexibility capabilities in container liner shipping.” *The International Journal of Logistics Management* 24(1): pp 22-48.
- Moon, J., Chadee, D., & Tikoo, S. (2008), “Culture, product type, and price influences on consumer purchase intention to buy personalized products online.” *Journal of Business Research* 61(1): pp 31-39
- Munim, Z. H., Schramm, H. J. (2017), “Forecasting container shipping freight rates for the Far East – Northern Europe trade lane.” *Maritime Economics & Logistics* 19(1): pp106-125
- Nielsen, P., Jiang, L., Rytter, N. G. M. and Chen, G. (2014), “An investigation of forecast horizon and observation fit’s influence on an econometric rate forecast model in the liner shipping industry.” *Maritime Policy and Management* 41(7): pp 667-682
- Notteboom, T. and Cariou, P. (2013), “Slow steaming in container liner shipping: is there any impact on fuel surcharge practices?” *The International Journal of Logistics Management* 24(1): pp 73-86.

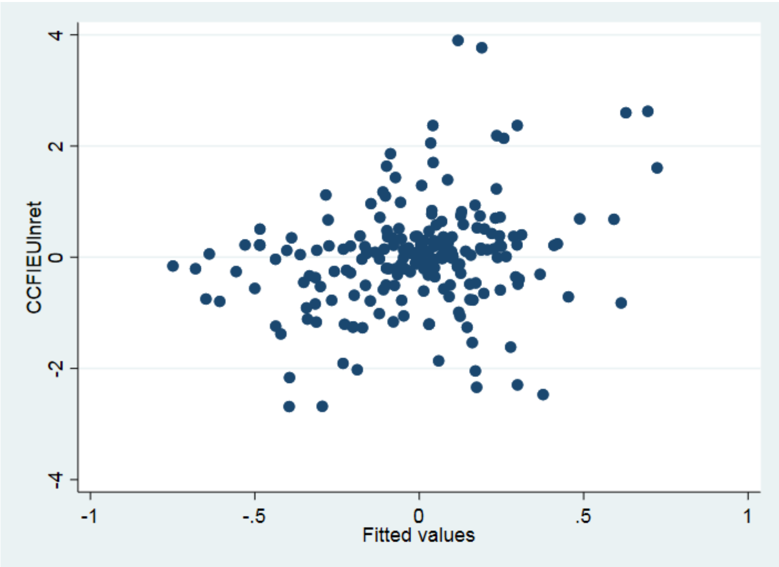
- Rezvani, S., Dehkordi, G. J., Rahman, M. S., Fouladivanda, F., Habibi, M., & Eghtebasi, S. (2012), "A Conceptual Study on the Country of Origin Effect on Consumer Purchase Intention." *Asian Social Science* 8(12)
- Schultze, C. (2003), "The Consumer Price Index: Conceptual Issues and Practical Suggestions." *Journal of Economic Perspective* 17(1): pp 3–22
- Slack, B. and Gouvernal, E. (2011), "Container freight rates and the role of surcharges." *Journal of Transport Geography* 19(6): pp 1482-1489.
- Stopford, M. (2009), "Maritime Economics", third edition, Abingdon, Oxon: Routledge, England.
- Sys, C. (2008), "Is container liner shipping an oligopoly?" *In Proceedings of the International Forum on Shipping, Ports and Airports* (ISFPA'08), 25-28 May 2008, Hong Kong
- Teo, P. C., Mohamad, O., & Ramayah, T. (2011), "Testing the dimensionality of Consumer Ethnocentrism Scale (CETSCALE) among a young Malaysian consumer market segment." *African Journal of Business Management* 5(7): pp 2805-2816
- U.S. Bureau of Labor Statistics. (2011), "Differences between the Consumer Price Index and the Personal Consumption Expenditures Price Index" 2(3)
- UNCTAD (2015), "Review of Maritime Transport."
- UNCTAD (2018), "Review of Maritime Transport."
- UNCTAD (2019), "Review of Maritime Transport."
- Wang, D. H., Chen, C. C., and Lai, C. S. (2011), "The rationale behind and effects of Bunker Adjustment Factors." *Journal of Transport Geography* 19(4): pp 467-474.
- https://data.oecd.org/leadind/consumer-confidence-index-cci.htm
- https://ec.europa.eu/eurostat/statistics-explained/pdfscache/65805.pdf
- https://en.sse.net.cn/indices/introduction_ccfi_new.jsp
- https://medium.com
- https://tradingeconomics.com/united-states/consumer-confidence
- https://unctad.org/system/files/official-document/rmt2015ch3_en.pdf
- https://www.bea.gov/system/files/2019-12/Chapter-5.pdf

- https://www.investopedia.com/terms/c/consumer-sentiment.asp
- https://www.investopedia.com/terms/d/disposableincome.asp /
- https://www.marineinsight.com

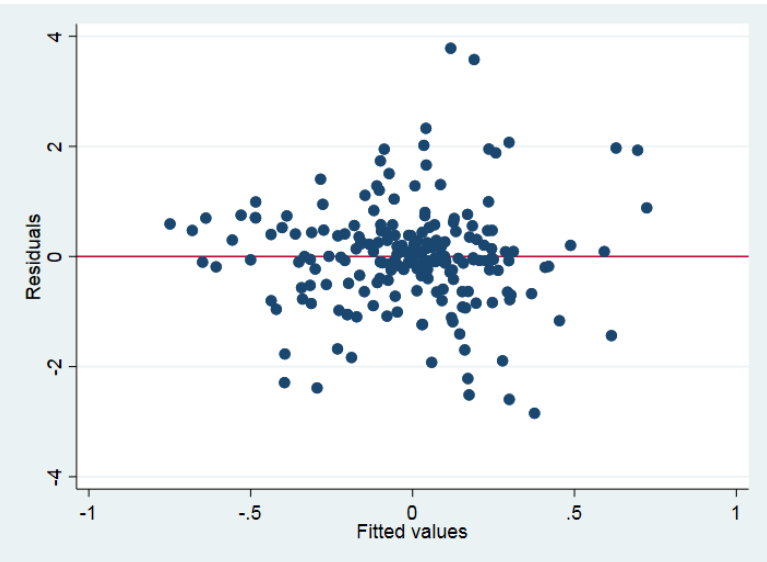
Section 9: Appendix

Model 1

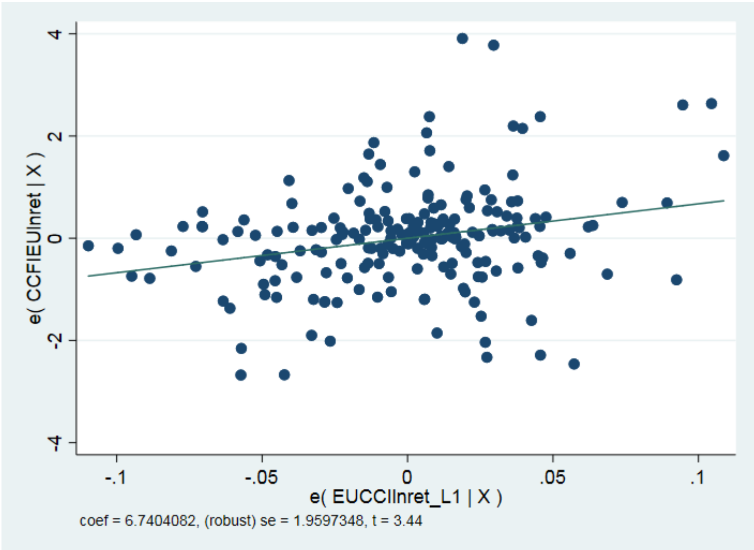
1. Observed vs. Predicted Values



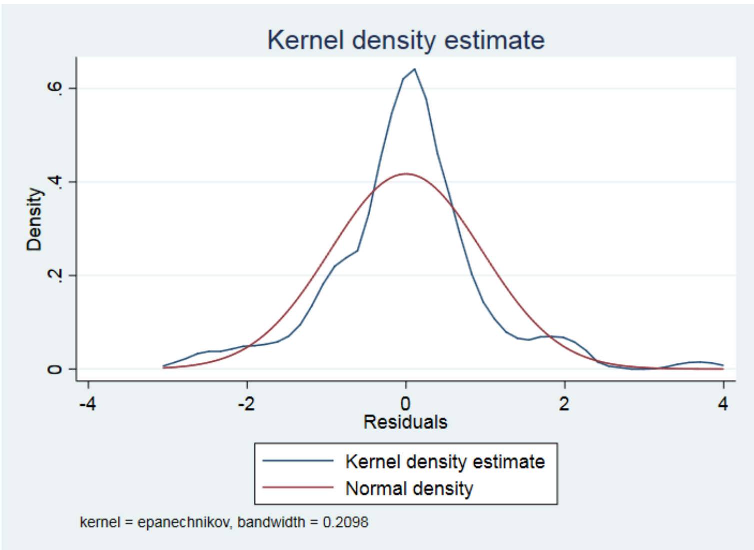
2. Residuals vs. Fitted Values



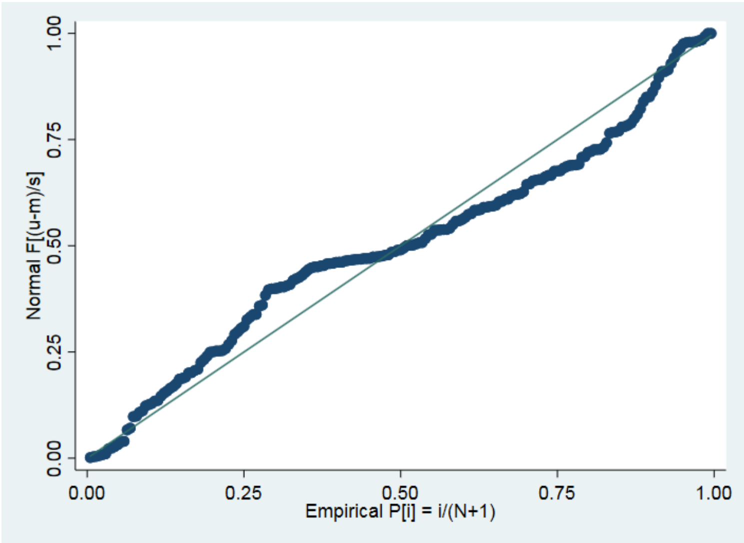
3. Added Variable Plots



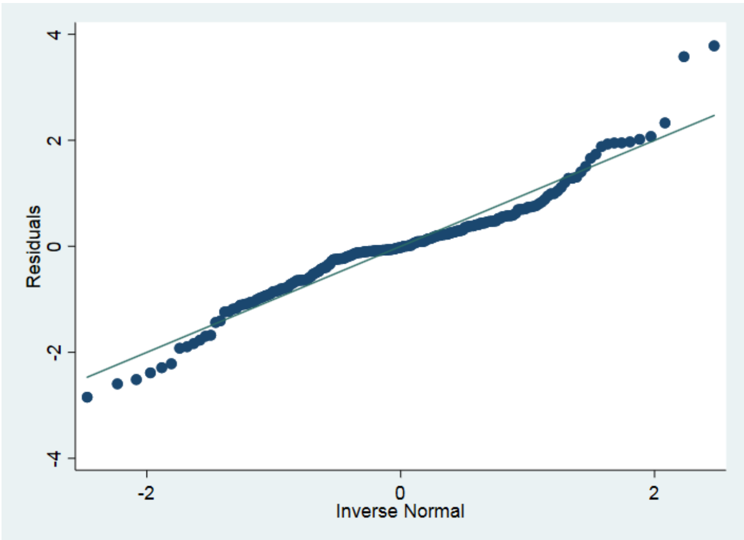
4. Kernel Density Plot



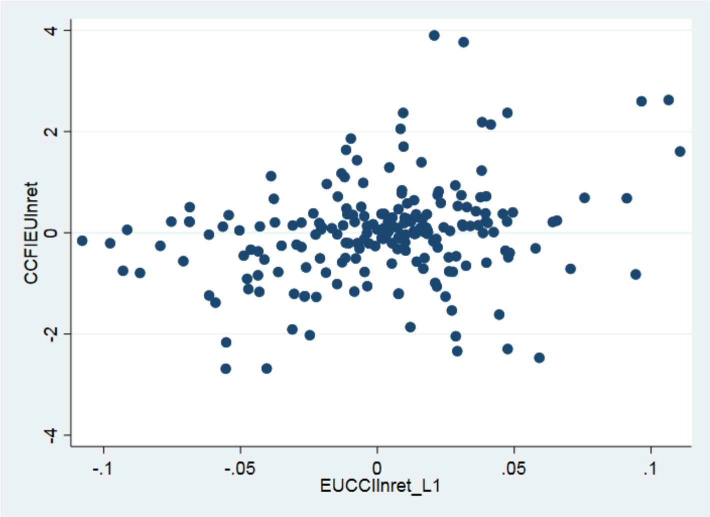
5. Normal Probability Plot



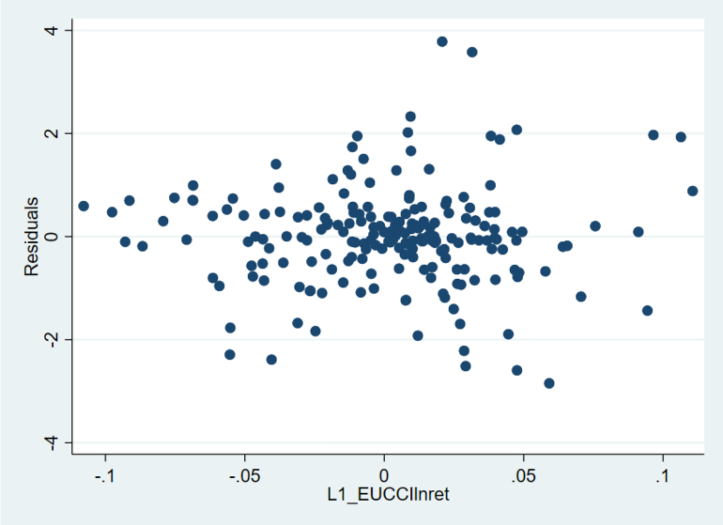
6. Quintile Probability Plot



7. Scatter Plot

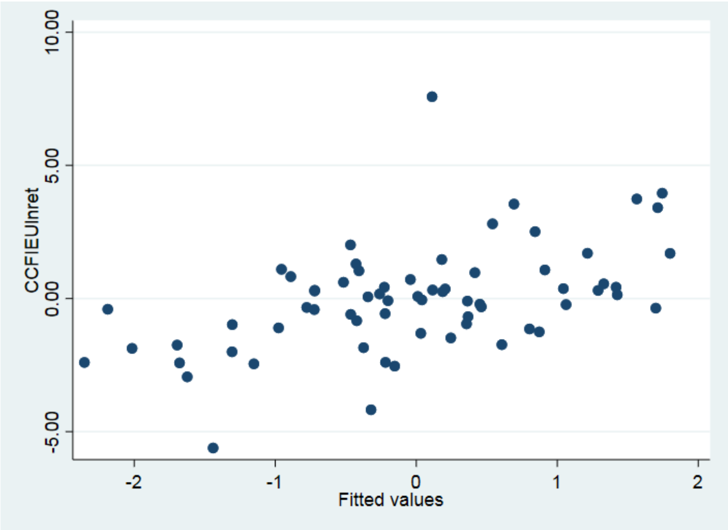


8. Residuals vs. Predicted Values

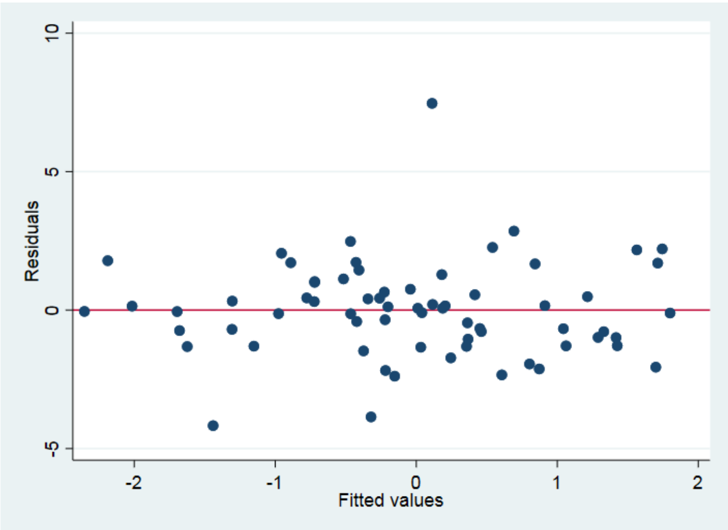


Model 2

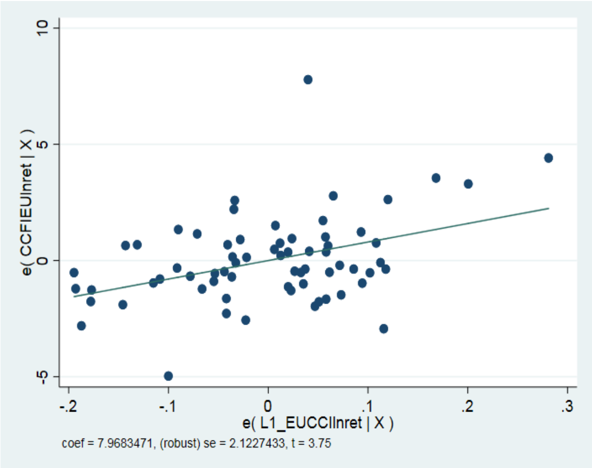
1. Observed vs. Predicted Values

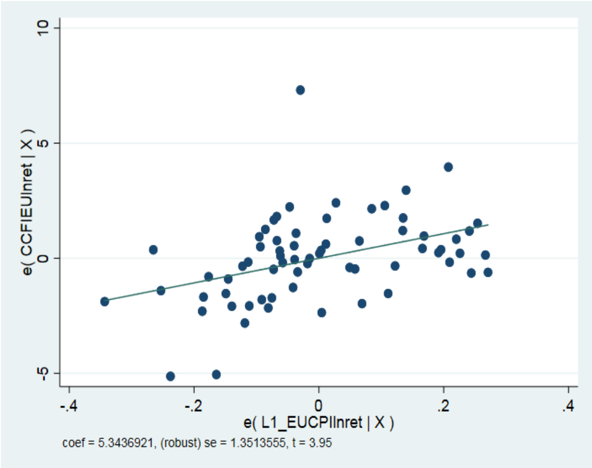


2. Residuals vs. Fitted Values

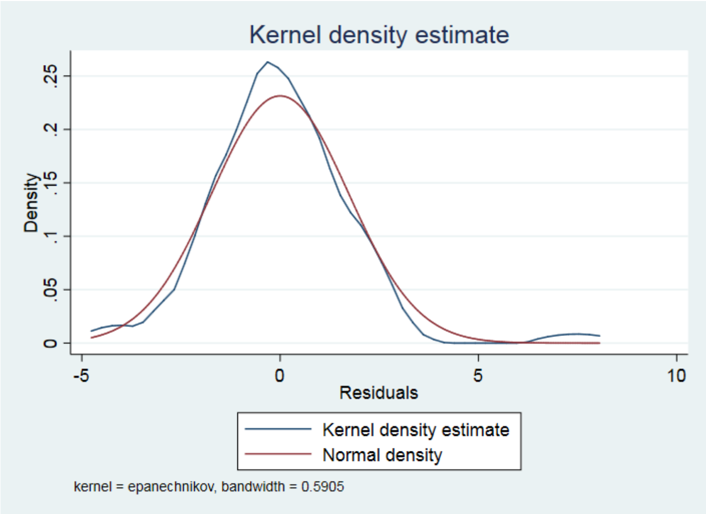


3. Added Variable Plots

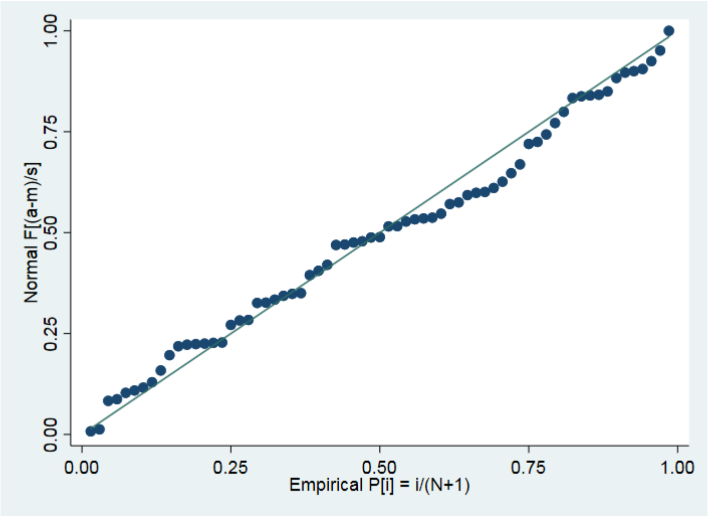




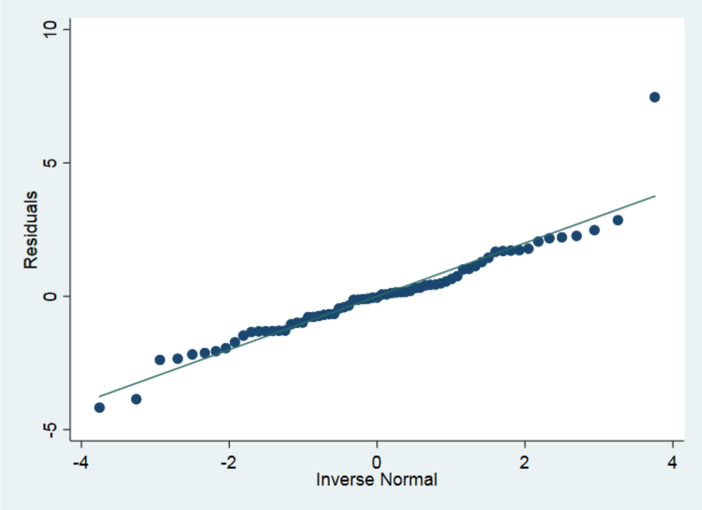
4. Kernel Density Plot



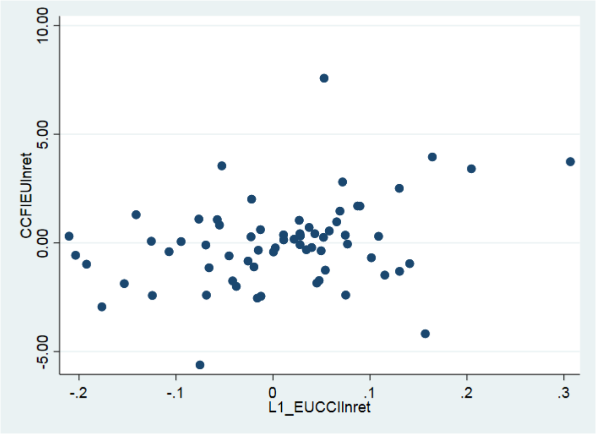
5. Normal Probability Plot

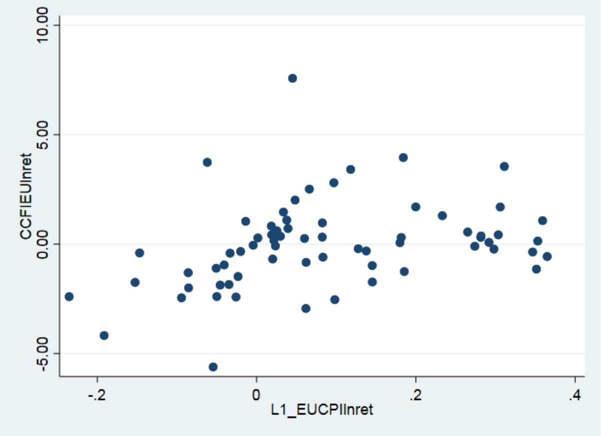


6. Quintile Probability Plot

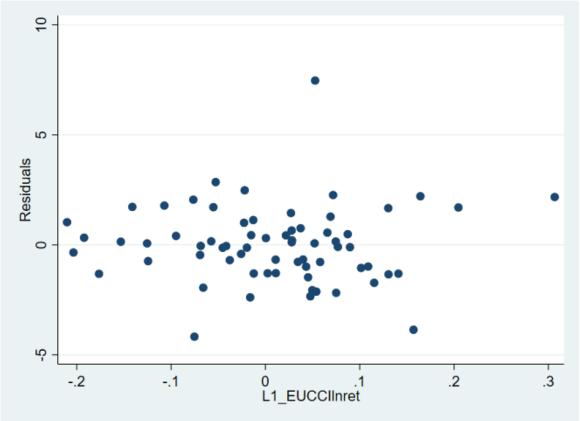


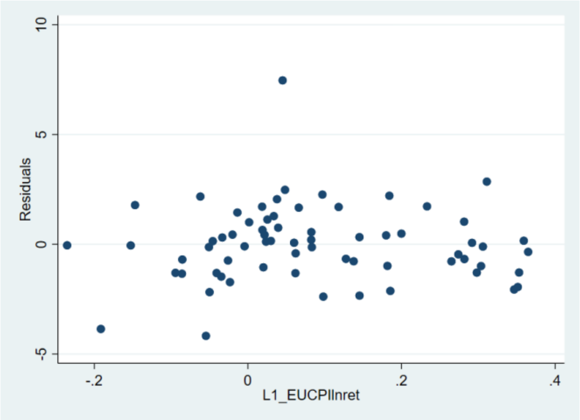
7. Scatter Plot





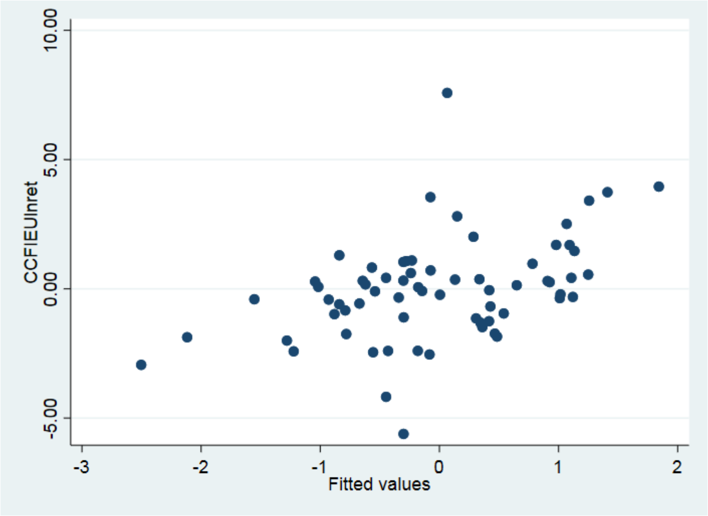
8. Residuals vs. Predicted Values



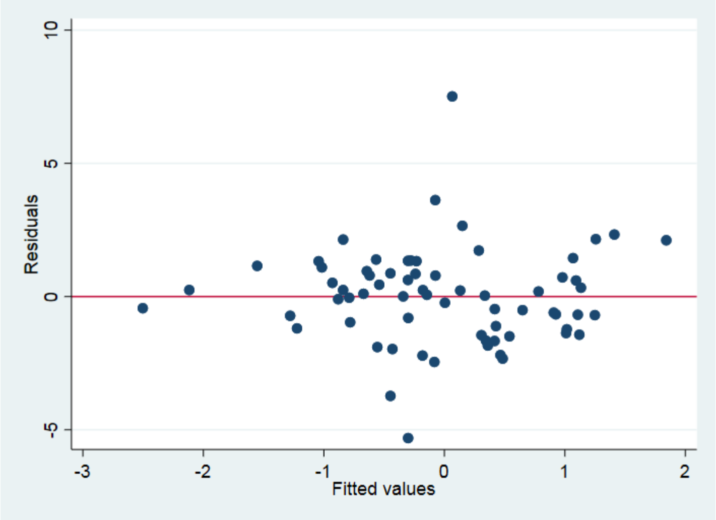


Model 3

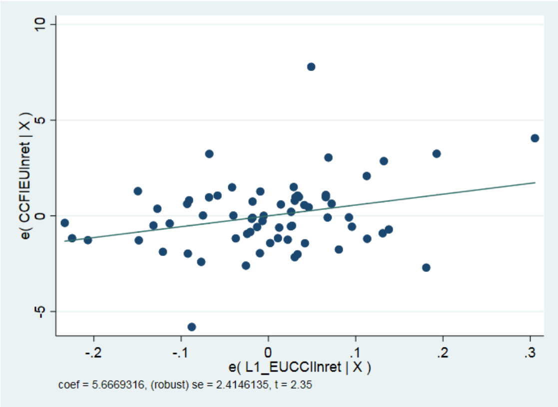
1. Observed vs. Predicted Values

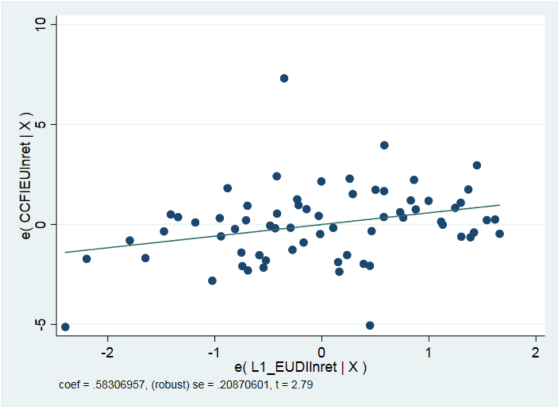


2. Residuals vs. Fitted Values

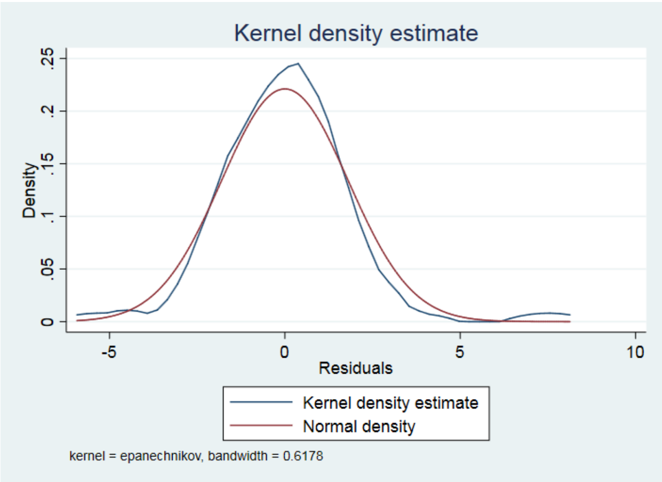


3. Added Variable Plots

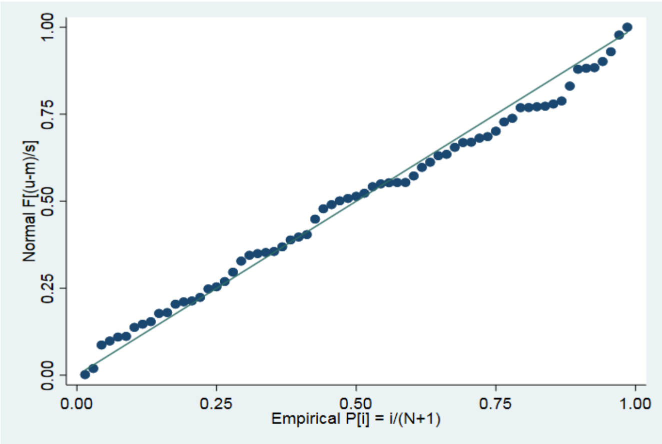




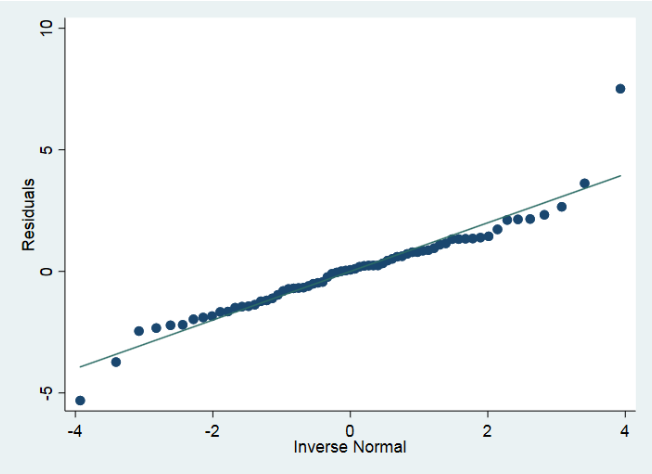
4. Kernel Density Plot



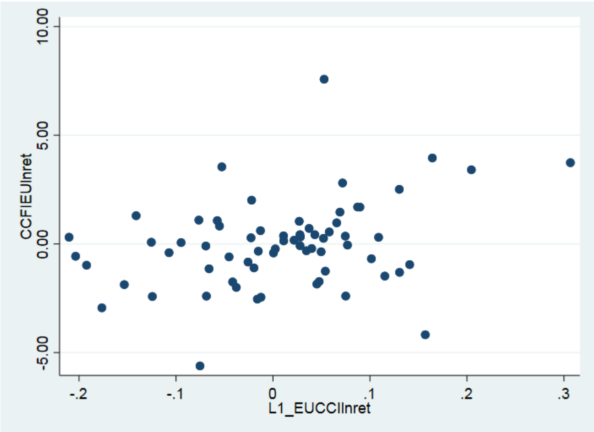
5. Normal Probability Plot

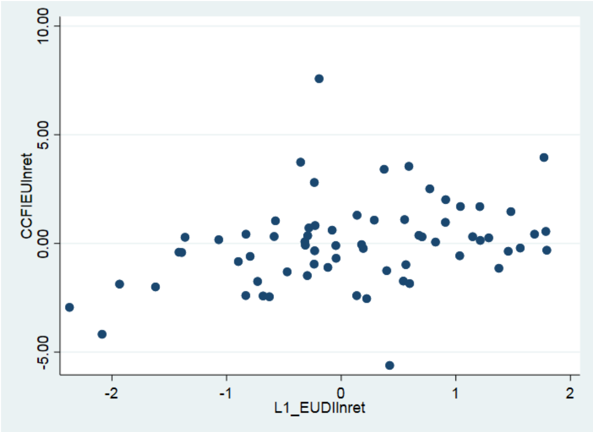


6. Quintile Probability Plot

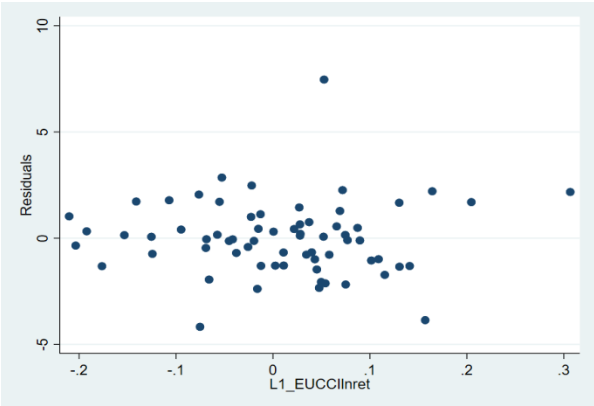


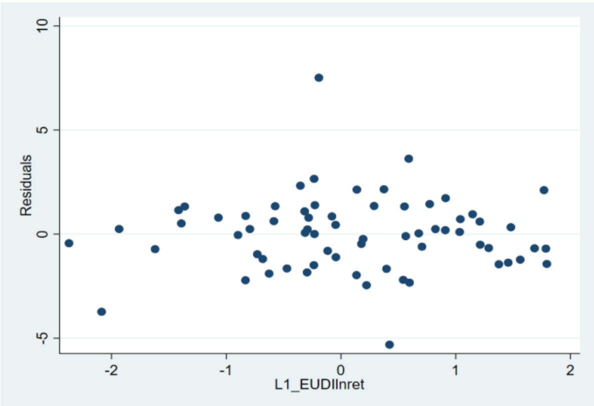
7. Scatter Plot





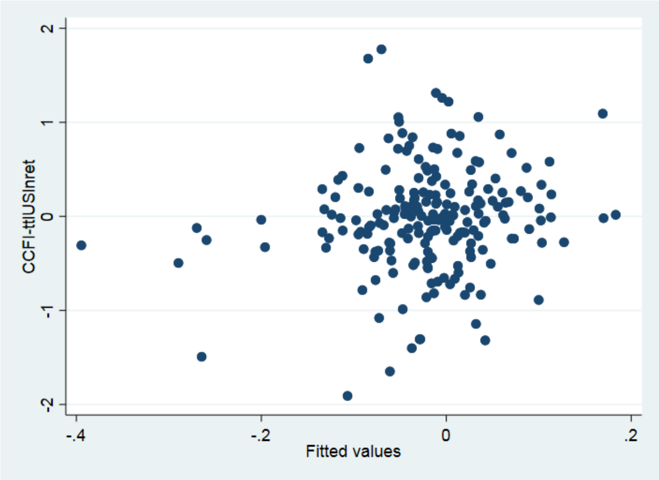
8. Residuals vs. Predicted Values



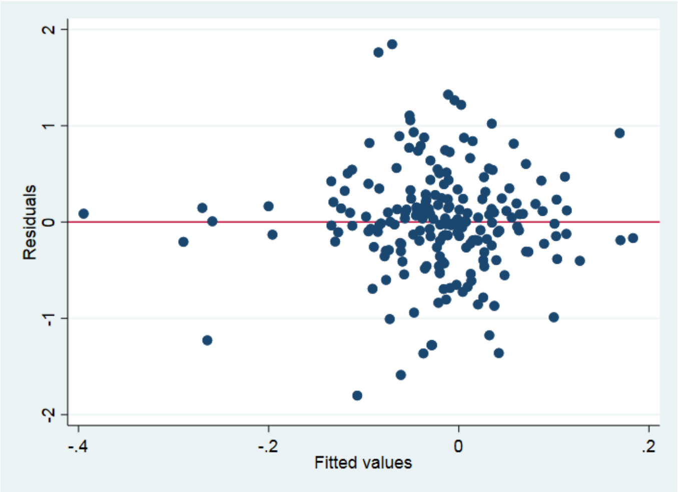


Model 4

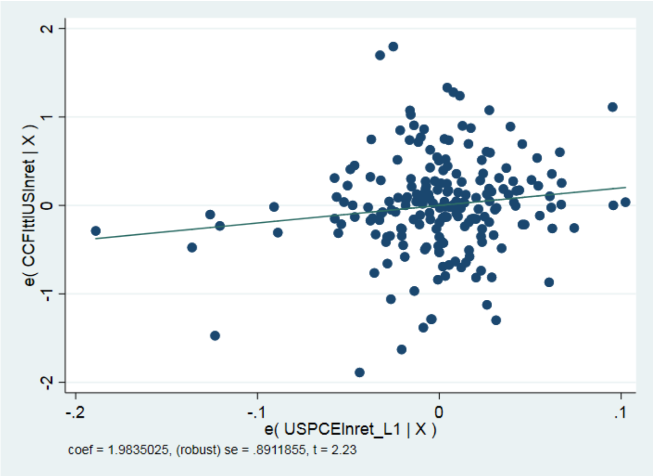
1. Observed vs. Predicted Values



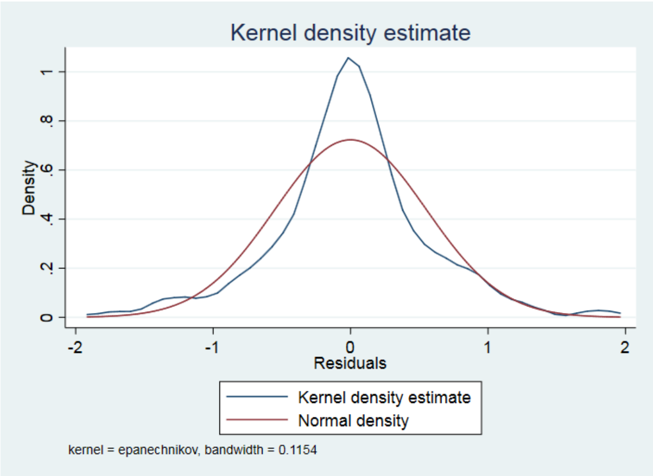
2. Residuals vs. Fitted Values



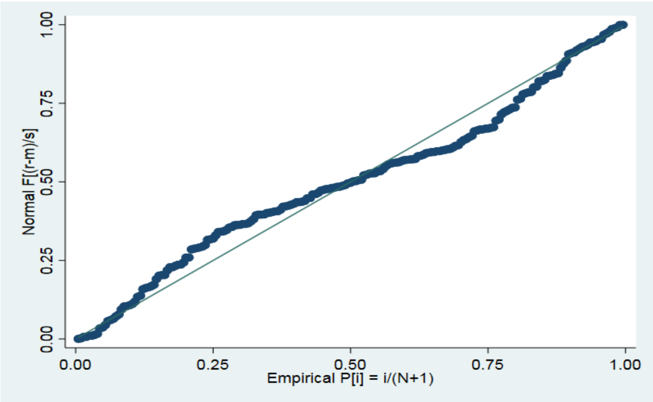
3. Added Variable Plots



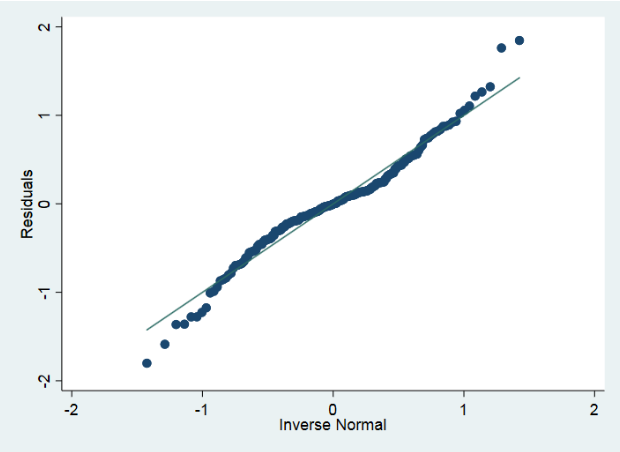
4. Kernel Density Plot



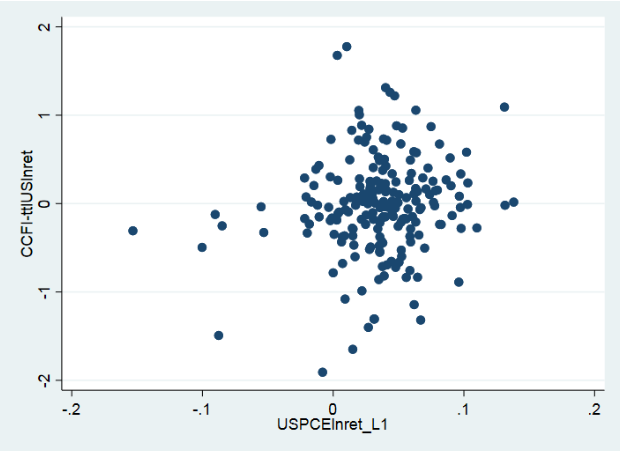
5. Normal Probability Plot



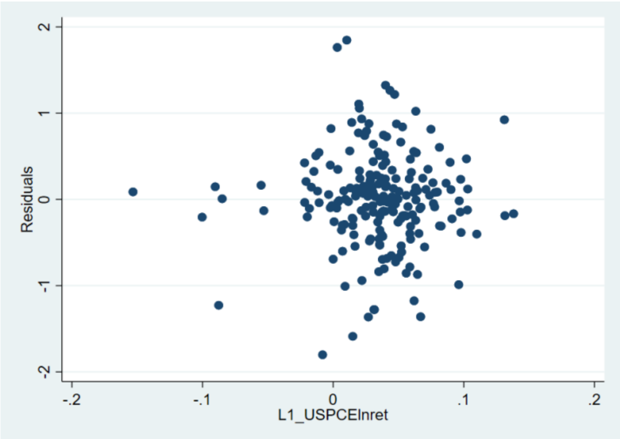
6. Quintile Probability Plot



7. Scatter Plot

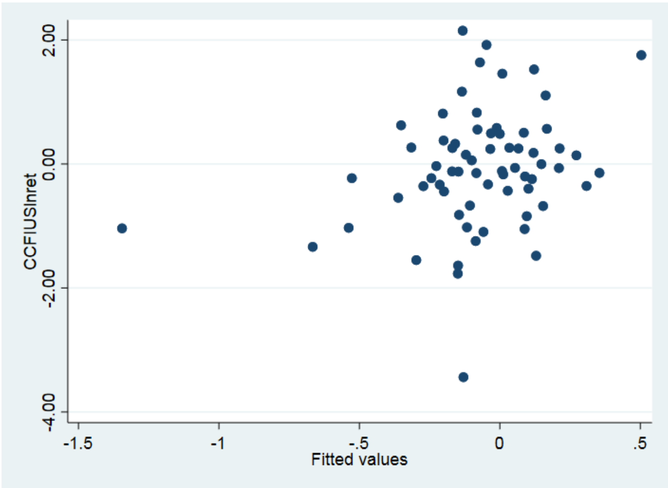


8. Residuals vs. Predicted Values

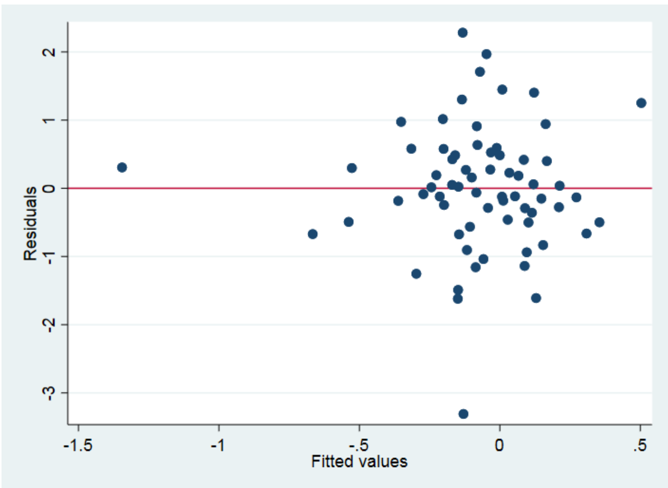


Model 5

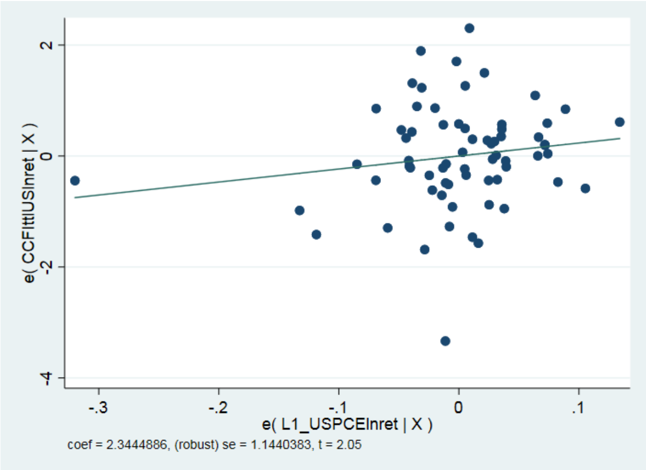
1. Observed vs. Predicted Values



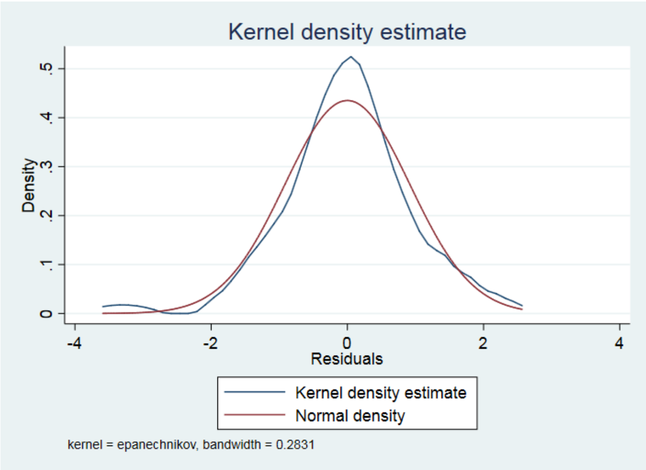
2. Residuals vs. Fitted Values



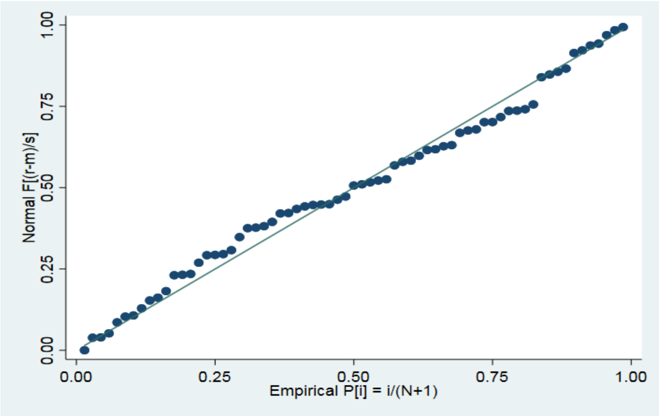
3. Added Variable Plots



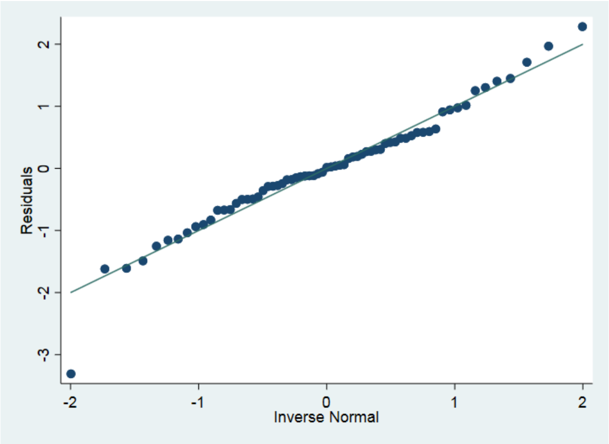
4. Kernel Density Plot



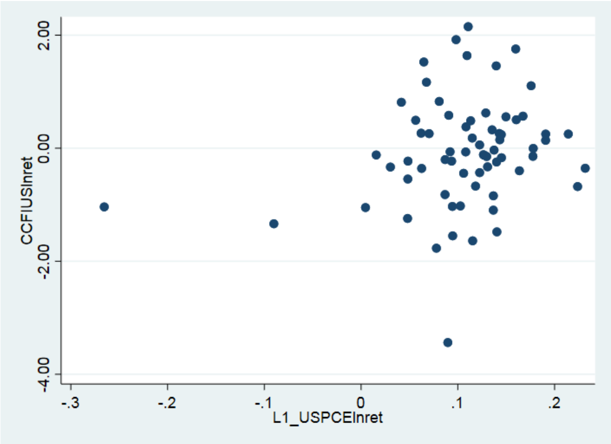
5. Normal Probability Plot



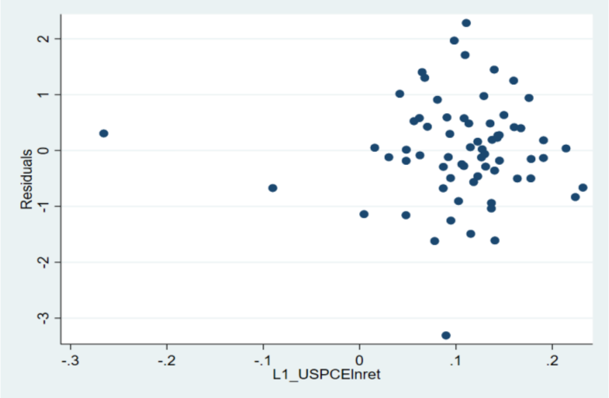
6. Quintile Probability Plot



7. Scatter Plot

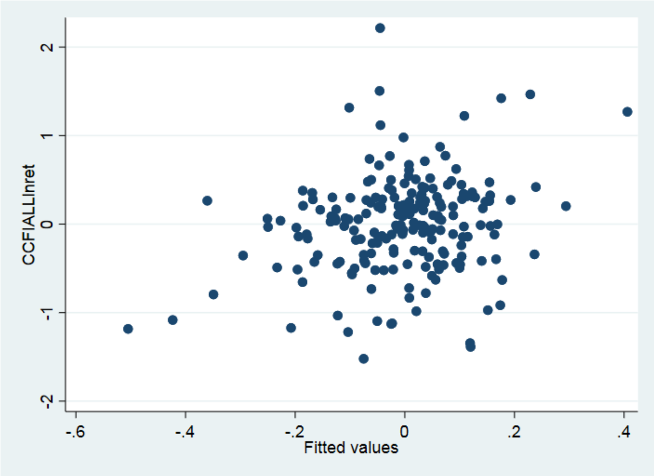


8. Residuals vs. Predicted Values

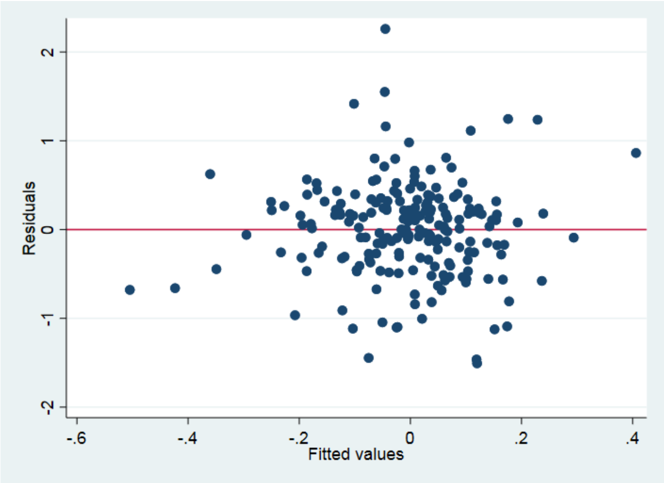


Model 6

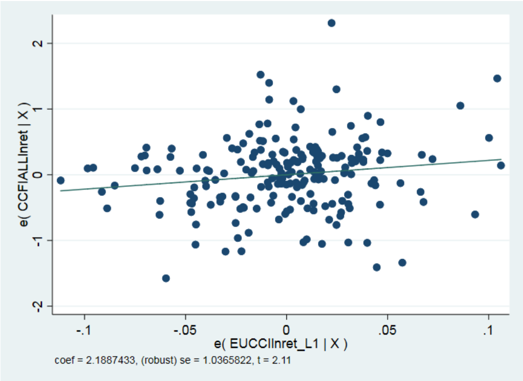
1. Observed vs. Predicted Values

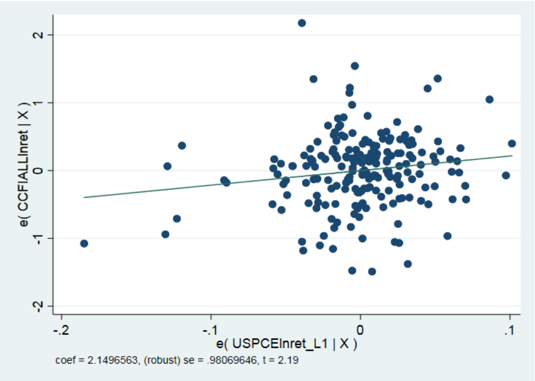


2. Residuals vs. Fitted Values

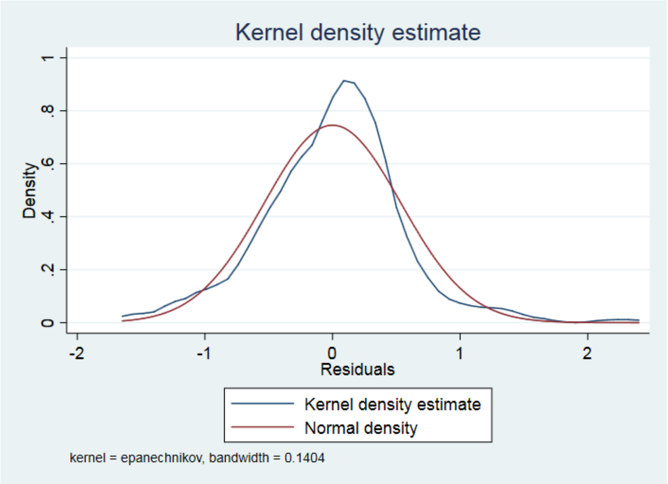


3. Added Variable Plots

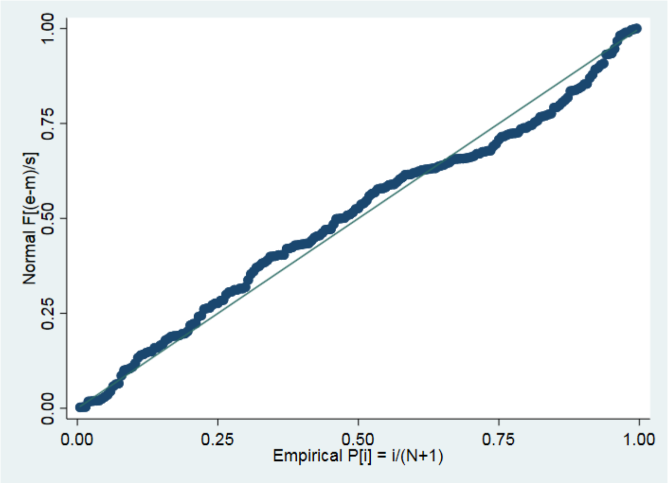




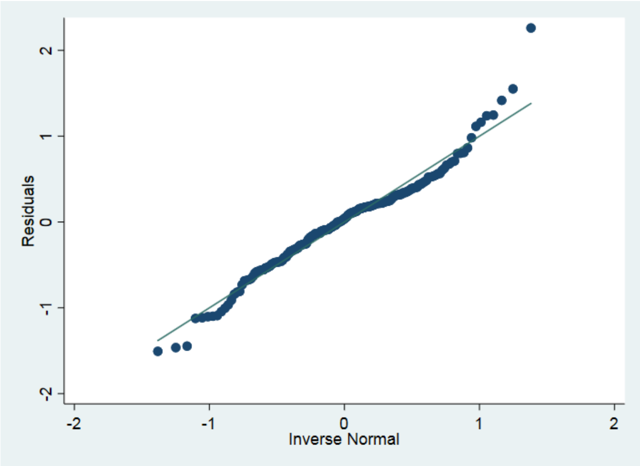
4. Kernel Density Plot



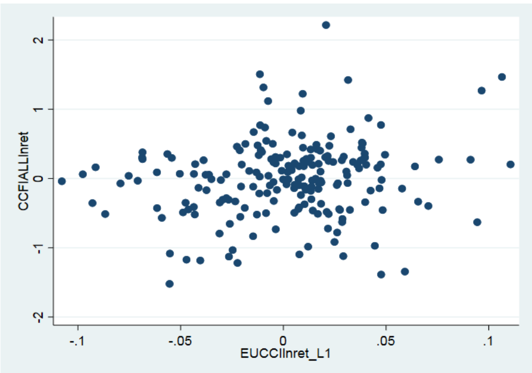
5. Normal Probability Plot

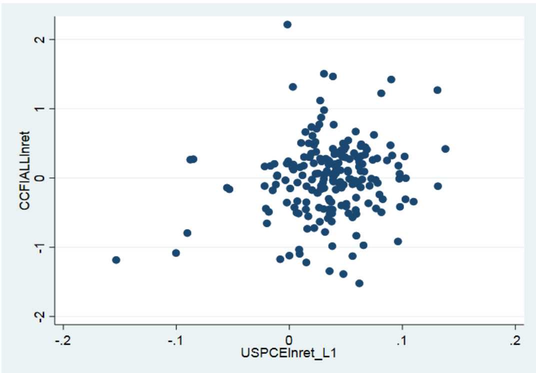


6. Quintile Probability Plot

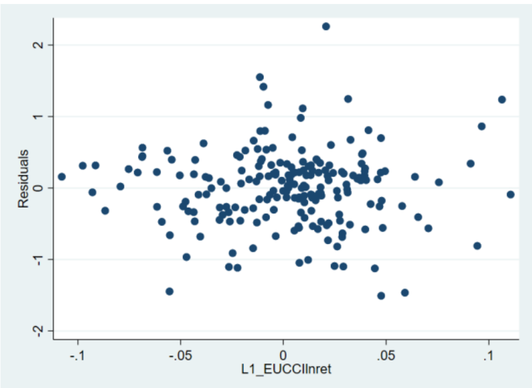


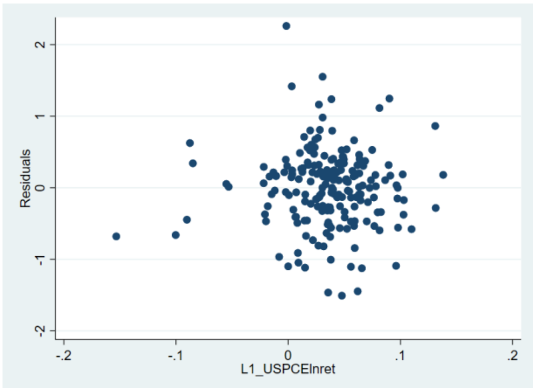
7. Scatter Plot





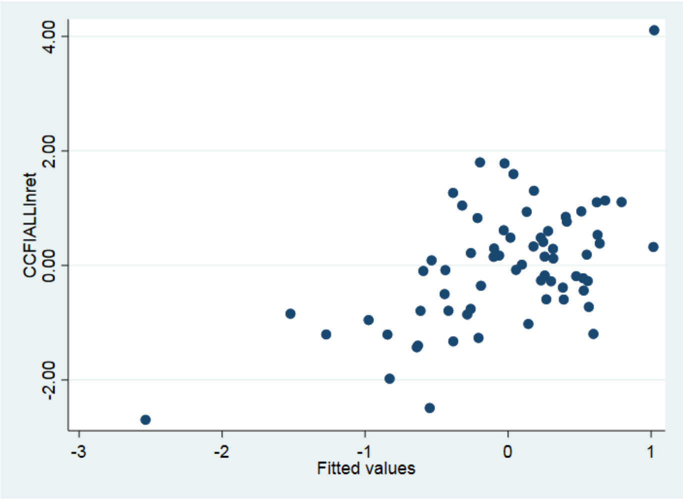
8. Residuals vs. Predicted Values



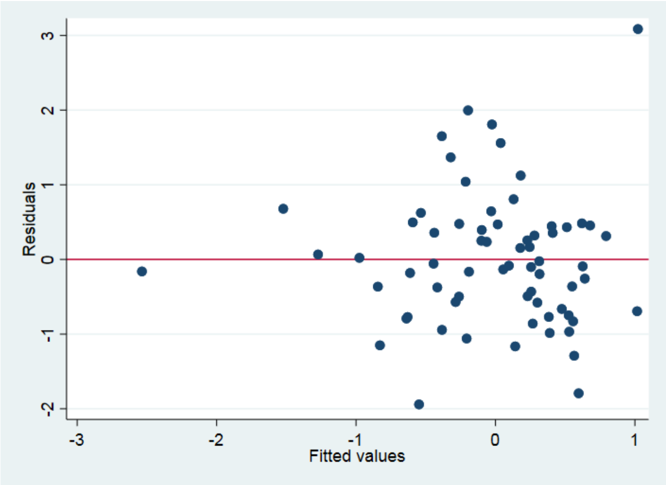


Model 7

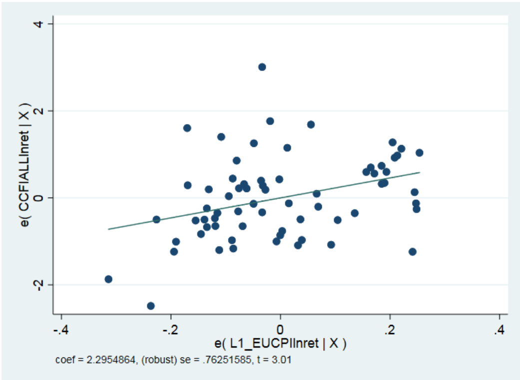
1. Observed vs. Predicted Values

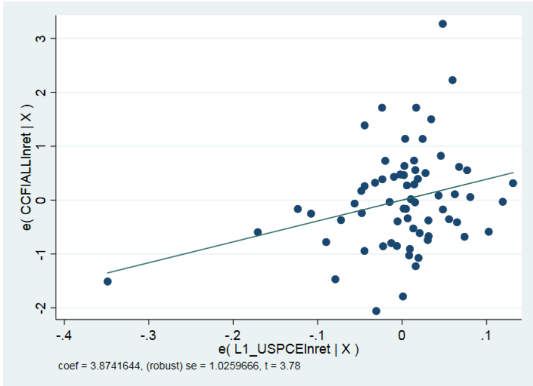


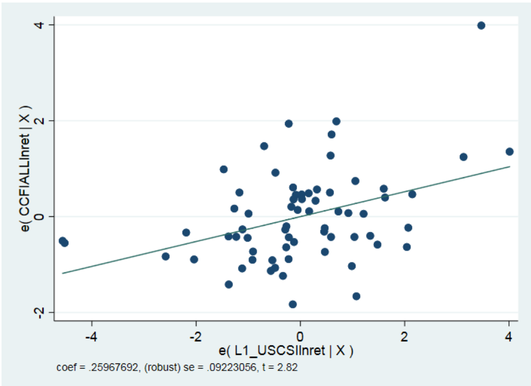
2. Residuals vs. Fitted Values



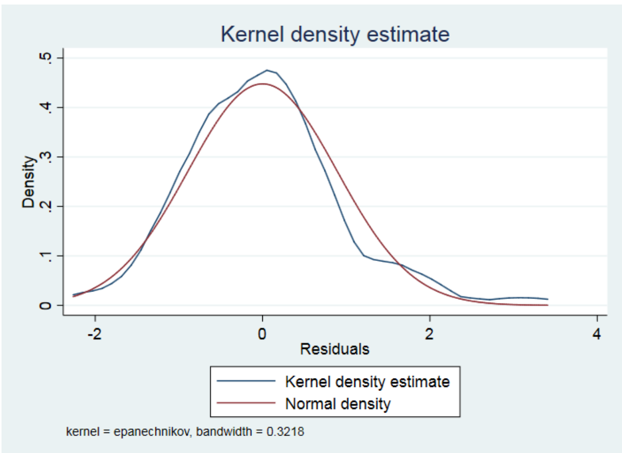
3. Added Variable Plots



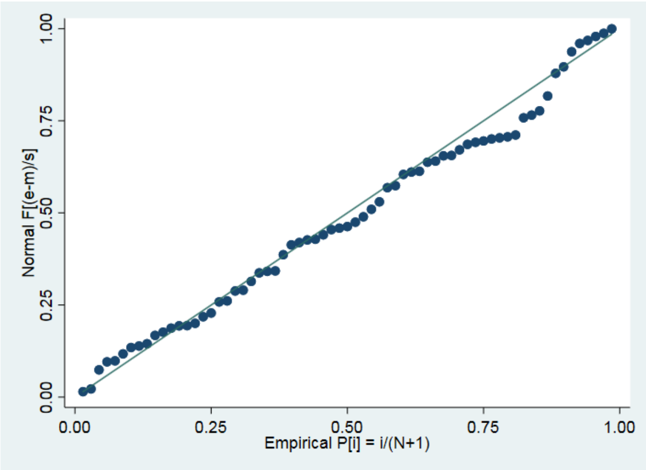




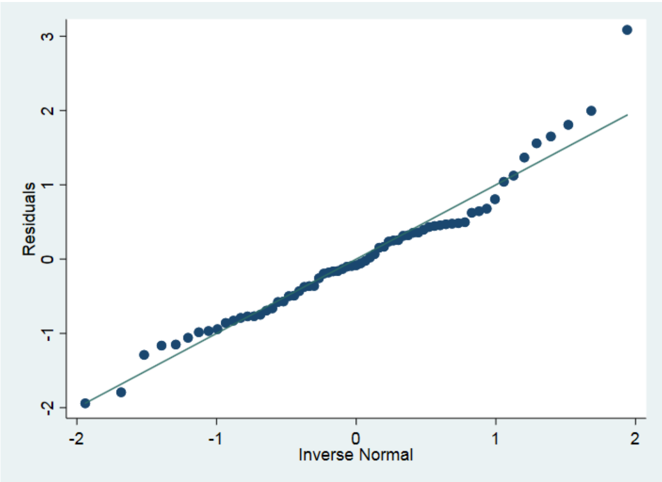
4. Kernel Density Plot



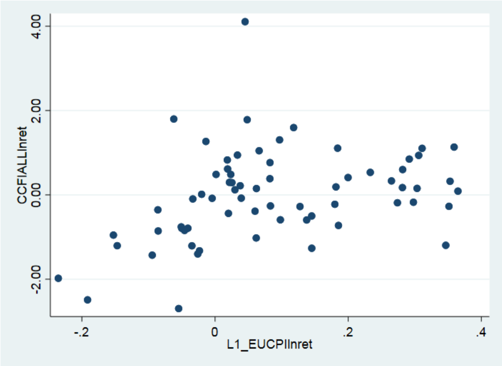
5. Normal Probability Plot

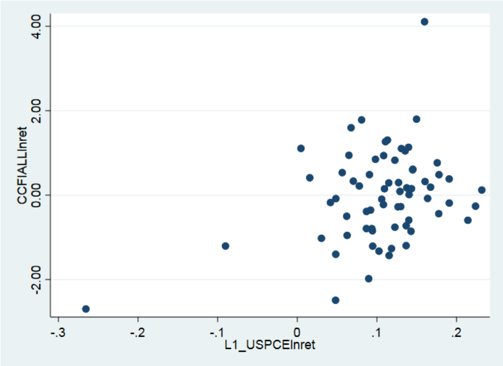


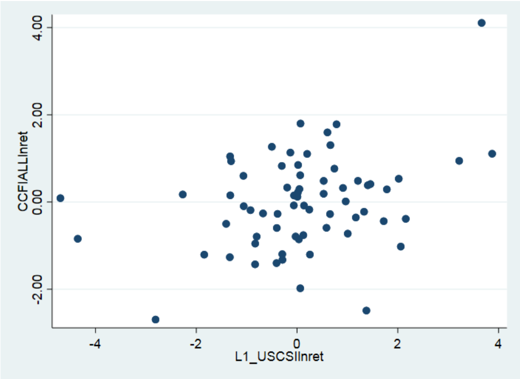
6. Quintile Probability Plot



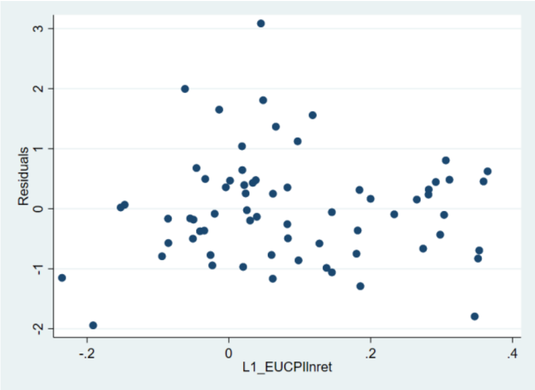
7. Scatter Plot

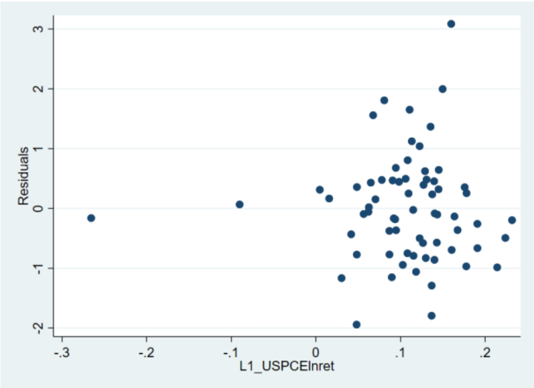


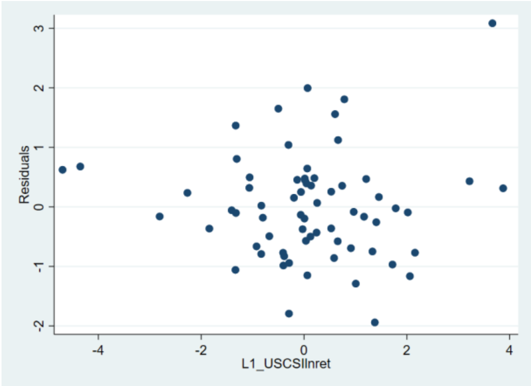




8. Residuals vs. Predicted Values






Residuals
L1_USCSIlnret
3
2
1
0
-1
-2
-4
-2
0
2
4