Using container flows to predict economic activity

An application to transpacific trade

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Challenge the future

Thesis for the degree of MSc in Marine Technology in the specialization of Shipping Management

Using container flows to predict economic activity

An application to transpacific trade

By

F.A. Mobbs

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Summary

There is a significant historical link between maritime trade and economic activity. With the rapid growth of containerised trade over the past 60 years, a significant share of global trade is transported by container nowadays. This suggests there is a connection between container flows and economic activity. There is also a time delay between containers with goods being imported and the announcement of quarterly Gross Domestic Product (GDP) numbers (a way to measure economic activity). With US container imports and exports being publicly available information, this leads to the research question of this thesis: *Can loaded and/or empty container flows be used to predict economic activity?*" If so, this could prove to be valuable information for economists, policy makers and, as this thesis highlights, professional traders working at investment banks or hedge funds.

This thesis focusses on analysing transpacific containerised trade as a potential so-called forward indicator of US GDP. It is important to understand the dynamics of container trade on this route and chapter 2 and 3 seek to understand the influence of the many variables that could possibly affect the supply-side of container shipping and therefore the transpacific container flows (the demand-side is seen as an expression of economic activity). To measure these transpacific flows, an aggregate of US West coast port data is produced and de-seasonalised. The container flows are separated into Loaded In, Empty Out and Loaded Out flows.

After analysing the Cross Correlation Functions (CCF) of the identified, data based influencing variables, five different GDP growth prediction models are constructed. This is done by performing OLS single and multivariate regressions of the individual container flows (together with the influencing variables) on historical GDP growth data from 2000 to 2017. The resulting models are tested against an existing, commonly used forward indicator: the Purchasing Managers Index (PMI).

The results show that three models, all using a form of loaded containers, outperform the PMI when predicting the direction of US GDP growth 3-months ahead over the 17-year time period of the dataset used. The probability of large prediction errors with these models are also smaller than the PMI benchmark model.

Contents

Nomenclature

Abbreviations

ADF	Augmented Dickey-Fuller (test)
AIC	Akaike Information Criterion
BDI	Baltic Dry Index
CCF	Cross Correlation Function
CCFI	China Containerised Freight Index
DWT	Dead Weight Tonnage
ECM	Error Correction Model
ECR	Empty Container Repositioning
EO	Empty Out (container flow)
EO++	Empty Out with two other variables prediction model
FEU	Forty-foot Equivalent Unit
GDP	Gross Domestic Product
GICS	Global Industry Classifications Sectors
ISM	Institue of Supply Management
LA	Los Angeles (Port of)
LB	Long Beach (Port of)
LI	Loaded In (container flow)
LI+	Loaded In with one other variable prediction model
LO	Loaded Out (container flow)
MoM	Month-on-Month
OLS	Ordinary Least Squares
OSCAR	Ocean Shipping Container Availability Report
PCE	Personal Consumption Expenditures
PMI	Purchasing Managers Index
PPI	Producer Price Index
QE	Quantitative Easing (policy)
ROI	Return On Investment
RTW	Round-The-World
S&P500	Standard & Poor's index (US stock market)
SAF	Seasonal Adjustment Factor
SAS	Seasonally Adjusted Series
STC	Smoothed Trend-Cycle Component
TEU	Twenty-foot Equivalent Unit

UMCSI	University of Michigan Consumer Sentiment Index
UNCTAD	United Nations Conference on Trade and Development
USDA	United States Department of Agriculture
WTI	West Texas Intermediate (oil price)
YoY	Year-on-Year
ZIRP	Zero Interest-Rate Policy

Greek Symbols

β	Regression Coefficient	[-]
ε	Error Term (in regressions)	[-]
μ	Mean of monthly change	[-]
σ	Standard deviation of prediction error	[-]
σ_{est}	Standard error of estimation	[-]

Latin Symbols

C	Consumer Spending	[$]
CF	Container flow (growth)	[-]
Ex	Exports	[$]
G	Government spending	[$]
GDP	Gross Domestic Product (growth)	[-]
H_0	Null hypothesis	[-]
I	Investment by businesses	[$]
Im	Imports	[$]
I_t	Irregular Component	[-]
S_t	Seasonal Component	[-]
SAS_t	Seasonally Adjusted Series	[TEU]
STC_t	Smoothed Trend-Cycle Component	[TEU]
T_t	Trend-Cycle Component	[-]
x	Monthly percentage change of a variable	[-]
y_t	Monthly raw container flow	[TEU

Introduction

“If you can look into the seeds of time, and say which grain will grow and which will not, speak then unto me.”

--William Shakespeare

In Act 1, Scene iii of *Macbeth*, a play written by Shakespeare in 1606, the character Lord Banquo speaks the words above to three witches in what can only be interpreted as an elegant request for a good prediction. Well before Shakespeare’s time, good predictions regarding love, power and money were sought after, and this still rings true up to the present day.

Prediction in essence is a statement about an uncertain future event. We acknowledge that nobody can know for certain what the future will bring, but we can make educated guesses based on past experience when a particular series of events or a set of indicators leading up to an event were the same.

Besides the three witches, people such as economic analysts, researchers, traders and consultants are often making or using predictions with regards to economic activity. The value of these predictions includes direct financial gains, more profitable business strategies or improved government policies. If one has a set of diversified, reliable indicators that show something is going to change or about to happen, the higher the probability of that event happening. It is therefore advantageous to put effort into developing new indicators to aid in the prediction of economic activity. This thesis seeks to investigate another possible indicator: marine container flows.

The goal of this thesis is to answer the question: “*Can loaded and/or empty container flows be used to predict economic activity?*” The global onset of containerisation since the 1960’s has led to a larger percentage of imports and exports of any one country to be transported via shipping container. This fact suggests that the number of containers entering and exiting a region’s ports every month is becoming an increasingly better measure of economic activity within that region. Economic activity in these regions drives container flows but, determining how the actual detailed supply and demand picture of goods is developing is a difficult task. The information would have to be collected on a per-company level and most of that information is unobtainable for anybody besides a company insider.

In this thesis it is demonstrated that, as an integral part of the global supply chain, container flows are one of the first signals of how physical supply and demand has been shaping up. It goes on to propose that container flows therefore could potentially be used as a forward indicator of economic activity. The homogenous nature of containerised transport makes the measurement of historic container flows dependable and comparable throughout the years, although this fact also hides the exact details of the individual contents, restricting the ability to make detailed statements about individual companies or sectors that utilise container shipping. To answer the research question, this thesis is structured around the thinking described in this paragraph, which is visualised in Figure 1.

An important aspect of this thesis, is that it considers loaded and empty container flows individually. This can reveal if a single type of container flow has more predictive potential than another regarding economic activity, but it also allows one to get a better understanding of whether imbalance issues affect transpacific container capacity i.e. the supply side of the liner industry. This supply side is usually considered constant in the short-term as it takes times for new ships to be built and added to the fleet.

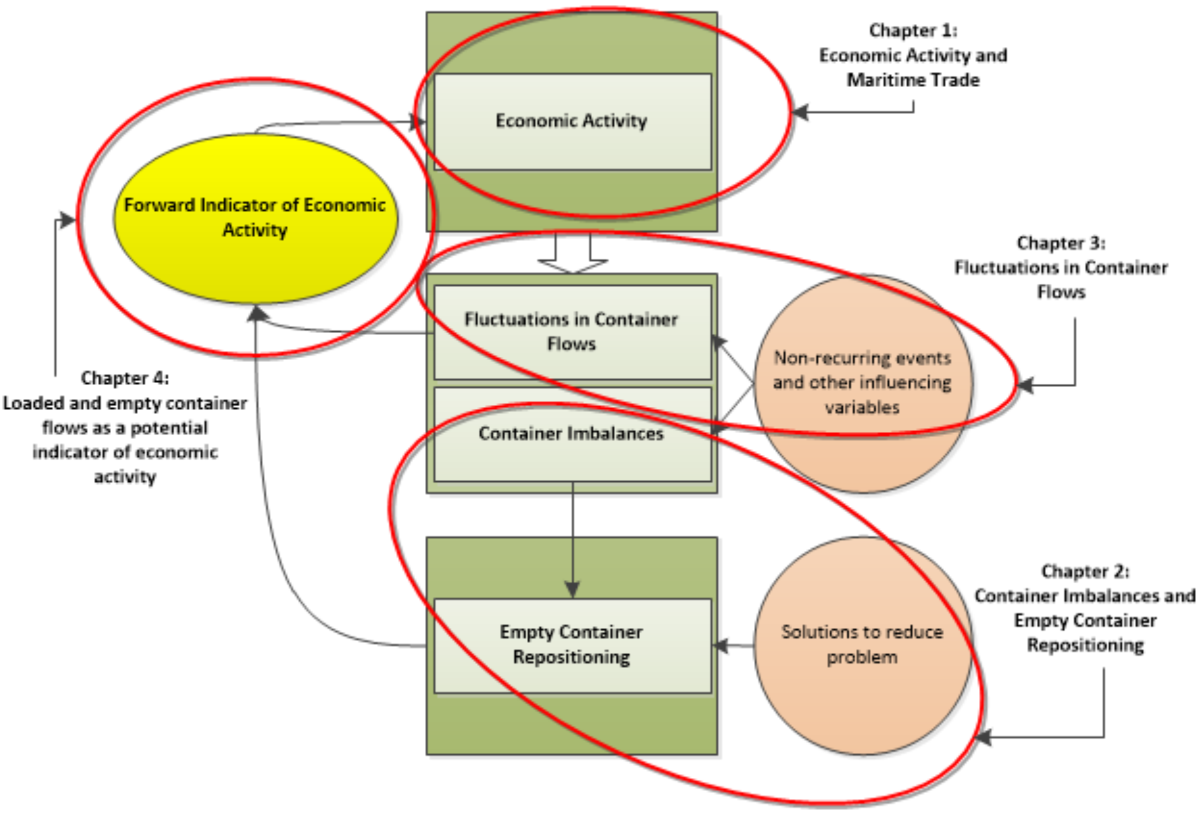


Figure 1 Framework determining how economic activity drives container flows and container imbalances. Because economic activity is difficult to measure in a timely manner, loaded and/or empty container flows could be a forward indicator of economic activity. Red circles indicate which chapter will cover the various sections of the framework

Chapter 1 makes the link between maritime transport and economic activity. It demonstrates that containerised transport has rapidly grown in the last 60 years to becoming the main way most products are shipped globally. Because so many goods travel via container nowadays, economic activity expressed in the form of GDP is inherently connected with container flows.

Why GDP is a good proxy for economic activity in a country is described, along with the time delay between the economic activity taking place and the official announcement of quarterly GDP numbers. The chapter finishes by highlighting the use case of accurate GDP prediction for a trader in financial markets.

Chapter 2 looks into the imbalances seen in global container flows, the problems they cause and the solutions proposed and implemented to minimise the issue.

Chapter 3 discusses the aggregation and preparation of the container flow data for further analysis. It then identifies outliers in this data and discusses possible causes of these outliers. The last part of this chapter identifies and analyses possible influencing variables that could affect the number of containers crossing the pacific in ways that are not directly linked with economic activity. The idea being that if other influencing variables on container flows are known, one can have a better idea when changes in flows are because of actual changes in economic activity.

Chapter 4 introduces the PMI as benchmark forward indicator to compare the models against. A cross correlation analysis identifies the monthly time lags with the highest correlations of the container flows and PMI with US GDP. This helps decide how far forward the GDP prediction will be made. OLS multivariate regressions are then performed to construct five models. These models are then tested and compared with the benchmark PMI model at the end of the chapter.

1. ECONOMIC ACTIVITY AND MARITIME TRADE

An interesting aspect of this thesis is that it starts where it finishes: Economic Activity. The goal of this chapter is to understand that economic activity drives fluctuations in demand for container transport, but that official figures of economic activity are only published long after it has occurred. This leads to the following research question: "*Can loaded and/or empty container flows be used to predict economic activity?*"

First of all, in '*A brief container* history' an overview of the historic growth of the container industry is given, which shows just how much global trade is transported in shipping containers nowadays. In the next section '*Measuring economic* activity' the connection between economic activity and maritime trade is made clear. It also covers the measuring of economic activity by GDP and equity markets. In '*The time delay of GDP announcements*', the reader learns that official GDP figures are published long after the actual economic transactions have occurred, which is key for container flows to be an indicator. '*Analysis of a typical supply chain'* uncovers the fact that container movements are one of the first pieces of public information available with regards to upcoming official GDP figures. This leads to the '*Research question*' being posed, a discussion of the '*Scope*' of the thesis and the '*Methodology*' used to answer the research question. The chapter is finished by identifying who could benefit from this work and how it can be of value to them in '*Who can extract value from this work and how?*'.

1.1 A brief container history

The advent of intermodal containerization in the 1960's marked the start of the single biggest leap forward in the logistics and transport industry of the twentieth century (Levinson, 2006), (Bernhofen, El-Sahli, & Kneller, 2016). It is often marked by the historic journey made by the *Ideal X* on April 26, 1956 from Hoboken, New York to Houston, Texas, carrying 58 standardized aluminium containers lifted directly off truck chassis. The brainchild behind this first sailing was Malcolm McLean founder of the company later to become known as Sea-Land, although it is to be remarked that this was not just an out-of-the-blue idea by McLean. Unitizing freight to increase port productivity in a form one would nowadays call containerization had already been experimented with as far back as the early 1900's (Klose & Marcrum, 2015). McLean took this idea and applied it to improving ship productivity. As containerized transport caught on around the 1970's, specialized ships and terminals quickly followed, paving the way for true globalization. For those not familiar with the impact of containerization and its rapid growth, the following section presents historic data showcasing this growth.

In Figure 2 one can see how the growth of total global containership deadweight tonnage has grown far quicker than the value of world merchandise trade, indicating the shift of the transport of these goods into container units. From 1990 onwards, the growth of global containership deadweight has also outpaced world seaborne trade growth in tonnes, which has been steadily increasing.

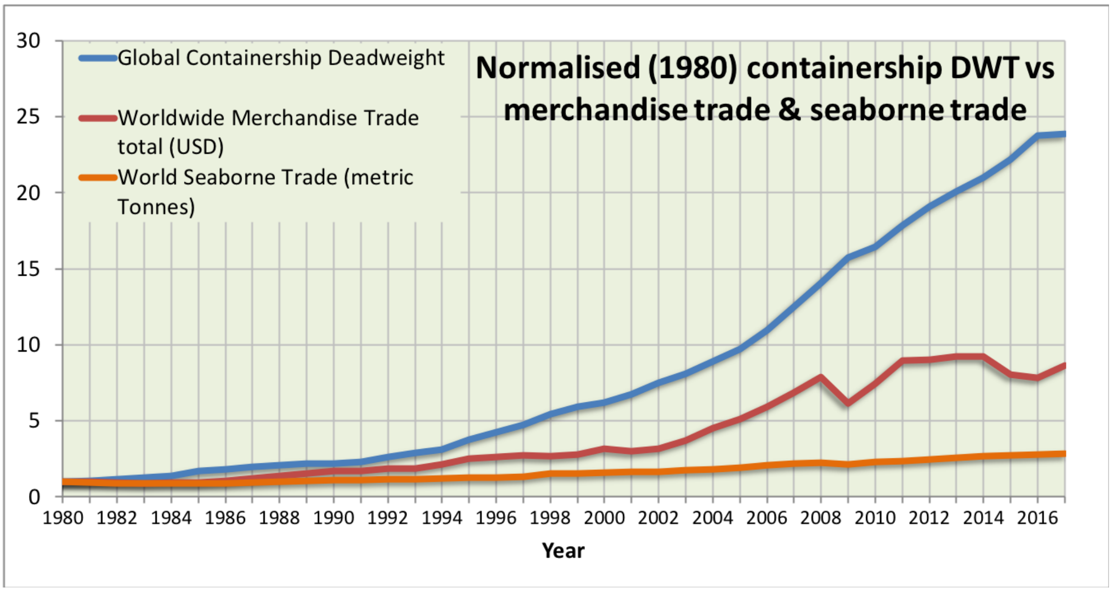


Figure 2 A comparison of global containership Deadweight Tonnage (DWT) with World merchandise trade value and World Seaborne trade data is normalised from 1980. World merchandise trade is the value of all goods (not services) traded valued in current US Dollars. Source: (UNCTAD, 2017a)

When world seaborne trade is broken down into the four main shipping sectors of container cargo, dry non-bulk cargo, bulk commodities and oil and gas, the rise of container shipping can be noted (Figure 3). Only the growth in tonnes loaded of bulk commodities has outperformed container cargo tonnes loaded. However, when one realises that the density of container cargo is lower than most bulk commodities, the increase in containership deadweight to account for the growth of tonnes loaded is actually far greater than the increase in dry-bulk dead weight tonnage (top chart of Figure 4). The bottom chart in Figure 4 shows the consistently higher annual growth rate of containership deadweight tonnage, although bulk carrier growth did overtake containership growth for a few years after the 2008 financial crisis and the peaking of the commodity cycle around 2011 (Dennin, 2016).

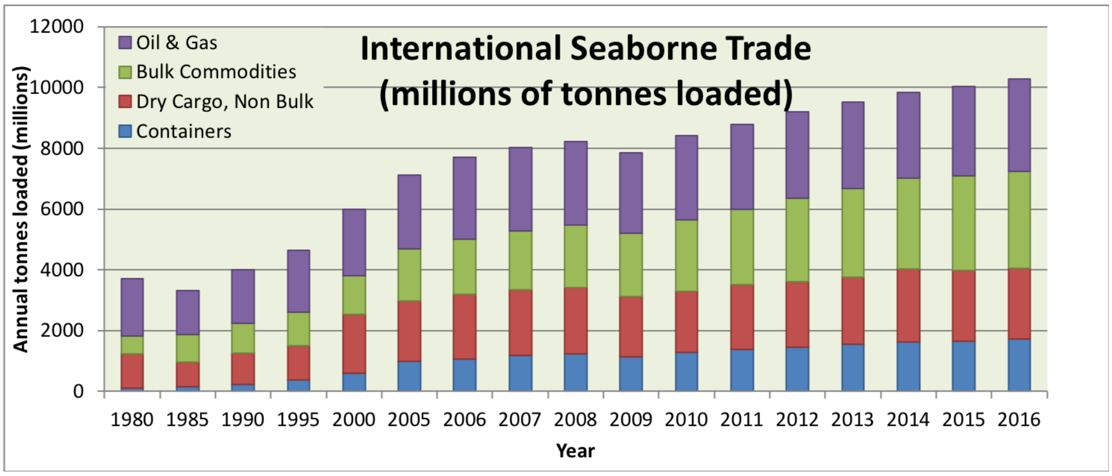
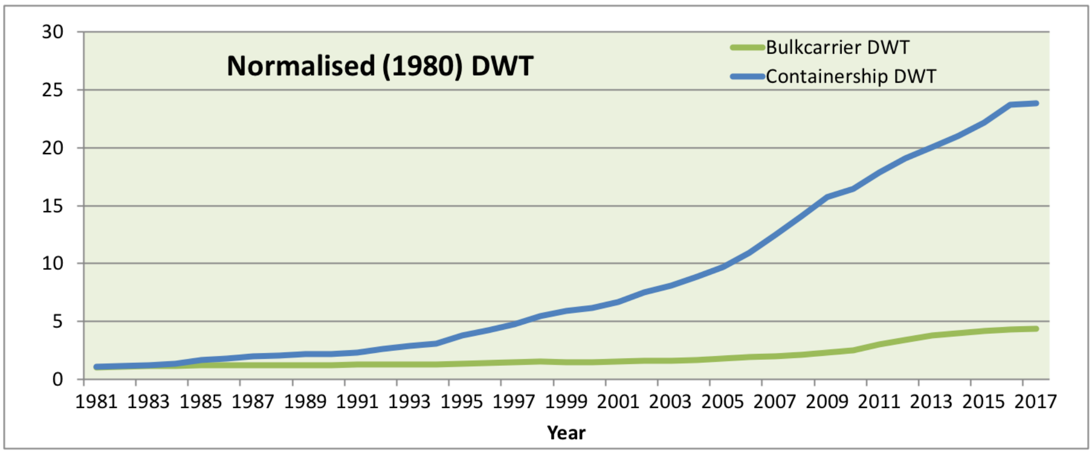


Figure 3 Annual seaborne trade per shipping category, measured by millions of metric tonnes loaded 1980-2015. Note pre-2005 data is shown in steps of 5 years. Source: (UNCTAD, 2017b).



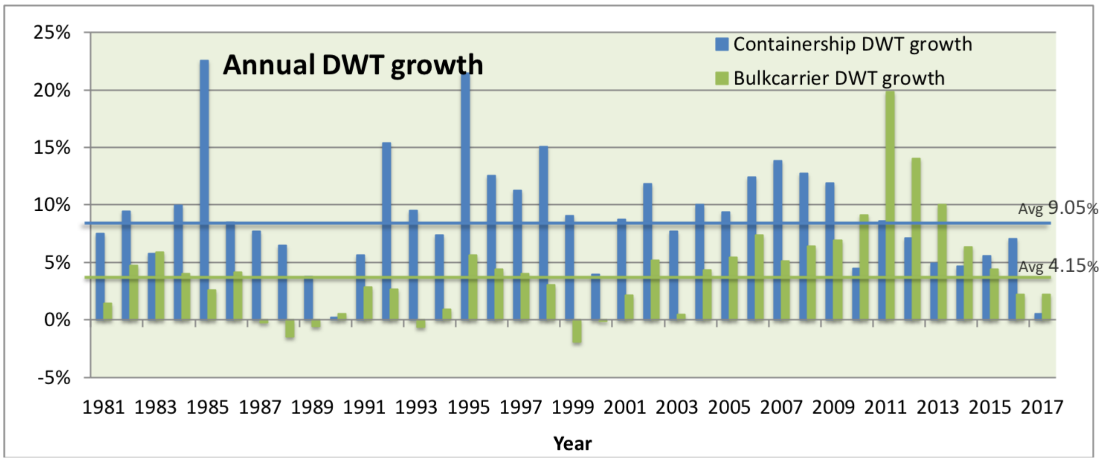


Figure 4 Top chart: Deadweight tonnage comparison from 1981 to 2017 of the global containership and bulk carrier fleets. Normalised from 1980 to capture the relative growth between the two fleets. Bottom chart: Annual growth rate of global containership and bulk carrier fleets including average annual growth rate per fleet between 1981 and 2017. Data compiled by author from (UNCTAD, 2017a).

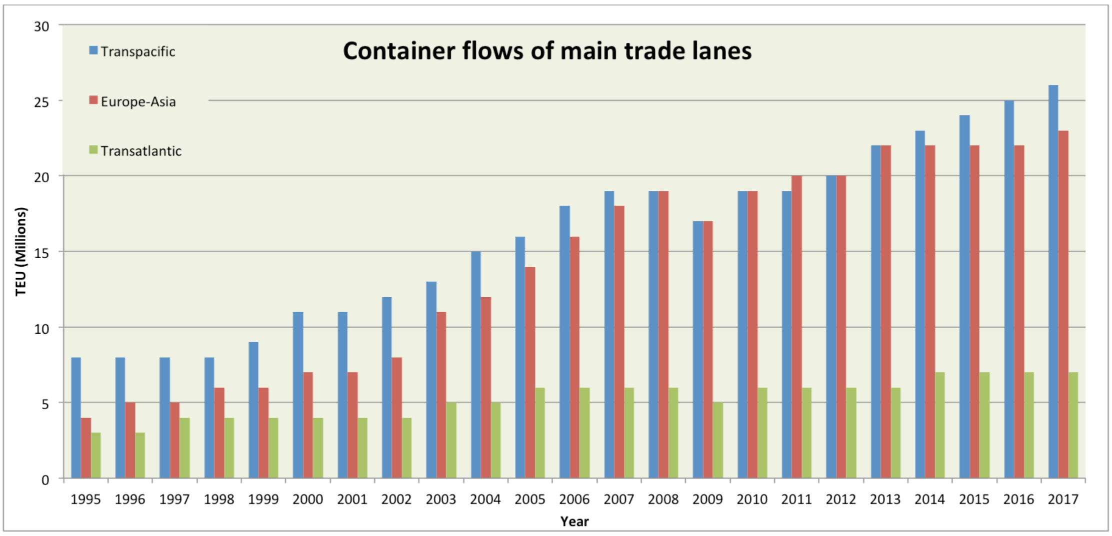


Figure 5 Annual container flows (both directions) in millions of TEU from 1995 to 2017 of the top three trade lanes. Source: (UNCTAD, 2017b)

Figure 5 gives an overview of the contribution to worldwide container shipment growth by the three main trade routes: transatlantic, transpacific and the Europe-Asia trade lane. The rise of Asia as a global manufacturing hub can clearly be seen in this figure, with the majority of growth coming from the two trade lanes connected to Asia: the transpacific and Europe-Asia lanes. One of the reasons this thesis focuses on the transpacific trade lane is because it has the largest volume of transported containers measured in Twenty-foot Equivalent Units (TEU).

The source of growth of container carrying capacity (and DWT) can be seen in Figure 6. With the growth of container trade, carriers have sought to increase price competitiveness as well as margins by utilising economies of scale by employing ever-larger ships. This trend can be clearly seen in Figure 6, with average delivered newbuild TEU capacity nearly doubling in size from over the past 10 years.

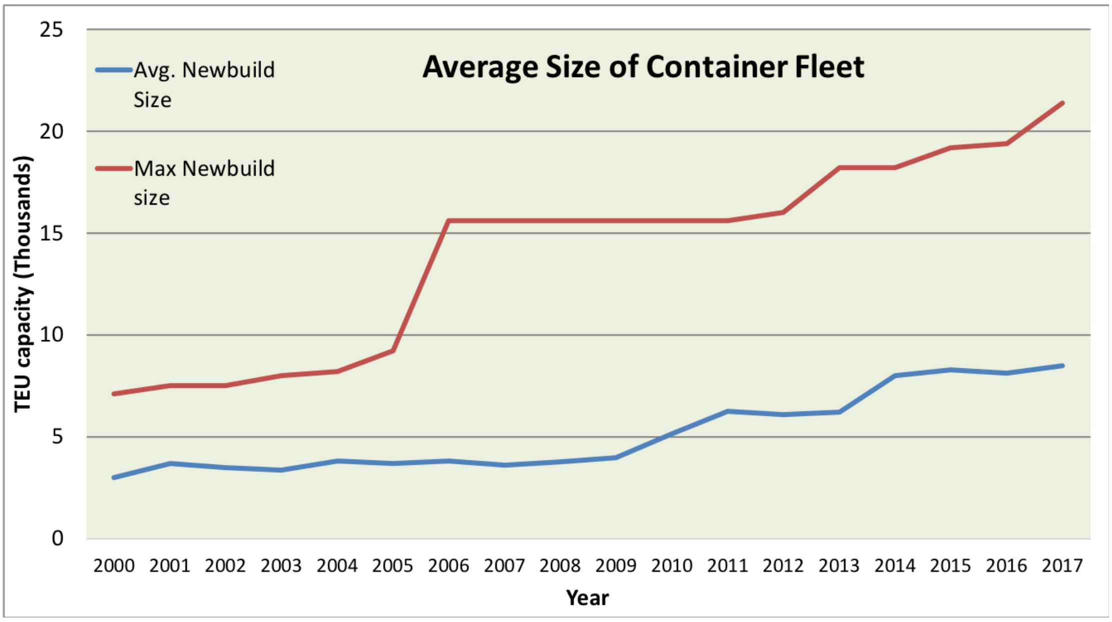


Figure 6 Average global container fleet TEU capacity development since 2000. Source: (Drewry, 2017)

With regards to growth within the container sector, described in the previous paragraphs by growth in containership deadweight tonnage, annual tonnes loaded and physical container flows on the trade lanes, one must note that the fundamental growth driving all this is a function of three different things (Rodrigue, Comtois, & Slack, 2016):

1. **Base load**: Also called organic growth, this is growth of businesses and product demand of items that have traditionally always been shipped via containers.
2. **Substitution**: This growth is caused by other goods that traditionally were shipped in specialized vessels and are now being shipped via (sometimes specialised) container. For example, some chemicals traditionally transported in chemical tanker vessels are now being transported in special container format tanks thereby contributing to the growth of container transport at the expense of the chemical tanker sector. Switching to the transport of a commodity by

container versus bulk can be incentivised by price, distribution flexibility and/or the ability to send smaller loads quickly.

3. **Induced**: Even with growth in ship sizes, distribution of containers to smaller ports must be ensured. This has led to the 'hub and spoke' type networks where different ship sizes and circulation routes come together at these hubs. This requires transhipment movements and additional containerised capacity.

1.2 Measuring Economic Activity

Chapter 1.1 illustrated the rise of containerisation over the last half century and the share of world merchandise trade transport it has taken over. This global onset of containerisation has led to an increasing share of imports and exports of any one country to be transported by shipping container due to both base load growth and substitution. A fact that suggests that the number of containers entering and exiting a region's ports every month is becoming an increasingly better measure of economic activity within that region.

In this chapter the use of Gross Domestic Product as a measure of a region's economic activity will be explored. The role of equity markets as an expression of economic activity is also discussed along with their connection to Gross Domestic Product. This is important to understand when looking at this work in the context of the intended end users of this work discussed in '*Who can extract value from this work and how?*'

The value within a container

Container flows are measured throughout this thesis in Twenty-foot Equivalent Units (TEU's). This number will always be higher than the actual amount of 'lifts' or 'moves' made within the ports considered (which is economically more important to the port terminal), as many containers are 40 feet in length and are therefore counted as two TEU's. The homogenous nature of containerised transport makes the measurement of historic container flows (expressed in TEU) dependable and comparable throughout the years, regardless of which shipping alliance transported them or which ship size was used.

Economic activity can be measured by a monetary value as explained in the following sections of this chapter, but when one measures the number of TEU moving between regions, this does not directly translate to an economic value: every container is an equal size 'packaging' of a cargo on the inside whose value is unknown. An extreme case could be envisioned whereby one container could be full of cheap pillows, whilst another exact same container could be full of expensive electronics with the difference in value being substantial. The value of goods within these containers is clearly non-homogenous and this fact would seem to make it impossible to know the total value of goods being imported into a country by looking at the number of containers entering it. Therefore, this would undermine the possibility of linking container flows to economic activity.

In reality though, the value of goods being transported in a container generally fall within a certain value bandwidth and the rest of this section aims to demonstrate that. There are two main factors that control the upper end of this bandwidth: time value and time pressure (for perishable goods or goods with a tight delivery deadline). Due to the time value factor (explained in this section), higher value goods generally shift to airfreight, whereas bulk carrier ships transport lower value goods. Time pressure, where applicable, forces a lower value product to use a more expensive transport method. In the case of perishable fruit, either time needs to be slowed down by using a more expensive refrigerated container or the goods need to be transported faster via airfreight.

The following paragraphs contain an elaboration on why there are economic upper and lower limits to the value of goods that make sense to transport via container. To keep things simple, only goods that are not under heavy time pressure are considered.

For any product not under the influence of time pressure, time value is the main reason there is an upper limit of the value bandwidth. A business that has produced, for instance, an expensive smartphone has working capital tied up in that phone (cost of parts, labour, etc.). This capital can only be redeemed once that smartphone is sold. In the time between manufacture and sale, this tied up capital is doing nothing. There is a cost to capital expressed by the return on investment (ROI) that a business could have made if they decided to not manufacture the phone, but instead simply placed their cash on a bank account or made conservative investments. When products are expensive, i.e. have a high amount of capital tied up in them, it becomes a better idea to ship them via airfreight. On the transpacific route this changes the journey time from around 30 days to 3 days. Simply put: if the higher air transport costs are offset by the cost of capital (ROI x time saved), it makes financial sense to ship via airfreight.

The lower limit of the value bandwidth is determined differently than the upper one because the lower value of goods makes them far less affected by the cost of capital tied up in them. At this lower value bandwidth, the decision to ship via (specialised or adapted) container instead of a bulk carrier or tanker is different per product and its overall transportation profile, i.e. it's door-to-door journey.

In terms of commodities such as petrochemicals or grains, they enjoy huge economies of scale when being transported in specialised infrastructure. The biggest reason that these commodities sometimes get transported in containerised units is due to the cost impact of the before and after transport. In cases where large quantities are being transported regularly and production and consumption facilities are located close to ports, such as crude oil, using containers will never make sense. When batches become smaller and/or production and consumption facilities are further inland, the savings made on before and after transport can be enough to warrant containerising commodities financially sensible.

Containerisation is becoming more common in the petrochemical industry as crude gets refined into many specialised petrochemicals that need smaller batches to be distributed to many customers in different locations. This is done by using specialised tanks that fit the existing container infrastructure (see Figure 7). For grains, the cost savings lie mostly in the after transport as production in the case of the US is nearly always on a large scale with most exports transported to the coast by specialised rail and barges (Denicoff, Prater, & Bahizi, 2014, p. 9). For cargoes that are voluminous and cheap or dense and cheap, such as waste paper and scrap metal, they simply stop being transported when freight rates rise too much as the geographic arbitrage opportunity ceases to exist.

Figure 7 Typical chemical tank encapsulated in 20ft standard container framework. Image source: CIMC ENRIC website.

So, where exactly the lower end of the value bandwidth lies, is more of a grey area dependant on a mix of variables that differ per product. This is interesting in terms of container imbalances and empty containers (covered in chapter 2). If a carrier can work out by how much they must lower their freight rate on a route that has a lot of commodity transport, they can open up a large additional demand for container transport. This could be valuable in minimising empty container transport on so-called backhaul routes, from container surplus to container deficit areas.

It can be concluded that there generally is a certain bandwidth of value of goods that typically will use container transport across the pacific. It is the goods within the packaging of a container that contribute towards economic activity. The value of these goods are non-homogenous across containers, although this chapter has shown that there is a general value bandwidth into which these goods will usually fall. Assuming that the average price of this bandwidth does not change considerably year on year, a container travelling across the pacific could be considered to contain an average monetary value.

Therefore, throughout the rest of this thesis, the packaging itself, i.e. the container, will be used as a homogenous measurement unit.

Gross Domestic Product

Gross Domestic Product or GDP, as it will be called from now on is traditionally the most widely accepted and standardised way of measuring economic activity within a country. Besides GDP, there are many other ways of defining and measuring the economic activity of a country. Examples of this include measuring industrial production or measuring the international trade deficit/surplus, each with their own caveats. More importantly, these kinds of measures only portray a specific part of a country's economy, whereas it can be argued that GDP better captures the overall picture.

GDP is defined as:

$$GDP = C + G + I + (Ex - Im) \tag{1.1}$$

Whereby:

C = Consumption: The purchase of all new finished goods and services by consumers

G = Government Spending: All government expenditures. For example, infrastructure projects, but also government salaries

I = Investment: The spending on capital goods and services by businesses used in production, such as machinery.

Ex = Exports: All goods transported away from a country

Im = Imports: All goods transported into a country

GDP is calculated on a Quarterly basis. In the US this is the task of the US Bureau of Economic Analysis (BEA) and is announced two weeks after the end of each quarter. It must be noted that whenever GDP is mentioned, or GDP figures are presented throughout this thesis, they are real GDP figures. Real GDP is GDP corrected for inflation. Just because the price of a bar of soap has doubled over the last 25 years due to inflation does not mean that the soap sales contribution to GDP has doubled. So real GDP better portrays real economic growth. The evolution of US (real)GDP constituents since 1980 are pictured in Figure 8.

Container flows affect GDP directly by adding to the Export and Import posts. The US imports far more loaded containers than it exports, so at first glance, one would expect this surplus of imports to negatively affect GDP and Figure 8 does indeed show net exports in red (Exports minus Imports) as a negative value. One of the reasons a surplus of imports is not necessarily negative for

GDP is that the values counted as imports are the cost prices that US wholesalers and retailers are paying for inventory. Once the wholesalers apply their margin and sell to retailers, who in turn apply their margins and sell to consumers a whole lot of 'value' has been added to GDP. Therefore, in most cases an import will actually add to GDP. Other reasons will be discussed later in this chapter.

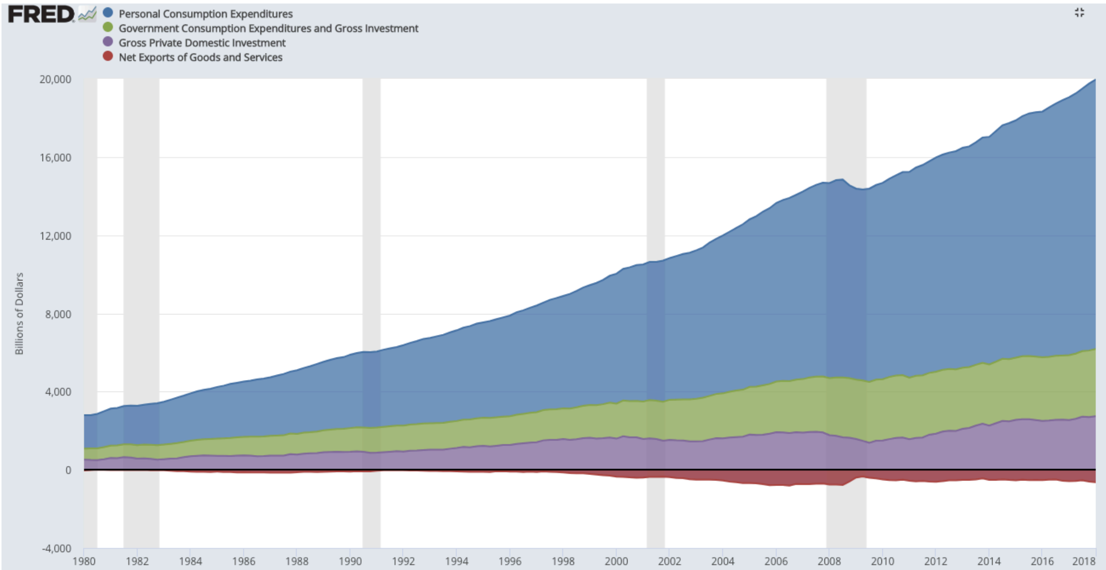


Figure 8 The four constituents of GDP: Consumption (blue), Government spending (green), Investment (purple), Net Exports (Exports-Imports) (red). Chart shows historic development of these constituents from 1980-2018Q1. Shaded areas are official US recession periods (two or more quarters of GDP contraction). Chart from (Federal Reserve Bank of St. Louis, 2018a).

The relationship between GDP and maritime trade

As discussed in the previous paragraph, even though imports are subtracted from GDP and the US has a substantial trade deficit (US$ -583 Billion for 2018 Q1), an increase in imports positively affects GDP. This effect will be discussed in more detail at the end of this section. This section will start with a helicopter view of the fundamental connection between global maritime trade and world GDP and how this relationship is slightly different per country and ever changing. After this, a more detailed look at US GDP and its connection to container imports and exports is made.

The fundamental relationship

Stripping out factors such as specialisation, economies of scale and/or speculation, the simplified basis of any trade, lies upon it adding utility to both the buyer in the point of destination and the seller in the point of origin. With the development of containerised maritime trade, opposite sides of the globe have been opened up to trade with each other. And nowadays, if one can sell an overseas product for less than a locally produced one and still make a profit after deducting import duties and freight costs, somebody will be doing it. This is modelled simply by (Stopford, 2009, p. 394):

$$TR_{ij} = f(p_i, p_j, T_{ij}, F_{ij})$$

(1.2)

This model states that the trade (TR) between two regions *i* and *j* is dependent on the price difference in countries *i* and *j* (p_i, p_j), the freight costs between these countries (F_{ij}) and any extra tariffs imposed (T_{ij}). When this model is tied together with comparative advantage theory, the foundation is laid for the connection between maritime trade and GDP.

Comparative advantage theory was developed by David Ricardo in 1817 and is treated in detail by (Dixit & Norman, 1980; Maneschi, 2008). His theory demonstrated that under free trade, a country focussing its efforts and resources on producing its most competitive product creates more wealth for itself than when closed to free trade. This is true even when other countries can produce the same product even more efficiently. The reason for this is because the country specialising in its most competitive product is utilising its limited labour and capital resources in its most productive way. Because it can import other goods that it is less efficient at producing, it can dedicate all of its resources to the most productive product it can produce, thereby creating the most wealth possible. To quote Ricardo: “Trade is beneficial, even if one country is more efficient than its trading partners at producing all goods”. This theory has provided the intellectual foundational of the free trade philosophy influencing political decision making over the last 50 years and the main reason maritime trade has grown so much in the same time period (Stopford, 2009, p. 398).

The relationship between seaborne trade and the wealth of a country is explored in (Stopford, 2009, p. 391). Here, regressions are presented of 2004 seaborne import data versus country specific GDP, land area and population data, showing that maritime trade mainly depends on GDP (economic activity). The data used by Stopford for his seaborne imports versus GDP regression is displayed in Figure 9.

Stopford displays a linear regression line through this data with a R^2 of 0.7118, mentioning an approximate, but significant relationship between seaborne imports and GDP and upon visual interpretation it seems this is the case. However, this is just one snapshot in time and in further discussion about this data, there is no mention of testing the GDP and seaborne imports time series for co-integration to reject the possibility of a spurious correlation.

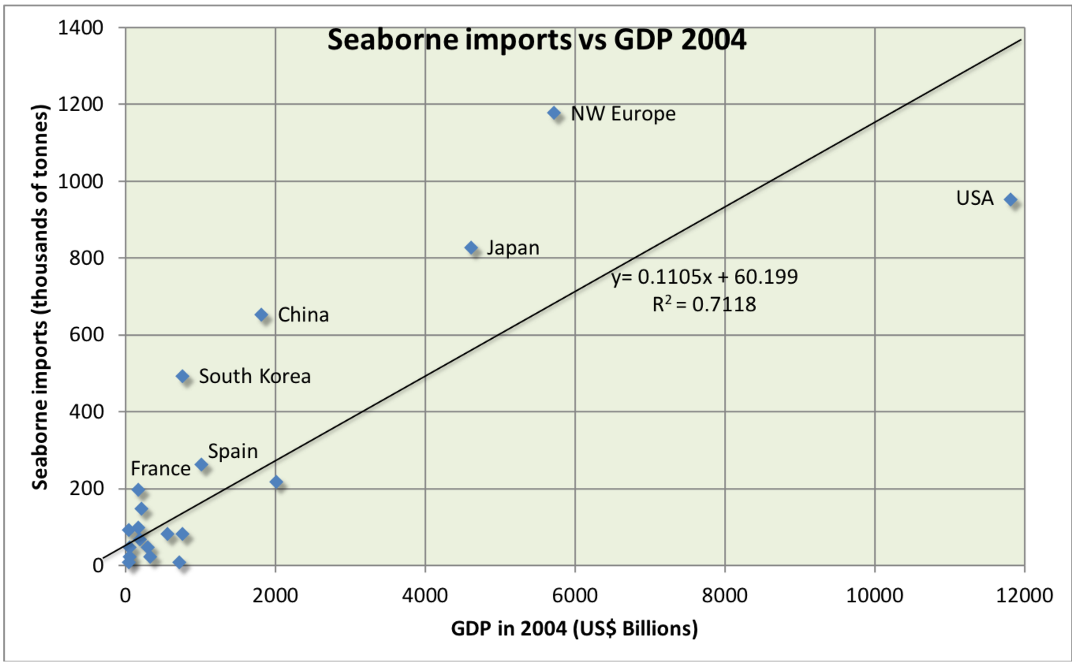


Figure 9 Seaborne imports versus GDP in 2004. Chart reproduced from (Stopford, 2009, p. 391), Data from UN *Monthly Bulletin of Statistics* and World Bank.

For this thesis, the same data source used by Stopford in 2005 was inaccessible to replicate Figure 9 for more recent years. Instead, aggregated country data from UNCTAD is used to look at the evolution of this relationship between 2006 and 2016. This is displayed in Figure 10, where it can be seen that China has displayed a stronger relationship between growth in seaborne trade and GDP, whereas the US and Europe have shown less seaborne trade growth in comparison to their GDP growth. The effects on European and US GDP during the 2008 financial crisis can also be seen.

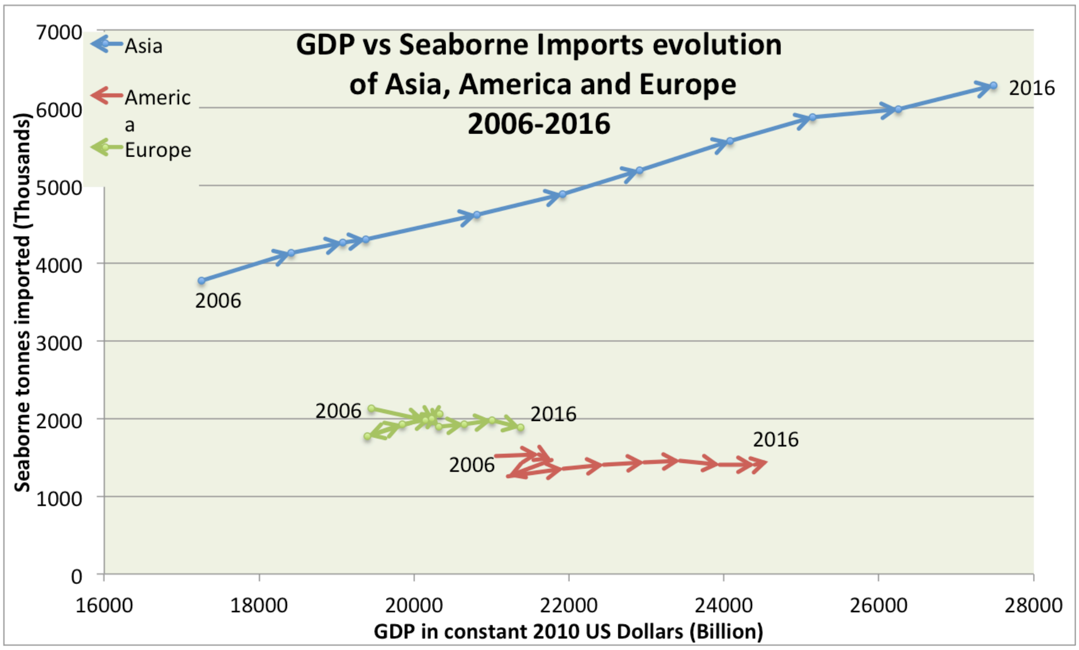


Figure 10 Evolution GDP versus seaborne imports of the three main maritime trading regions between 2006 and 2016. GDP is expressed in constant 2010 US Dollars (Billion). Data compiled by author from (UNCTAD, 2016a) and (UNCTAD, 2016b).

The underlying explanation for the differences in strength of the relationship between seaborne trade and GDP in Figure 10 can be found in the seaborne trade development cycle proposed in (Stopford, 2009, p. 410) based upon Rostow's five stages of economic development. Here it is explained that as countries develop economically, their needs for importing different products changes. The US has been in the final stage (stage 5) called *mass consumption* for some time now, which is characterised by the leading sectors of industry becoming durable goods producers and especially service providers. Another characteristic is that a stage 5 population is affluent enough to consume far more than just basic food, shelter and clothing. These shifts necessitate less of a need for raw materials and that is why a drop or levelling off in import tonnes is seen for the US data in Figure 10. China is earlier in the trade development cycle than the US and could be described as just starting to enter stage 4, *maturity*. In this stage a shift in industry takes place from steel and heavy engineering industries to more refined and complex processes such as chemicals, machine tools and electrical equipment manufacturing. Again, this shift requires slightly less imported tonnes of materials, which can be seen in Figure 10 from the slightly lower growth in imported tonnes from 2014 onwards.

The difference in stages of economic development between China and the US can be seen when looking at the historic composition of the sectors that make up the economy of each country and their output as a percentage of GDP (Figure 11). As China became the world's manufacturing powerhouse, the share of agriculture related activities diminished (a key signal an economy is moving out of its initial development stages according to Rostow). As a mature economy, the United States shows a picture where services and government combined contribute to a large part of GDP, whereas agriculture only makes up a tiny fraction of the overall GDP. It must be noted that Chinese data does not specifically include a sector for government (public administration), but it would be expected to have a smaller contribution to GDP than the US public administration sector.

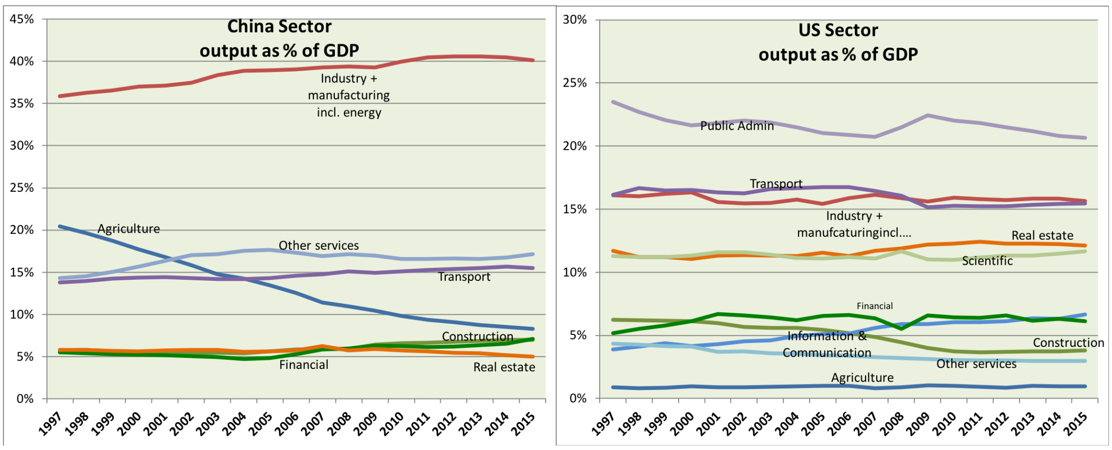


Figure 11 Comparison between China and United States of their various economic sector output as a percentage of annual GDP. Source: (OECD, 2018)

Clearly economies change over time (Figure 11) and these fundamental changes affect the relationship between GDP and maritime trade (Figure 10).

This change also holds true in the relationship of GDP growth and container trade growth.

In a report by Boston Consulting Group (BCG) analysing developments in container supply and demand to make a 5-year forecast for global container shipping (Egloff et al., 2016), the changing relationship between maritime trade and GDP is visualised via the so-called 'GDP Multiplier' (the annual ratio of container trade growth to GDP growth). Figure 12 shows their chart and the fundamental changes affecting the maritime trade to GDP relationship can clearly be seen in the variability of the annual GDP multiplier

Figure 12 Historic annual growth of global container trade and world GDP in % (blue and green bars respectively). The green line resembles the ratio of these two growth rates and is called the 'GDP Multiplier'. The outlier values from 2009 are omitted. Source: (Egloff et al., 2016)

(Meersman & Van de Voorde, 2013) found that it was difficult to find a common trend in the relation between aggregated freight transportation and GDP over the period 1970-2010 citing changes in GDP composition as well as changes in the link between economic activity and freight transport due to policies and business behaviour as drivers behind the unstable freight to GDP relation. They conclude that the relation cannot be used for long-term forecasting and that more disaggregate models are needed to capture the changing relationship.

These big structural changes in GDP composition and the relation with economic activity take place over long time periods though, and while one must be aware of these changes, they do no significantly affect relative monthly changes in maritime trade. Predicting economic activity in the context of this thesis does not entail looking further forward than, at a maximum, one year and therefore the assumption is made that there is a reasonably stable link between GDP and maritime trade within this timeframe.

<u>*The details of US GDP and container flows*</u>

With the relationship between GDP and maritime trade established, it is time to look more specifically at the constituents of US GDP and their connections to container flows.

The first thing that must be noted is that the US has a substantial trade deficit, as can be seen by the red net exports (negative) GDP constituent back in Figure 8. This figure also clearly shows that Personal Consumption Expenditures (PCE) is by far the largest constituent to US GDP, which goes hand in hand with Rostow's fifth stage of economic development: '*mass consumption*'. By dividing PCE into expenditures on either goods or services, the domination of services in the US economy shows up. Figure 13 shows that roughly two thirds of PCE are spent on services.

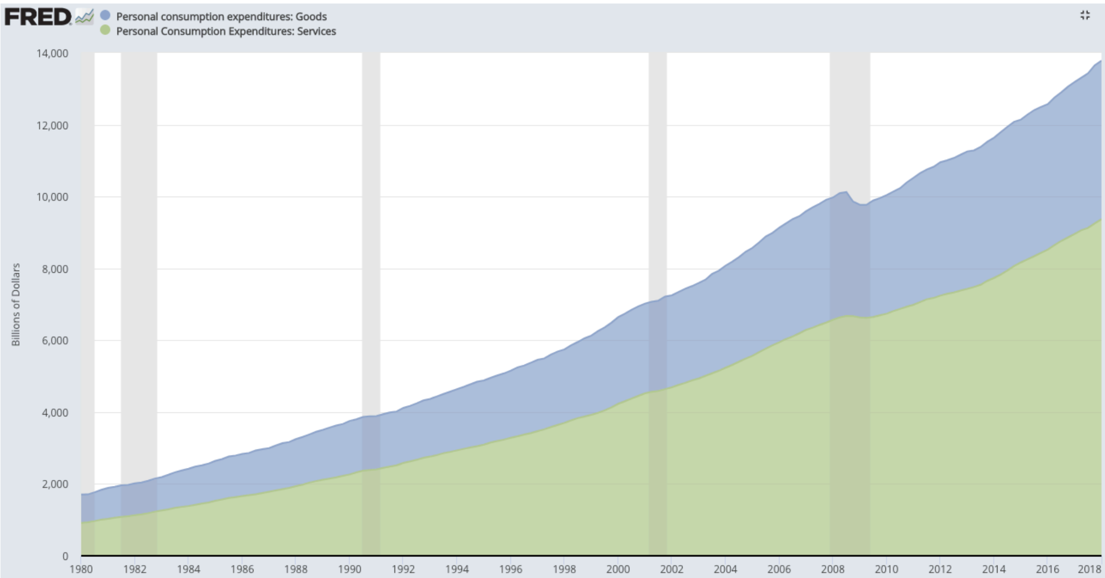


Figure 13 The Personal Consumption Expenditures (PCE) constituent of US GDP broken down into expenditures on goods (blue area) or services (green area) (1980-2018). Chart from (Federal Reserve Bank of St. Louis, 2018a)

Using GDP data, Census Bureau international trade statistics data and the Bureau of labour statistics Input-Output matrix data, (Hale & Hobijn, 2011) analysed what percentage of US consumer spending (PCE) went towards goods labelled 'made in China'. This study was done with 2010 figures but is still relevant assuming that structural economic trends have not largely changed (Figure 11). They found that in 2010, 88.5% of US PCE was on US made goods and services. Of the 11.5% of foreign spending, two thirds went to services and one third to foreign goods. When looking specifically at China, 2.7% of US PCE went towards Chinese goods and services.

Zooming in on the 11.5% foreign spending, it was found that in general 64% of this was made up of the actual cost of imports and 36% went towards the cost of US transport, wholesale and retail operations. For Chinese goods (2.7% of US PCE) the split was 45% to import costs and 55% towards US made costs. The higher amount of US costs was due to the products coming from China (clothing and electronics) having higher margins (that go to US wholesalers and retailers). The percentages described above are visualised in Figure 14, with 'Final goods imported from China (1.2%)' and 'US content of made in China (1.5%)' combining to the 2.7% of US PCE on Chinese goods and services.

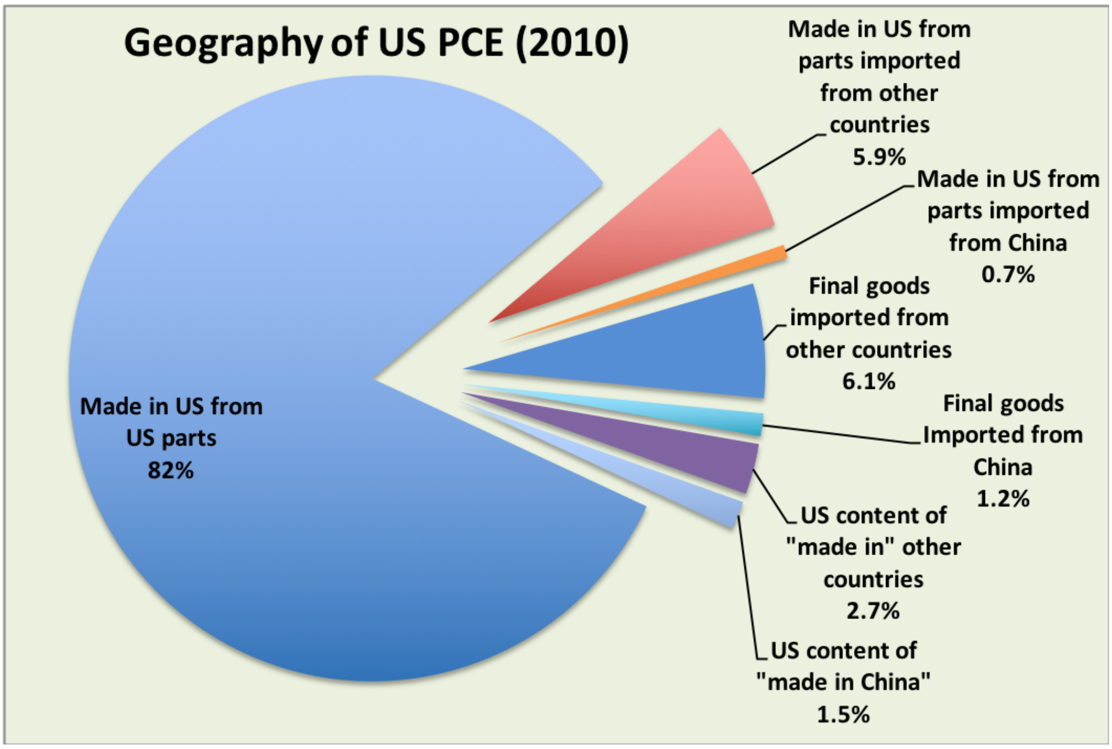


Figure 14 Geographic breakdown of 2010 US Personal Consumption Expenditures. Adapted from (Hale & Hobijn, 2011)

For this thesis, transpacific trade is being considered and a large part of this trade comes directly from China, although other exporters include Japan and South Korea. Using the information from (Hale & Hobijn, 2011) it can be concluded that merely a third of the 2.7% of US PCE that was spent on China went towards goods (0.9%) and only 45% of that was actually for the cost of the imports. Assuming all those goods were shipped via container that is only 0.4% of US PCE being spent on imports of containerised goods from China. Hardly a number that would make one think that changes in transpacific container imports have much influence on US GDP.

However, there are number of reasons why container flows actually have more of a say what is going on with GDP:

1. Many transpacific container units that arrive to the US positively contribute to US GDP through US transportation, wholesaling and retailing operations. Imagine a handbag costing $150 retail, of which the bulk of this cost pays for transportation within the US, warehousing costs, rent of the store where it is sold, profits for shareholders of the US retailer and marketing costs for the handbag. This also includes all the salaries and benefits paid to US workers and managers who run these operations.

2. Besides the final goods that are imported into the US, many intermediate products arrive by container as well (the red and orange sections in Figure 14). These are then assembled or further manipulated into final products that are sold. All this ‘added value’ minus the import cost of the intermediate product contributes to the Consumption part of US GDP.

3. Looking beyond the largest constituent of US GDP (Consumption), Investment in capital goods is also connected with container imports. A large percentage of machinery that US businesses invest in comes from Asia and much of it is transported by container.

Besides the above arguments, which could be classified as explicit connections between container flows and US GDP, there is also a more implicit connection:

When considering that this thesis aims to predict economic activity over the shorter term (< 6 months), it could be safe to assume that longer term structural trends that affect the share of foreign goods that US consumers spend their money on will not significantly change on a quarter on quarter basis. This means that any shorter-term changes in imports will reflect US consumer demand for goods in general. Therefore, in the case of a Chinese handbag, if less Chinese handbags are being imported (measured by less loaded containers entering the US), this can be extrapolated to there being less demand for handbags in general. Of course, it is difficult to measure the amount of handbag filled containers arriving to US ports, but when generalised, a fall in the number of containers being imported could implicitly signal a fall in demand of goods (both foreign <u>and</u> domestic) by the US consumer.

Equity Markets

In this section the connection between equity markets and GDP is described. It is important to understand this connection to comprehend the importance of being able to predict GDP ahead of time and the potential profits that are tied to these predictions being correct. When using the term equity markets in this thesis, public equity markets, also known as stock markets are being referred to.

The fundamental value of a company besides the existing assets it owns lies in its earnings and, more importantly to equity markets, its ability to retain and grow future earnings. Growth in GDP (equation 1.1) can translate into growth in company earnings through increases in consumption, government spending, business investment and increased exports. This in turn leads to the valuation of these companies increasing and therefore the value of equity markets rising.

However, equity markets themselves are also a forward indicator of GDP (and therefore earnings). This is because GDP and earnings are published on a quarterly basis and are backwards looking (further explored in chapter 1.3) whereas equity markets are forward looking. The reason equity markets are forward looking is because market participants use them as an expression of their view on the ability of a company to retain or grow future earnings. A view that is expressed by buying or selling individual stocks. This is important, because if one takes all these views combined, the overall equity market behaviour should give a consensus view as to what future GDP and company earnings will be. This causality between GDP and equity markets described above is depicted in Figure 15.

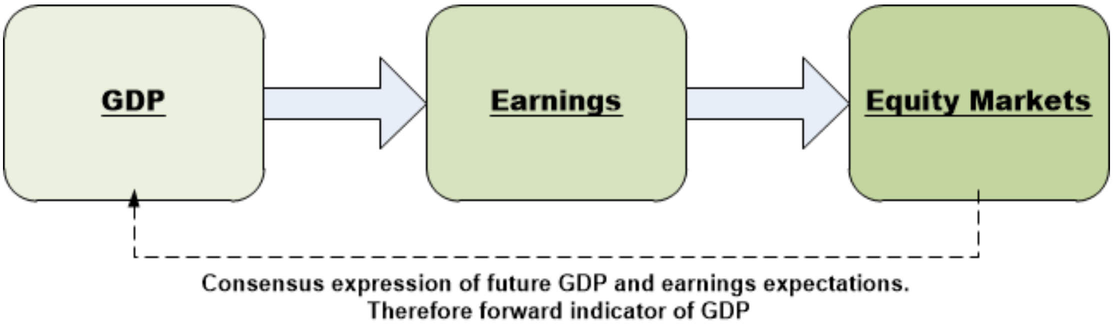


Figure 15 Causality model of GDP, Earnings and Equity market growth

Equity markets could be described as a partial forward indicator of GDP as sometimes these markets can get ahead (or behind) of themselves due to factors such as human psychology (greed/fear etc.) or become skewed due to fiscal and/or monetary policy. Despite this, equity markets more often than not, do correctly price in upcoming quarterly GDP growth announcements. Once GDP is reported, the market has already moved and it is only surprises when there is a discrepancy between predictions and the GDP number that move a market on the actual day of publication. But most of the time the bigger market moves have occurred in the preceding 3-months.

By understanding that GDP is backward looking and equity markets are forward looking, but fundamentally valued upon GDP growth, one can begin to understand the value of being able to predict upcoming GDP announcements. Chapter 1.8 takes a deeper look into how one might profit from being able to correctly predict GDP and this thesis overall looks at how one might be able to add to the probability of getting that prediction correct using container flows.

Sectors of equity market exposed to containerised trade

Throughout the rest of this thesis, when referring to the US equity market, the Standard and Poor's 500 index (S&P 500) will be used as a proxy for the US stock market as a whole. This index includes many companies that have no direct exposure to changes in transpacific containerised trade, just like a large part of GDP is made up from products sold by service-oriented companies with no exposure to transpacific trade. In this section sectors within the S&P 500 are identified that are most connected to containerised trade and therefore would be expected to react the most to changes in transpacific container flows.

These specific sectors can then also be compared to container flows in chapter 4.

Companies listed in the S&P 500 index divided into 11 Global Industry Classifications Sectors (GICS), who can further be divided into 157 GICS Sub-Industries. Table 1 shows the GICS and indicates in green which of these sectors have the most exposure to container shipping.

Table 1 The 11 GICS of the S&P 500 Index and their respective weight in total market capitalisation (as of June 2018).

S&P 500 Sector:	% of total market cap.
Information Technology	23.11
Financials	16.56
Healthcare	13.83
Consumer Discretionary	12.06
Industrials	10.41
Consumer Staples	7.1
Energy	6.26
Telecommunication services	3
Utilities	2.78
Materials	2.67
Real Estate	2.22

Consumer Discretionary contains businesses producing goods and services whereby demand and fall generally rises and falls with general economic conditions, i.e. products consumers want but don't necessarily need. This is the most exposed sector to container shipping in the S&P 500 index and makes up a sizeable 12% of the complete index. Of its sub-industries, apparel retail, household appliances and general merchandise stores are some of the most containerised trade dependant.

Industrials is mainly exposed to containerised trade through raw materials and unfinished products that are imported into the US to be turned into final products. The most exposed sub-industries are: electrical equipment, machinery and building products

Materials has two main sub-industries that make use of containerised trade: specialty chemicals and construction materials. Specialty chemicals uses container trade for exporting to Asia for further processing into products.

Broadly speaking around 25% of the S&P 500 market capitalisation is made up of sectors exposed to container shipping. Most of the container movements occur before the companies make their final sales and earnings (as will be discussed in more detail in chapter 1.4), so changes in container flows may be able to directly predict how a large section of the S&P 500 index listed companies will perform.

1.3 The time delay of GDP announcements

As mentioned in the discussion of equity markets in chapter 1.2, GDP is backward looking. This entails, that when the official quarterly GDP figure is released, all the economic events that make up that number have already transpired. In Figure 16 the official 2018 US GDP announcement dates have been visualised in a timeline against a backdrop of when the actual financial quarters are occurring. These announcements are published on the last Friday of the month following the quarter. It should be mentioned that these numbers get revised 1 and 2 months after the initial announcement.

The US Bureau of Economic Analysis is considered one of the most timely and accurate providers of GDP statistics globally with small (+/- 0.1%) revisions in the following months to their initial announcements. This is not the case for many other countries, including countries within the European union, where large (+/- 0.5%) GDP revisions can be made a year later (Zwijnenburg, 2015), causing initial announcements to be considered unreliable.

This thesis is focussed on transpacific trade and the predictions it can make regarding US economic activity, but with other container flow data, the same could possibly be done for other countries or regions. Knowing that these other regions have less accurate and more delayed GDP announcements than the US, would only make the possible use of container flows as predictor of economic activity even more valuable.

Figure 16 Timeline of 2018 quarterly US GDP announcements. These announcements are actually only advance estimates and a second and third estimate revision get published 1 and 2 months respectively later. Dates from Bureau of Economic Analysis (www.bea.gov)

To quote the US Bureau of Economic Analysis:

> *"GDP is one of the most comprehensive and closely watched economic statistics: It is used by the White House and Congress to prepare the Federal budget, by the Federal Reserve to formulate monetary policy, by Wall Street as an indicator of economic activity, and by the business community to prepare forecasts of economic performance that provide the basis for production, investment, and employment planning."*

So, GDP is important to many entities, but as Figure 16 shows, the problem is that GDP is announced late and is essentially 'old news' when the quarterly figures are released (even though the US has one of the smallest time delays). The reason it is old news is that anybody with an interest in knowing what the next quarter's GDP will be does not wait until the announcement, but looks to indicators that can tell them what GDP is likely to be. Some of these indicators will be discussed later in chapter 4.1, but for now the definition of what a leading and a forward indicator is will be given.

The difference between leading and forward indicators

By now it will be clear that an indicator that could help predict what GDP growth will be is a valuable tool. Because such an indicator is giving an indication about the future it is called a leading or a forward indicator. These terms are used interchangeably throughout most financial and academic literature. There is however a subtle but important difference between the two.

A leading indicator conveys pure data that says something about an underlying phenomenon that happens after the leading indicator data becomes known. An example that might sound surprising, is the US unemployment number being a leading indicator for US gasoline sales. The simple underlying phenomenon is that when more people are employed, more gasoline is consumed to commute to work and therefore gasoline sales will rise. It does not say anything about expectations of gasoline sales or changes in the future employment rate and is therefore just a leading indicator.

On the other hand, a forward indicator is a leading indicator that has the power to predict changes. This is because a forward indicator always incorporates some level of human interpretation, sentiment or emotion in it. An example could be the monthly number of packages being sent via the (more expensive) DHL Express service. This serves as a forward indicator of the quarterly results of businesses in general. With a drop in packages sent via DHL Express signalling that businesses are experiencing tougher times, because managers are deciding to cut costs by opting for cheaper post options (van de Voorde, 2018).

Loaded and/or empty container flows can be considered a forward indicator in the case of this thesis, as embedded within the pure numbers of containers traversing the pacific are the sales expectations of all retail managers and companies in the US. The next section will provide more insight into how container flows are the first publicly available expression of these sales expectations within a retail supply chain.

1.4 Analysis of a typical retail supply chain

As the previous chapters already illustrated, GDP is an important number, but it is published after all the transactions that add up to make the GDP number have taken place. In this chapter, a retail supply chain is described in order to understand where in the supply chain container shipping plays a role and to understand where transactions that affect GDP take place. It is the final part in the chain of thinking that results in the research question.

Imagine a sunny day at a beachside town. If you wanted to know if the sales of the ice cream sellers were going to be larger than the previous day, you could wait until the end of the day and then ask all the ice cream sellers what their sales amounts were. If however, you wanted to know this information earlier, you could also go and stand by the main road to the beach and count the amount of cars arriving throughout the morning. Seeing a larger number of cars arrive in the morning could be extrapolated to estimate a larger amount of ice cream sales for that day. There are other ways of knowing even earlier what the estimated ice cream sales will be, for instance, if you had access to the weather forecast for the upcoming weekend. A forecast for beautiful beach weather could be extrapolated to more visitors (cars arriving) and in turn, more ice cream sales.

The point of this imaginary scenario is that it is an analogy to the argument this thesis presents of containers being a forward indicator of economic activity. The total sales of ice cream suppliers at the end of the day is US GDP, the flow of cars to and from the beach represent transpacific container flows and the weather forecast represents product demand forecasts or factory orders.

To understand the forward indicating role of container flows better, one must look at their role in the complete supply chain. A typical retail supply chain is presented in Figure 17. In this figure the (simplified) network that is involved to produce and sell a laptop is shown (assuming that ocean shipping instead of airfreight makes sense in the case of this laptop as discussed in “The value within a container’). The lower grey boxes provide an example of one of the pathways within the network that must be completed (left to right) to achieve a final sale. Each black arrow between boxes represents a logistical move and to keep the example simple, it is assumed all manufacturing and assembly is for this laptop is done in Asia and then shipped via container to wholesalers in the US. The smaller red circle indicates the moment that the laptop container shipment takes place and the larger red circle shows the moment the sale of the laptop to a consumer is completed, thereby adding to US GDP through consumer spending.

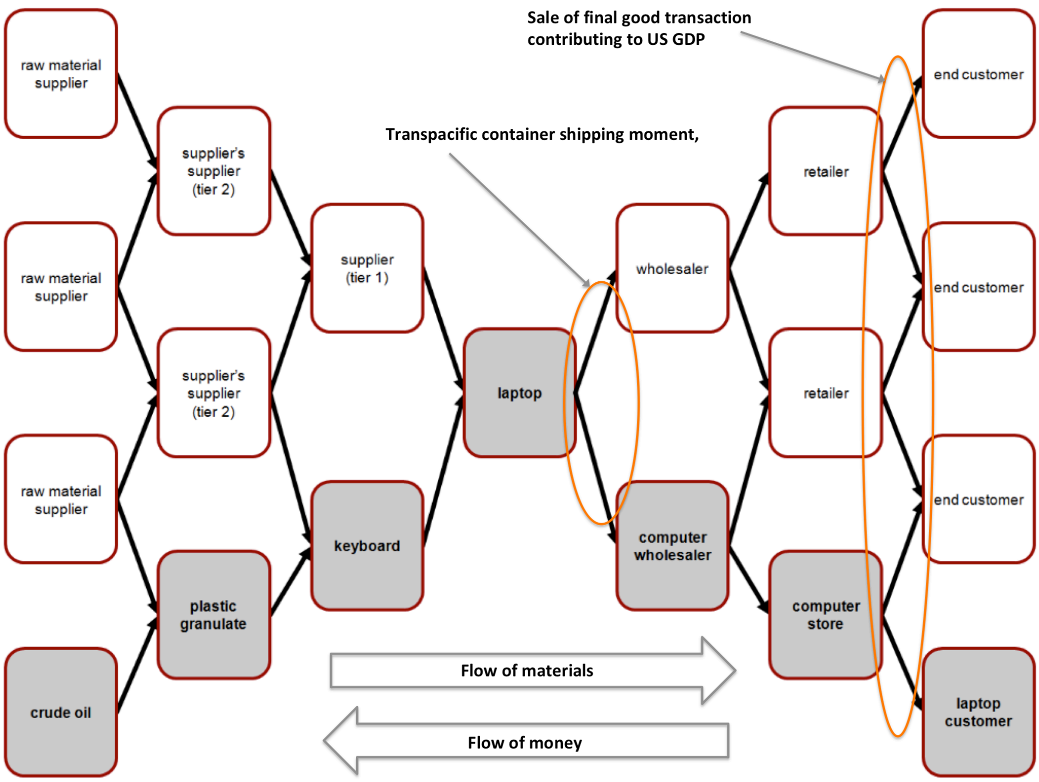


Figure 17 Supply chain for a laptop Source: (Wieland & Wallenburg, 2011)

In the case of the laptop, if a member the public wanted to know how the retail sales of the laptop company were doing, then the first official chance they would get would be by reading the quarterly company earnings report. If they had access, they could have analysed the internal demand forecasts made by the laptop company for that upcoming quarter or looked at the orders placed at the factories that manufacture parts for the laptop production. Herein lies the issue though: access to the aforementioned information is not publicly available and if wanting to know how retail sales in general were doing then a lot of different, difficult to obtain sources would need to be aggregated. To compare this to the case of ice cream sales, this would be analogous to the weather forecast being inaccessible. The next option to forecast ice cream sales would then be to count the flow of cars arriving to the beach, which in this thesis are container flows.

So, by understanding the flow of goods in a supply chain and where container shipping fits in, it can be seen that a container movement happens before the sale of a final product and also before the official reporting of this sale. Specific products that are in the container are unknown, but the aggregate of these products stays relatively stable in the shorter-term (as covered in 'The value within a container' and 'The relationship between GDP and maritime trade'). It seems that analysing container flows could give an indication of the near-term future final goods transactions and therefore give an indication of upcoming quarterly GDP figures.

1.5 Research question

The above explained time delay of GDP and the reasoning that container movements can be early information about upcoming economic activity quarterly figures leads to the research question: "*Can loaded and/or empty container flows be used to predict economic activity?*" Other questions posed are: "*How precise/reliable are these predictions?*" and "*What is the time horizon of these predictions?*"

1.6 Scope

The discussion of container flows within this thesis is limited to one of the largest trade routes in the world: the transpacific trade lane between Asia and the US. The measurement of these transpacific container flows will be done by using monthly US West coast port data. This main dataset of container flows ranges from July 1997 to December 2017.

The homogeneity of containerised transport makes the measurement of historic container flows dependable and comparable throughout the years. A limitation of this however, is the fact that this homogeneity also hides the exact details of the individual contents, restricting the ability to make statements about individual companies or products that utilise container shipping.

Economic activity is expressed as GDP and this is linked to maritime trade. The pitfalls and limitations of this are acknowledged in the section '*Measuring economic activity*'. Unless specified in the text, all US dollar amounts are shown in 2010 US dollars.

Predictions of economic activity will be focussed on the US economy in the form of GDP and when referring to the US equity market the broad-based S&P 500 will be used as a proxy for the US stock market.

The time scale of these predictions is deemed short-term, with predictions being made one quarter (three months) in advance of GDP announcements using container data from the previous three months. 'Short-term' throughout this thesis therefore refers to six months or less.

1.7 Methodology

To answer the research question: "Can loaded and/or empty container flows be used to predict economic activity?" this thesis first introduces the reader to the history and dynamics of the loaded and empty container market by reviewing existing literature to provide an understanding of how container logistics work and distilling from this all the possible influencing variables that can affect these markets.

In chapter 3 the aggregation and modification of the container flow data to be used for further analysis is explained. Then container flow influencing variables found in the literature are discussed in detail and compared using charts and cross correlation function data. All variables that include data are tested for stationarity to avoid finding spurious correlations in the cross correlation functions.

Chapter 4 selects the most promising variables to be used in conjunction with container flow data to make predictions of GDP. OLS multiple regressions are done in a systematic manner based on the variable's correlation strength with each container flow.

The results are compared with an existing, often-used forward indicator. A statistical analysis is done to determine the probabilities of predicting GDP growth correctly and accurately using container flows over the studied time period.

1.8 Who can extract value from this work and how?

Quoting the US Bureau of Economic Analysis once more:

> "*GDP is one of the most comprehensive and closely watched economic statistics: It is used by the White House and Congress to prepare the Federal budget, by the Federal Reserve to formulate monetary policy, by Wall Street as an indicator of economic activity, and by the business*

community to prepare forecasts of economic performance that provide the basis for production, investment, and employment planning."

All of the above mentioned are potential stakeholders in this work, but it has been chosen to highlight how an investment institution active in the financial markets uses economic activity predictions to their advantage and how this thesis could potentially add value.

This thesis focuses on investigating if container flows have an economic predictive quality. Professional investing in financial markets is most often done on the basis of economic predictions for the future and this work can potentially contribute to raising the probability of these predictions being correct. Therefore, natural stakeholders for this work are professional investment institutions such as investment banks, pension funds and hedge funds.

How this work could be of value to such as stakeholder will be highlighted by examining the approach of a professional trader working for a hedge fund or proprietary trading firm, the difference being that the former trades with investor money and the latter trades with the firm's own money. He or she is most free to take positions in markets compared with pension fund managers (often strict limits on risk exposure to equity markets) and investment bank traders (mostly limited to market making and trades for hedging purposes only since the implementation in July 2015 of the Volcker rule within the Dodd-Frank act).

The next section will depict a typical approach used by a professional trader to assess market opportunities and generate trade ideas. The reason to analyse this process is to understand exactly where economic predictions from container flow information can fit into this process and how it could add value to a trader.

A professional trader's approach

There are many different styles of trading in financial markets, some better known and/or successful than others. For the purpose of this thesis an 'all-round' professional trader is assumed who utilizes an investment framework that could describe the approach of most general hedge funds and other institutions. The time horizon of trades for this kind of approach is usually around 3-12 months. Figure 18 shows a depiction of a typical investment framework used within the investment industry.

In the case of a trader developing a thesis to trade a certain stock, they would start with a 'top down approach' by building a (macroeconomic) view on the global economy and national economy of where the company does business. This allows them to determine whether they are bullish, bearish or neutral on the world and national economy in general. A further intermediary step of researching industry outlooks for the various cyclical and defensive sectors within a stock market allows a trader to filter potential winning and losing sectors. Finally, within these sectors individual stocks can be filtered and analysed for potential trade ideas. This is the 'bottom up' part of the work where the individual company is analysed using earnings reports and balance sheet statements. This process is captured in the top left box '*Idea Generation*' in Figure 18.

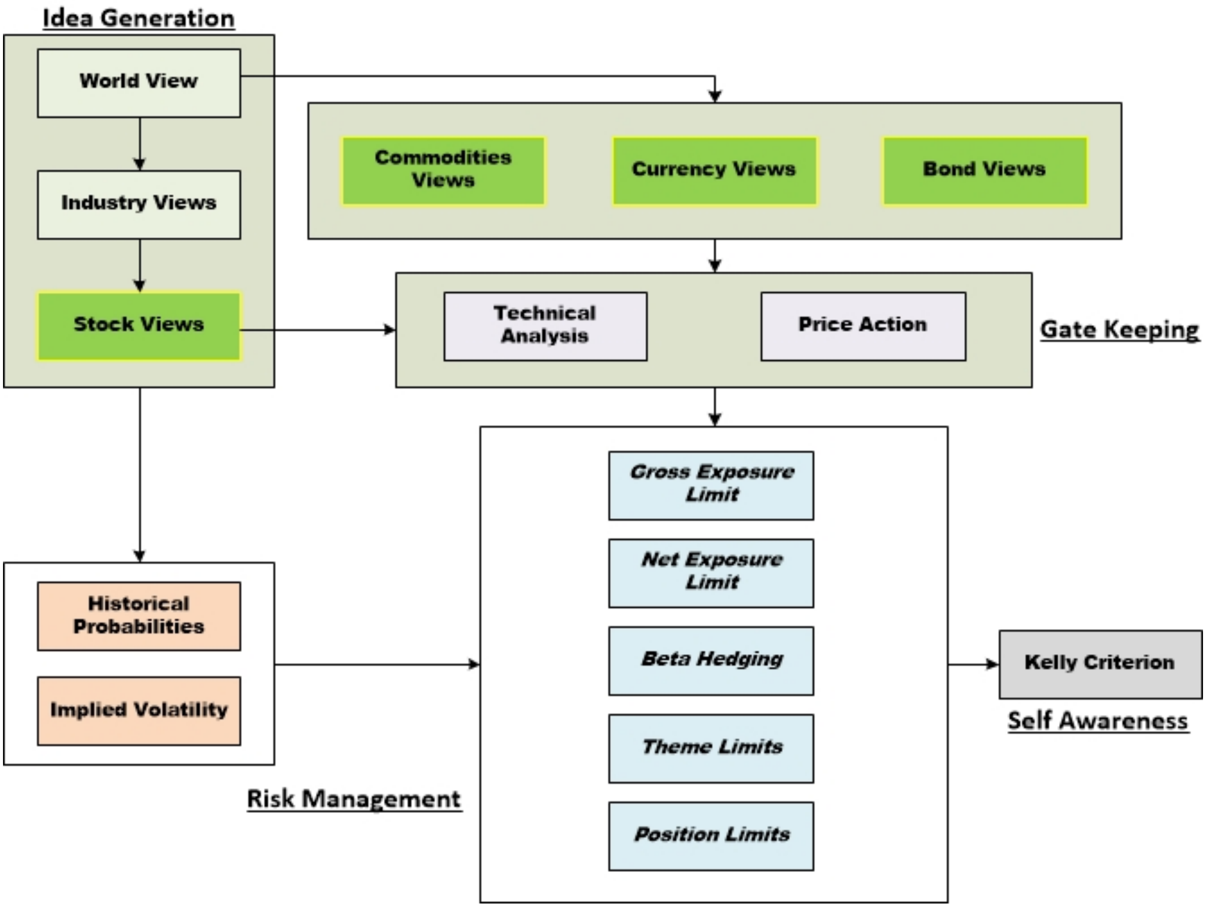


Figure 18 General framework of a professional trader. The process of generating a world view is where this thesis aims to add value.

It is at the point in this process of building a world/regional view, where this thesis could potentially contribute. To build their macroeconomic view, a trader uses various leading and forward indicators to decide whether they think the economy and therefore the stock market in general, will rise, fall or stay level. As described in '*Equity Markets*', GDP is an important driver of the stock market so being able to predict this will help in building a macroeconomic view. Loaded and/or Empty Container flows could potentially aid in increasing the probability of getting that prediction correct and therefore increasing the probability of getting a trade correct with potential profits as a result.

In chapters 2 and 3 a closer analysis of container flows and their specific dynamics will be made to better understand when changes in flows are from changes in economic activity or just a peculiarity within the container market. Chapter 4 will return to assessing whether Loaded and/or Empty Container flows can be successfully used to predict GDP, but first this section is concluded with a short summary of how the rest of the framework in Figure 18 is implemented for those interested in professional investing:

Once an initial trade idea has been generated by the trader that is in line with their macroeconomic world view, it is just that: an idea. The next step before actually being placed as a trade is to identify and manage risk by analysing statistics on historic performance as well as implied future performance by using the data from the options and futures markets (Risk management area at bottom left Figure 18). By doing this, a good understanding of the probabilities of certain movements occurring is obtained thereby allowing trades with the odds stacked in one's favour to be identified. After the probabilities of opportunities and risks have been calculated a final gatekeeping step of using technical analysis to determine optimal trade entry (and exit) points (middle right of Figure 18). Only now does a trader have a complete thesis and strategy for a trade: A combination of a top down approach analysing market fundamentals with the bottom up approach of analysing the specific stock fundamental and its historic and implied future movements together with an overlay of technical analysis determining optimal entry/exit points. Once a trade has been initiated a whole set of risk management controls comes into play (bottom right of Figure 18) to manage and protect the trader's portfolio, the discussion of which will be left out of this thesis.

2. CONTAINER IMBALANCES AND EMPTY CONTAINER REPOSITIONING

In chapter 1 it was made clear that economic activity drives container flows, but that these flows could also possibly provide early information on upcoming GDP figures due to the non-availability of relevant data and the time lag of GDP announcements. In Figure 19 this can be seen in the loop made up of economic activity driving container flows and these container flows then becoming a forward indicator of economic activity itself.

This chapter focuses on a consequence of differing economic activity between regions: container imbalances. These imbalances lead to the phenomenon of interregional and international empty container repositioning. Because this thesis differentiates between loaded and empty container flows, it is important to understand the dynamics at play with empty containers if they are also going to be used as forward indicator. To do this, the chapter '*Trade Imbalances'* starts by examining why container imbalances have come to be, how big they are and the costs associated with them. '*Empty Container Repositioning*' contains a literature review on the multitude of solutions that have been proposed to reduce the amount and/or costs of empty repositioning moves.

After examining empty containers in this chapter, chapter 3 '*Fluctuations in Container Flows*' moves on to covering the various factors besides economic activity that drive changes in container flows full and empty.

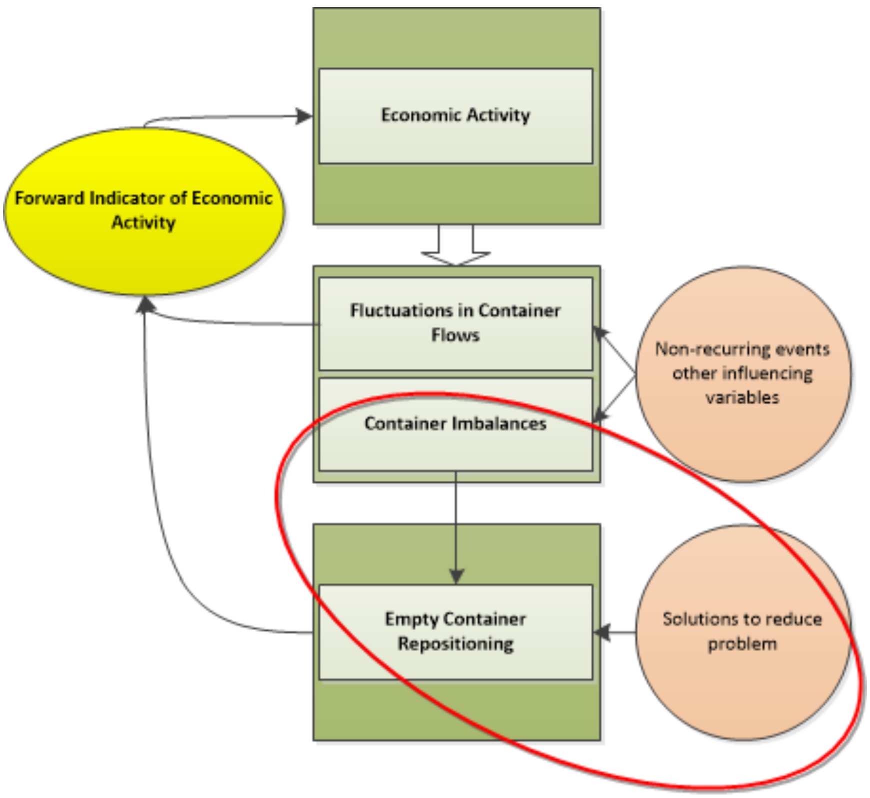


Figure 19 Red circle indicating the area covered in chapter 2.

2.1 Trade Imbalances

In a perfect world for liner companies, global trade would be in equilibrium, with goods flowing in equal measure from one region to another and back again. In reality though, the situation is far from this; due to fundamental manufacturing (wages, materials) and trade (currency, country specific demand) imbalances there often exists a trade deficit or trade surplus in certain regions of the world. Figure 20 and Figure 21 illustrate the development and the size of the trade imbalance for containers on the transpacific route by looking at US West coast port flows (the main recipients of transpacific containers).

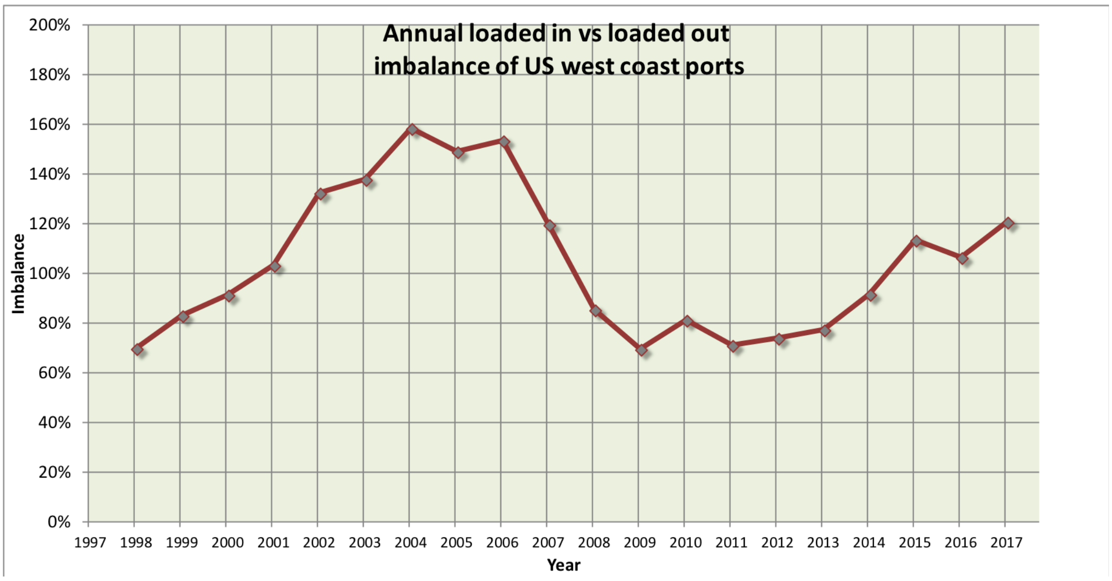


Figure 20 Annual imbalance of loaded containers imported into US West coast ports versus loaded containers exported from the same ports. In 2004 there were nearly 160% more loaded containers imported than exported. Data compiled by author from individual port websites.

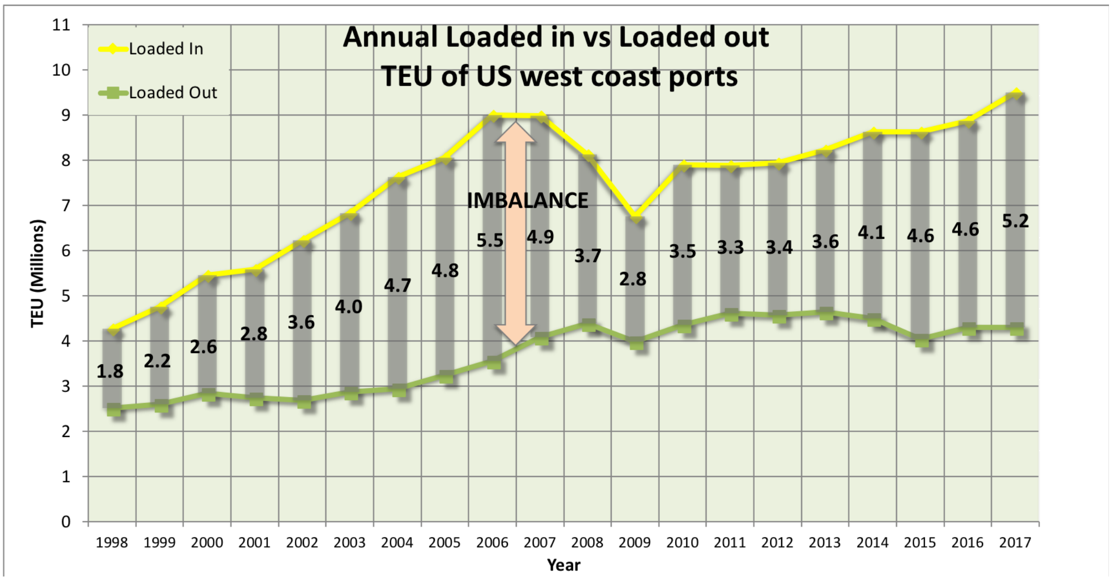


Figure 21 Annual Loaded in and loaded out TEU of Los Angeles, Long Beach and Oakland ports combined. Grey bars indicate the imbalance amount in millions of TEU. Data compiled by author from individual port websites.

Due to these imbalances, empty containers accumulate in trade deficit regions and subsequently decisions need to be made as to how to deal with them. To understand the interactions and dynamics between the various stakeholders when it comes to empty container repositioning (ECR), an overview of empty container flows on an interregional and local level is pictured in Figure 22. The stakeholders involved in this figure are:

- **Consignees –** These are the recipients of goods
- **Consignors –** These are the shippers of goods
- **Ocean carriers –** The operators of ocean liner services
- **Marine terminal operators –** The operators of the container ports
- **Depot operators –** Operators of container storage yards located outside the port
- **Drayage operators –** Specialised trucking companies that transport containers short distances between railroads, waterways and ocean ports. They can also make final deliveries over short distances
- **Other transport modalities –** These are railroad, inland waterway or long-haul trucking operators, making container transport 'intermodal'

Starting at the bottom of the figure with a full container arriving via ocean carrier to a US West coast port (Marine terminal), this container can be delivered to the consignee directly via a drayage operator or intermodally. The process of 'stripping' (emptying the container of cargo) and the container is then returned to the marine terminal or a storage depot. In some cases, the container may be 'street turned' (indicated by 'Empty direct interchange in Figure 22) whereby it goes directly to the next consignor to be 'stuffed' (loaded with export cargo). In other cases, consignors receive empty containers either from a local empty depot, the marine terminal or from an interregional repositioning operation. In the case of the US, interregional repositioning usually entails repositioning containers between the West and East coasts, which is most often done via railroads. Once stuffed by the consignor, full containers are drayed straight to the marine terminal or to an intermodal terminal to be exported.

Empty containers can be stored for different amounts of time at storage depots, to eventually be picked up and taken to a consignor, repositioned either interregional or overseas. Older containers that have been in storage for long amounts of time may be sold into the secondary markets (alternative housing, storage, etc.). An empty can also be repositioned between marine terminals and/or storage depots to keep capacity balanced. 'off leasing' movements between the marine terminal and storage depots will be covered in chapter 3.

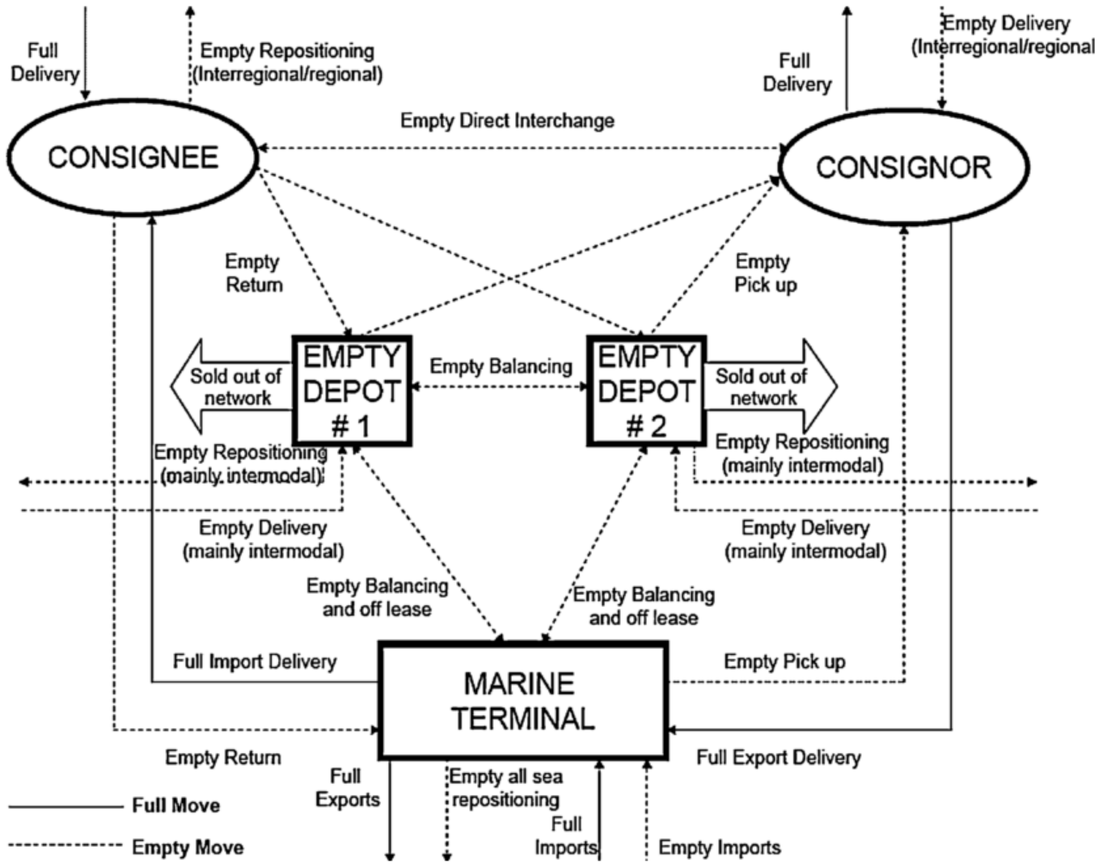


Figure 22 Schematic overview of dynamics of full and empty containers on a regional and local level. Source: (Theofanis & Boile, 2009, p. 60)

It should now be clear that throughout its lifetime a container makes many empty movements and that each of these needs to be paid for by somebody. An average container spends over half its working life either idle (and empty) or being repositioned as an empty (Right side of Figure 23). As can be seen on the left, these repositioning costs make up a significant part of the overall cost that an average container makes for its owner over its lifetime. An average lifetime for a container is around eight years (Alderton, 2011).

There is an important economic difference between loaded and empty container movements: A loaded movement occurs in response to customer demand and the customer naturally bears the transportation cost, whereas an empty movement only generates costs for the carrier and is an unavoidable part of the transport cycle whenever trade is not in balance.

Carriers are not the only stakeholders who incur costs due to empty containers. Ports and storage depots once saturated with containers, experience decreases in terminal productivity. Furthermore, any expansion of terminal facilities to enable extra empty storage will cost millions and takes up land often close to ports, which could otherwise be used more profitably by industry (Olivo, Zuddas, Di Francesco, & Manca, 2005). In the next section ' Empty Container Repositioning', the problem of ECR and its associated costs is further discussed along with a review of proposed solutions.

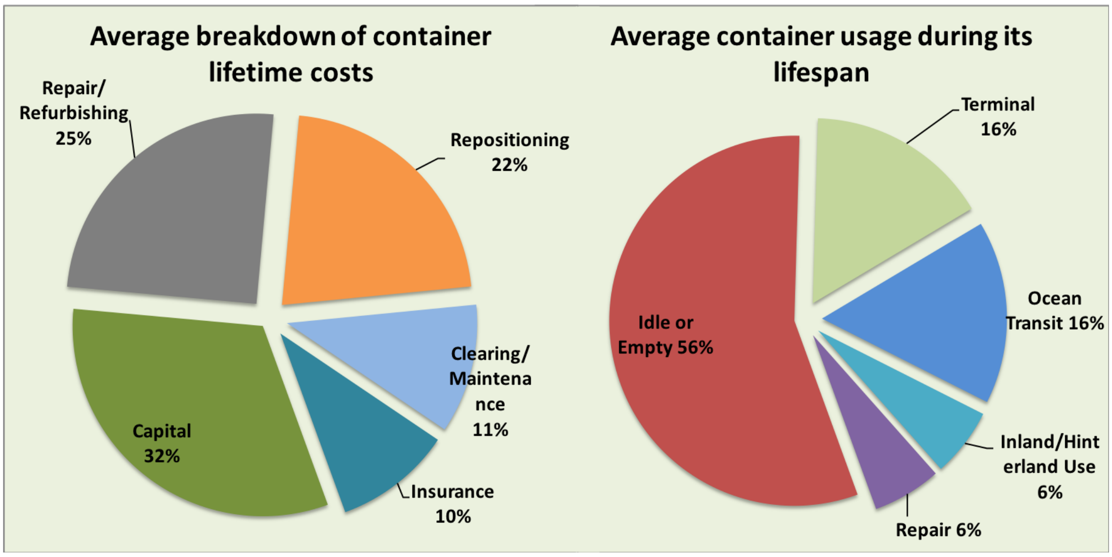


Figure 23 Left: Breakdown of lifetime costs an average container incurs. Capital includes new building costs as well as financing costs. (Alderton, 2011) Right: Breakdown of an average container's status over its lifetime. Adapted from (Rodrigue et al., 2016)

2.2 Empty Container Repositioning

The original concept of containerisation was beautifully simple and it still is highly effective in enabling affordable global trade, but nowadays the container shipping market is a complex system with many factors influencing its dynamics across different time-scales which will be discussed later in chapter 3. Due to the ever-changing nature of global trade and the response of shippers to this, trade imbalances are constantly fluctuating along with the number of empty containers being repositioned to deficit destinations. With these global trade imbalances being the fundamental and chronic driver of empty accumulation in certain regions of the world, container owners must look to solutions on how to best deal with ECR at any given moment.

Let it be emphasized that ECR is not a small, trivial problem, but a large expense to the maritime container industry. Various literature sources from the 2000's already highlighted the size of the problem around that time with (Boile, 2006) estimating the cost of container management inefficiencies to be around US$ 17 billion in 2001. The calculations made by (D. Song et al., 2005) indicate that empty repositioning makes up 27% of the total world container fleet operating costs, which depending on how you calculate capital costs is in line with the 22% in Figure 23 calculated by (Alderton, 2011). (Theofanis & Boile, 2009) cite a source based upon 2002 Drewry Consultants information that estimated an industry-wide yearly repositioning cost totalling around US$ 20 billion. With the number of containers on the transpacific route more than doubling since those crude estimates were made (see Figure 5), one can rest assured that the costs are even higher nowadays.

Repositioning costs

The cost structure of repositioning a container is made up of various different costs. There are three main categories that make up these costs:

- **Intermodal transport costs**
  These costs are dependent on the distance of transport and the mode of transport (Rail, Truck or a combination) and whether or not drayage to and from intermodal rail terminals is necessary.
- **Port and terminal costs**
  These consist of tariffs levied by port authorities (dockage & wharfage), terminal operator rates, stevedoring charges and on-dock intermodal lift and drayage costs.
- **Ocean shipping costs**
  Depending on who is responsible for repositioning the container, the full backhaul freight rate must be paid for repositioning. If it is the carrier itself doing the repositioning, these costs will not explicitly be incurred.

Of these costs, the historical data of ocean shipping rates and intermodal costs are discussed in more detail in chapter 3.3. Port and terminal costs proved difficult to come by and this thesis will not use any data on this cost. In most cases port and terminal costs make up the smallest of the three repositioning cost categories (Figure 24). It is also assumed that port and terminal costs are the least volatile of the three categories.

Figure 24 displays the total cost breakdown of shipping a container from Asia via the Port of LA/Long Beach to different locations in the US. This cost breakdown is done for inbound containers, so the ocean shipping cost in dark blue is the (higher) headhaul rate. For repositioning this would actually be the lower backhaul rate (historic prices can be seen in the section 'Freight rates' of chapter 3.3). This figure does however give a good representation of what share each cost item takes up of the total as well as which type of intermodal transportation is used most for containers in LA/LB (light green bars on the left of Figure 24).

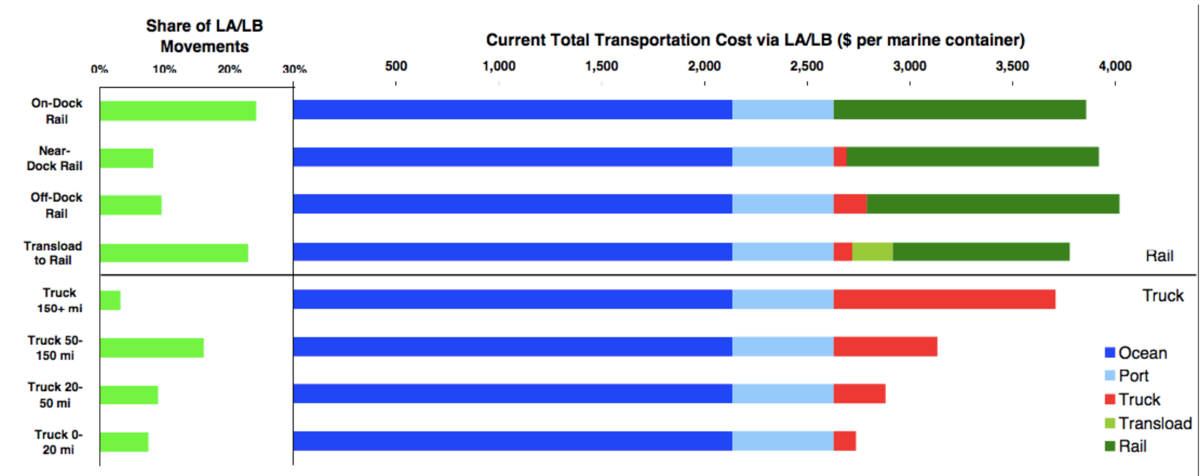


Figure 24 Transportation cost of container from Asia entering the US via the LA or LB ports. Source: (Moffat & Nichol & BST Associates, 2007)

Repositioning of an empty container will usually only be done as a very last option, as when that decision is made, the carrier will incur costs. Carriers will try to 'cross subsidize' their repositioning costs by charging a higher rate on their headhaul route. This can only be done to a certain extent, otherwise their prices will be non-competitive in the marketplace. If there is a chance that the container could pick up a cargo on the backhaul leg, it might pay off to store the empty in a storage depot until there is a cargo for it.

These kinds of decisions get made on different management levels with operational decisions being made on local level, tactical decisions on the interregional level and strategic repositioning decisions being made on the global level. The relationship between the repositioning cost and whether or not a repositioning decision strategy gets carried out is shown in Figure 25. The upper repositioning cost cut-off being the cost of manufacturing a new container in the container deficit area (Asia). This is not just a theoretical limit as, since the beginning of the data series used in this thesis (1997-2017), there have occasionally been times where the it has been cheaper to manufacture a new container in Asia rather than reposition one back from the US.

In the previous chapter it was mentioned that loaded container movements are a response to customer demand, whereas empty repositioning is based upon the decision/strategy of the container owner. The question then arises: ‘Do empty repositioning strategies change on the basis of customer demand?’ If so, one may ask whether transpacific empty flows can be useful in predicting economic activity and it is because of this possibility that this thesis examines loaded and empty container flows individually.

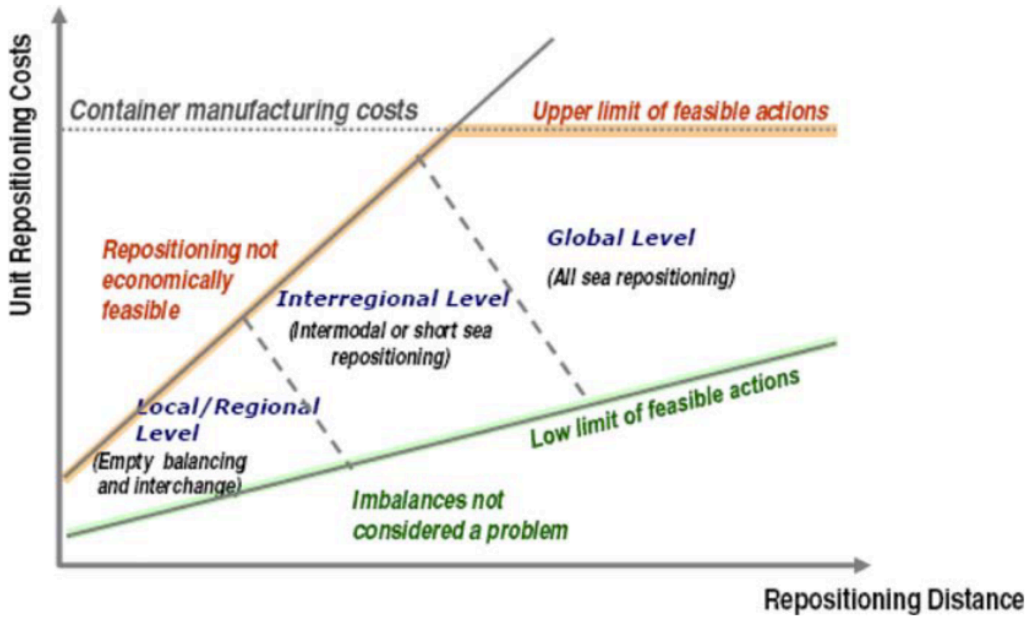


Figure 25 Empty container management strategies at various levels. Source: (Theofanis & Boile, 2009).

Review of ECR solutions

In this section existing literature is consulted to be able to understand if flows of empty containers are strongly influenced by the various types of solutions that have been proposed and/or implemented over the past 20 years. If so, this will need to be taken into account when using empty container flows to predict economic activity. What follows below is a short overview of academic literature focussed on the various aspects of the ECR problem. Besides identifying whether these solutions affect empty container flows significantly for the purpose of this thesis, it is also a good starting point for any reader wishing to dive deeper into the various approaches to the problem.

Planning optimisation solutions

By far the most amount of literature published on ECR falls into the category of planning optimisation solutions. These types of solutions attempt to optimise the networks in which empty container move in various different ways. Papers that provide a good overview of ECR literature in this category are (Feng & Chang, 2008), (Furió, Andrés, Adenso-Díaz, & Lozano, 2013), (Boile, 2006) and (Li, Wang, & Cook, 2015). (D. P. Song & Dong, 2012) categorise research on ECR solutions into three categories:

- **ECR in seaborne shipping networks**

This type of research typically aims to minimise the cost of ECR. Papers within this category consider solutions focussed on one liner route within a company, a network of liner routes with a specific structure (Meng & Wang, 2011a), hub-and-spoke style networks (Imai, Shintani, & Papadimitriou, 2009) or multiple port routes (Du & Hall, 1997). (S. Wang & Meng, 2012) also take the size of a carriers' fleet into account. Research methodologies used in this type of research include simulation-based optimization (Dong & Song, 2009), linear programming (Feng & Chang, 2008) and near-optimal repositioning decision making structures in stochastic dynamic environments (Teodor Gabriel Crainic, Gendreau, & Dejax, 1993; Meng & Wang, 2011b). Most of these works do not consider transshipment movements.

- **ECR in inland or intermodal transportation networks**

The research done in this category focusses on the more regional ECR operations of inland and intermodal transportation networks. This includes papers focussed on flows of empties between (single) ports and inland depots (Teodor G. Crainic, Gendreau, Soriano, & Toulouse, 1993), the consideration of different intermodal routes (Erera, Morales, & Savelsbergh, 2005) and container transshipment in intermodal networks. Research methodologies used on the problems within this category include branch-and-bound parallelization strategies (Bourbeau, Gabriel Crainic, & Gendron, 2000), heuristic solution procedures (Bandeira, Becker, & Borenstein, 2009) and integer programming (Olivo et al., 2005).

Compared with the seaborne shipping network problem, intermodal network problems are generally far more complex. Due to this fact, most research considers container movements as flows and do no model individual ships and their sailing schedules (Erera et al., 2005; D. P. Song & Dong, 2012).

- **ECR treated as a sub-problem or constraint embedded in other decision-making problems**

Research in this category treats ECR as a joint optimisation problem together with other decisions made within a shipping business. These decisions include container fleet sizing, fleet deployment, ship fleet planning (Meng & Wang, 2011b), transport pricing (Zhou & Lee, 2009) and shipping route design (Imai et al., 2009; Meng & Wang, 2011a). Because these joint optimisation problems are naturally more complex to solve, the ECR element in these works are modelled in less detail than the previous two categories. Also due to this complexity, the use of metaheuristics to find (non-exact) solutions to the optimisation is more common.

Another way to classify the ECR research as suggested by (Furió et al., 2013), is by differentiating whether the work focusses on the single port level (as with most intermodal repositioning research) or a more global, multi-port level. A further differentiatior is whether the research considers deterministic or stochastic (uncertain) data. Table 2 categorises the most noteworthy works in this way. The most amount of research centres around global level networks that assume uncertainty (stochastic data) in supply and demand of empty containers. These type of studies aim to determine the optimal policies for internationally balancing empty container flows.

Table 2 Classification of empty container repositioning research based upon global or local port level and whether deterministic or stochastic data is considered.

	Deterministic approach	Uncertainty approach
Multi-port level	(Di Francesco, Lai, & Zuddas, 2013a)	(Cheung & Chen, 1998)
	(B. Wang & Wang, 2007)	(Shen & Khoong, 1995)
	(Shintani, Imai, Nishimura, & Papadimitriou, 2007)	(Di Francesco, Lai, & Zuddas, 2013b)
	(Bandeira et al., 2009)	(Dong & Song, 2009)
	(Hajeeh, Behbehani, Hajeeh, & Behbehani, 2011)	(B. Wang & Tang, 2010)
		(Chou et al., 2010)
		(D. P. Song & Dong, 2011)
Single port level	(Choong, Cole, & Kutanoglu, 2002)	(Teodor Gabriel Crainic et al., 1993)
	(Boros, Lei, Zhao, & Zhong, 2008)	(D. P. Song & Zhang, 2010)
	(White, 1972)	
	(Braekers, Caris, & Janssens, 2013)	
	(Dejax & Crainic, 1987)	
	(Teodor Gabriel Crainic, Dejax, & Delorme, 1989)	

It is difficult to determine the amount of adoption of this academic work into actual industry processes, but due to the competitive nature of the liner industry, it would be safe to assume that any new advantage found would be quickly implemented. Even an incremental improvement would imply considerable cost savings for a carrier when taking into account that 27% of container fleet operating costs consist of repositioning costs as mentioned at the start of 2.2.

What can be concluded though, is that any solution involving planning and/or route optimization does not aim to avoid ECR, merely to reduce it (or its additional costs) as much as possible. The underlying chronic imbalance and the accompanying global empty repositioning will still exist. The incremental affects these optimization solutions have upon the total empty container flow are assumed to be non-significant for the way empty container data is used within this thesis.

Physical solutions

Folding containers

The general idea behind using folding containers is that after use they can be folded into a smaller package (depending on the model, 4 or 6 folded containers take up the space of a standard container (Figure 26)). This reduces the space used as well as handling time, thereby reducing the associated transportation costs back to a container deficit area. Studies by (Bandara, Garaniya, Chin, & Leong, 2015; Moon, Ngoc, & Konings, 2013) found that there are considerable ECR cost savings to be made by utilising foldable containers, especially on trade routes with chronic imbalances, such as the transpacific route considered in this thesis.

Figure 26 Demonstration of a 40-foot folding container. Note that it requires 3 people and a crane to operate. Source: (Holland Container Innovations, 2018)

The question then remains: ‘Why does one not see many foldable containers in use today’? The concept of foldable containers is not new and relatively well-known throughout the industry (Konings & Thijs, 2001, p. 337). This also means there is no real first-mover advantage to be had by any company employing this strategy on a large scale as the technology is freely available and the strategy could be quickly mirrored by a competitor. A further barrier to widespread adoption are the operational procedures and extra costs (port facilities, extra workers, etc.) needed to actually do the (un)folding as well as deciding who is accountable for these costs. These arguments along with the higher cost and tare weights of the containers themselves, are why it seems like folding containers will stay a very niche solution to the ECR problem for now.

Round-the-World (RTW) services
This is not a new concept and has captured the imagination of many a carrier owner over the years. It can be done by either operating a service in one direction around the world or by running two services in opposite directions at different frequencies. In a comprehensive paper by (Lim, 1996), the many advantages are clearly described and an analysis is made of United States Lines and Evergreen RTW services, the former being an unsuccessful venture ending in bankruptcy and the latter being discontinued in 2003.

With respect to ECR, an East-West RTW service has advantages in that it encompasses flows of the three largest trade routes in one circumnavigation allowing it to achieve high load factors on the head haul section(s) and reposition empties along the backhaul leg(s). A service working in both Eastbound and Westbound directions, such as Evergreen operated from the mid 1980's until 2003 (Tran & Haasis, 2015), seems the most efficient in dealing with ECR. Cost reduction is achieved by the improved full/empty ratio aboard ships and the reduction of total miles that empties are transported. It must be noted, that a RTW service is not able to reduce the amount of empty containers movements and their associated fixed costs of terminal handling and ship (un)loading.

One of the main reasons why there is no RTW service these days is the Panamax size limitation placed upon ships that would be used in such a service. These ships do not enjoy the economies of scale of today's 18000+ TEU ships. Since June 2016 the new Panama Canal has been officially opened, which could allow larger more competitive containerships to be employed in a RTW service. Setting up such a RTW service requires massive investments in ships and a capable feeder network (Lim, 1996) and with a liner industry faced with overcapacity and low to negative profits, timing just does not seem to be right at the moment.

Physical solutions to the ECR problem currently do not affect empty flows. Folding containers have not been adopted on any significant scale (that would affect the number of empty containers leaving ports) up to the present day. RTW services are not in operation nowadays, but more significantly, they would not affect the port data on empty containers exported that are used in this thesis to determine empty flows, as the empties still exist.

Managerial or policy solutions

So far, most of the ECR research discussed has mainly been focussed on strategic level decisions (global shipping network design, implementing folding containers, etc.). The research dealing with intermodal and inland networks has been slightly more tactical and operational level decision focussed but is still focussed on 'planning' based solutions.

As mentioned in their work, (Monios & Wang, 2014) state that it is unusual for authors to consider managerial or policy solutions that are specifically designed for the empty container problem. They interviewed regional stakeholders of ECR to find out what managerial decisions could be made to improve the number of empty containers available in the ports of Scotland (a container deficit area). They found that shipping lines could make minor changes to their schedules to give their ships more turnaround time to load empties in other ports and that by deciding to make more use of generic feeder services (instead of only feeders from their own alliance), carriers could lower the amount of container repositioning movements necessary. Port management was recommended to lower their empty storage costs to attract more empties (the opposite would be necessary in a container surplus port) and to work together with carriers to provide more transparency to their key local customers on the availability of empty containers, so that they could make better use of capacity by knowing earlier when empties will be available. This data would need to be protected and only given to trusted parties.

The decision-making process for a carrier regarding empty containers on a global level (the level which affects transpacific shipments), is shown in Figure 27. Of the decisions on the left (for container surplus areas), an increase in demand for containers would lead to more containers coming out of temporary storage depots and being repositioned. Exactly when carriers make these decisions and how 'reactive' they are (i.e. last-minute decisions as opposed to decisions based on forecasts ahead of time) was not found mentioned anywhere in the literature.

Anecdotal evidence from a Mediterranean Shipping Company (MSC) case (van de Voorde, 2018) suggests that when an acute demand for containers in Asia arises, storage depots in Europe have been instructed by carriers to work day and night to speed up repairs and inspections to reposition empty containers back to Asia, suggesting a reactive policy approach to ECR. A similar type of behaviour would be expected in US storage depots as well.

Going back to the question posed at the start of the chapter: 'Do empty repositioning strategies change on the basis of customer demand?', there still is no clear answer. When these customer demand situations become more acute, ceteris paribus one would expect to see a change in the ratio between loaded inbound containers and empty outbound containers. It could be hypothesized that this could be an early indicator of an upcoming increase in loaded containers departing from Asia.

By looking at the seasonally adjusted ratio Loaded In/Empty out for US West coast ports (Figure 28), one can notice some clear changes in ratio. The discussion of the exact composition of this data and how it has been de-seasonalised can be found in chapter 3.1. A drop of the ratio indicates a rise in empties going back to Asia compared to the number of loaded containers arriving to the US. Whether or not these turning points in the ratio are based upon strategic managerial decisions, they could prove meaningful when interpreting the actual container flows and therefore the Loaded In/Empty Out ratio (LI/EO) will also be tested for its predictive properties (of economic activity) in chapter 4.

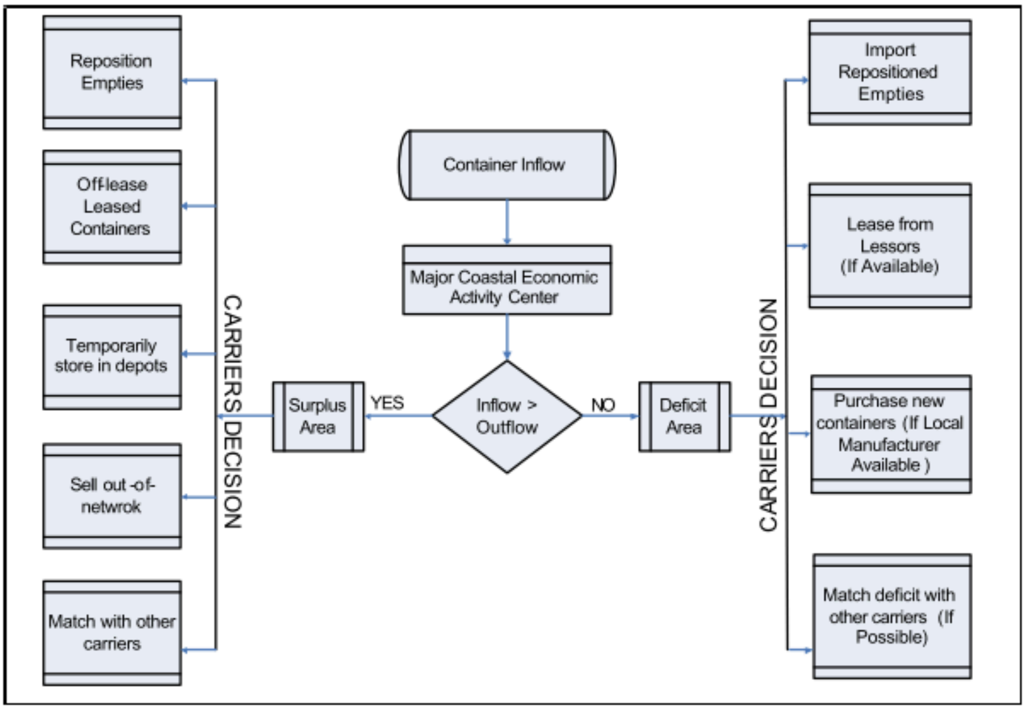


Figure 27 Decision making process for carriers. Left hand side shows decision options related to US West coast ports. Source: (Boile, 2006, p. 43)

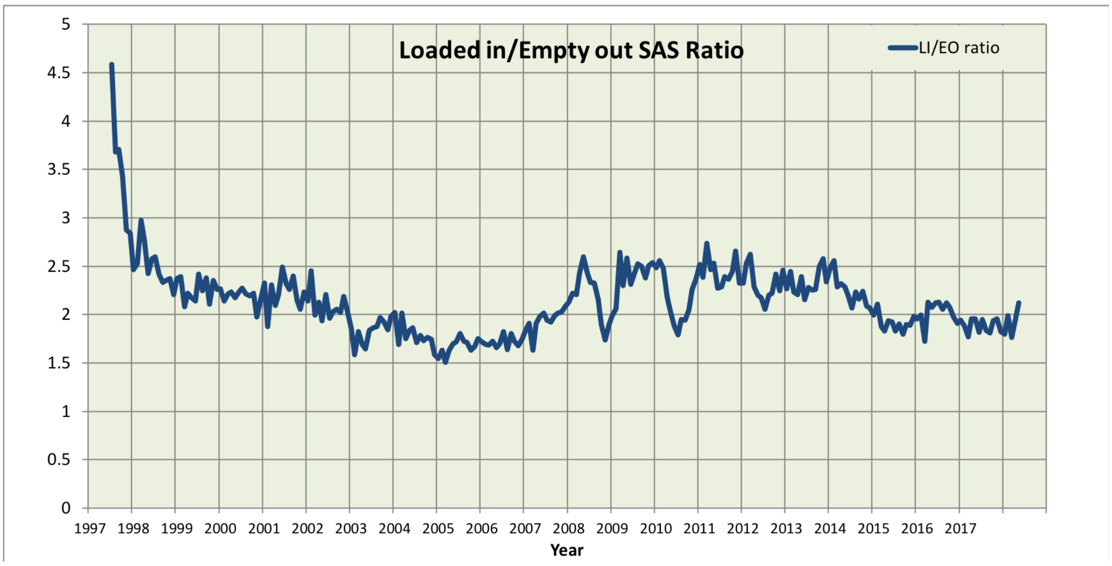


Figure 28 Seasonally adjusted US West coast port Loaded In/Empty Out ratio. Data compiled by author from individual port websites.

3. FLUCTUATIONS IN CONTAINER FLOWS

To use container flows as a forward indicator one must first understand all the dynamics of the container market and take them into account when making predictions about economic activity. The previous chapter already looked at the specific dynamics associated with empty container flows. In this chapter the aim is to further understand general container market dynamics and then identify all possible factors that can affect either loaded or empty container flows besides direct demand for container transport stemming from economic activity. Non-recurring events affecting flows are also discussed.

The chapter starts with a thorough discussion regarding the container flow data that will be used throughout the rest of the thesis. It is important to understand how this data is aggregated, as further modelling and analysis in chapter 4 will be based upon this data. Then it is time to start identifying and analysing any outliers in the data that were caused by special (non-recurring) events. In chapter 3.3 the criteria for selecting factors that affect container flows are presented along with the methodology of how they will be further analysed. They are then categorised before being individually discussed in more detail.

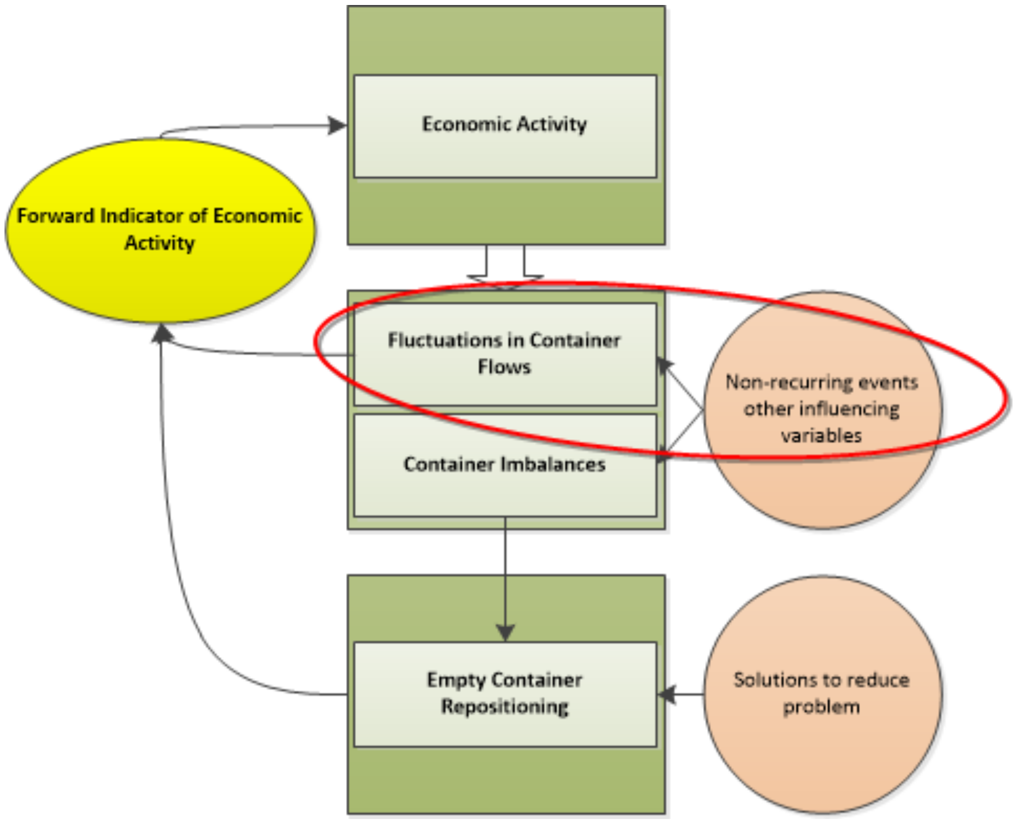


Figure 29 Red circle indicating the area covered in chapter 3.

3.1 Main Data discussion

The data that will be used to represent transpacific container flows is an aggregate of the monthly container movements from the three largest US West coast container ports. In order of total amount of TEU equivalent handled these ports are: Los Angeles, Long Beach and Oakland. Figure 30 shows the location of the top 20 US ports ranked by 2016 TEU imports and Figure 31 puts the total 2016 TEU throughput of the selected West coast ports compared with all other US ports into perspective.

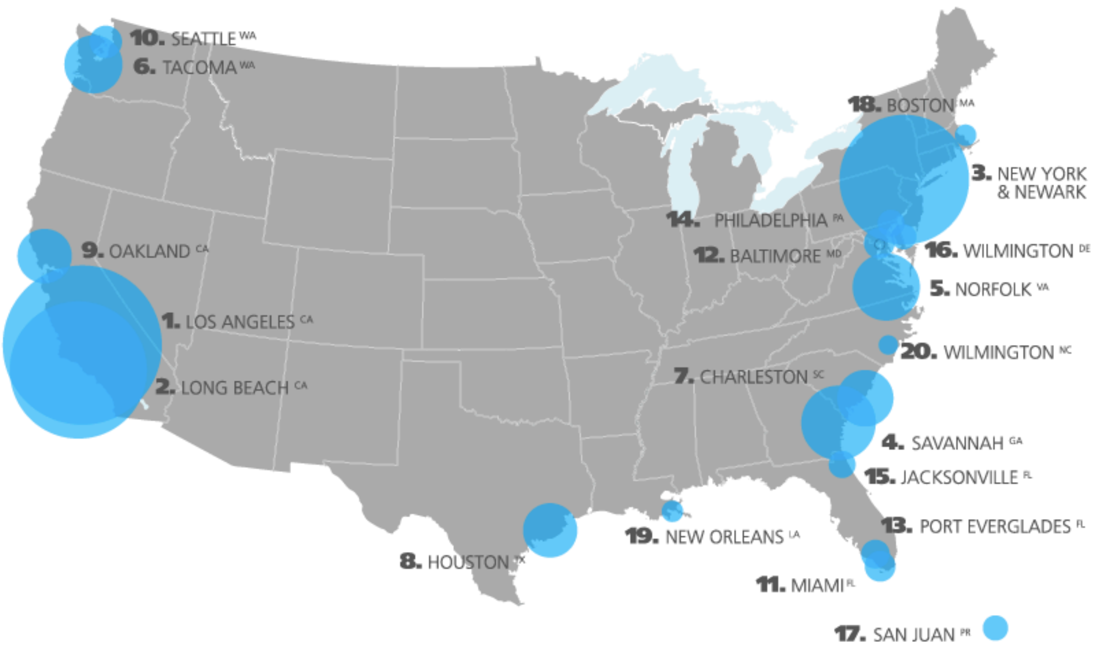


Figure 30 Top 20 US ports based upon 2016 TEU imports. Source: (Descartes Datamyne, 2017)

The evolution of total number of containers handled by these ports is shown in Figure 32. The top two US East coast ports (New York/New Jersey and Savannah) are also included for reference. At first glance an annual seasonal component can be observed as well as a general growth trend. Both of which will be discussed later. It also seems Oakland seems to be limited in growth at around 200,000 total TEU per month throughput. The excess capacity demands have been taken up by LA and Long Beach since around 2004.

A specific choice was made to only use data from US West coast ports, as the bulk of their container flows are from Asia. Of course, a certain number of containers from Asia intended for the US make it through the Panama Canal (discussed in more detail later in this section) directly to US East coast ports but it is difficult to distinguish these from container flows on the transatlantic trade using (East coast) port throughput data. By focussing only on West coast port data, the transatlantic trade route is avoided. This trade route makes up a big part of the container numbers for East coast ports and would disturb the predictions of transpacific economic activity between the US and Asia.

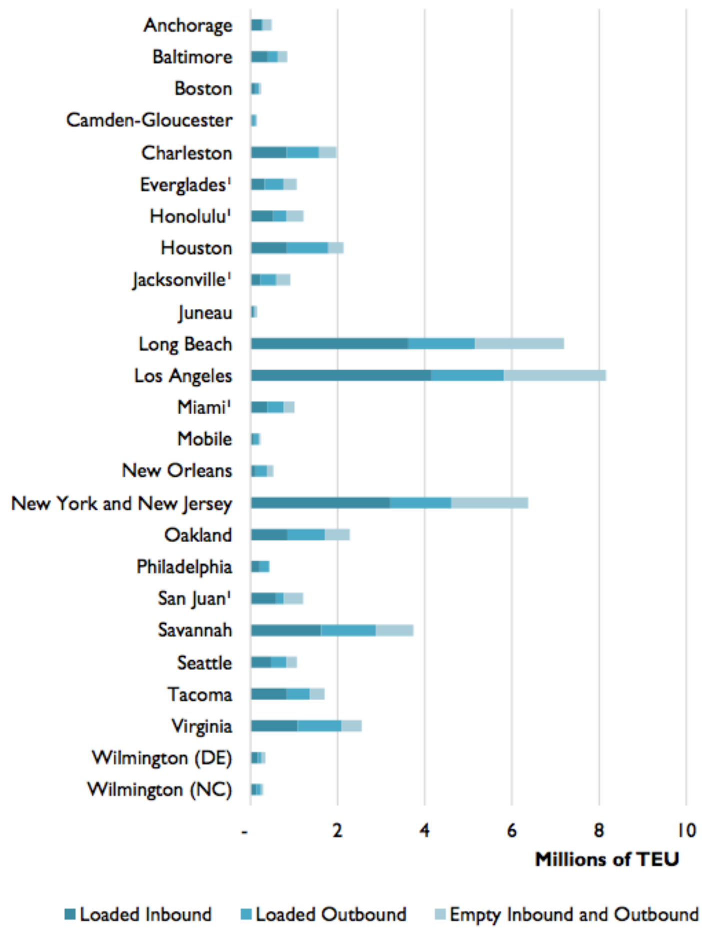


Figure 31 2016 TEU throughput of top 25 TEU handling US ports (U.S. Bureau of Transportation Statistics, 2016)

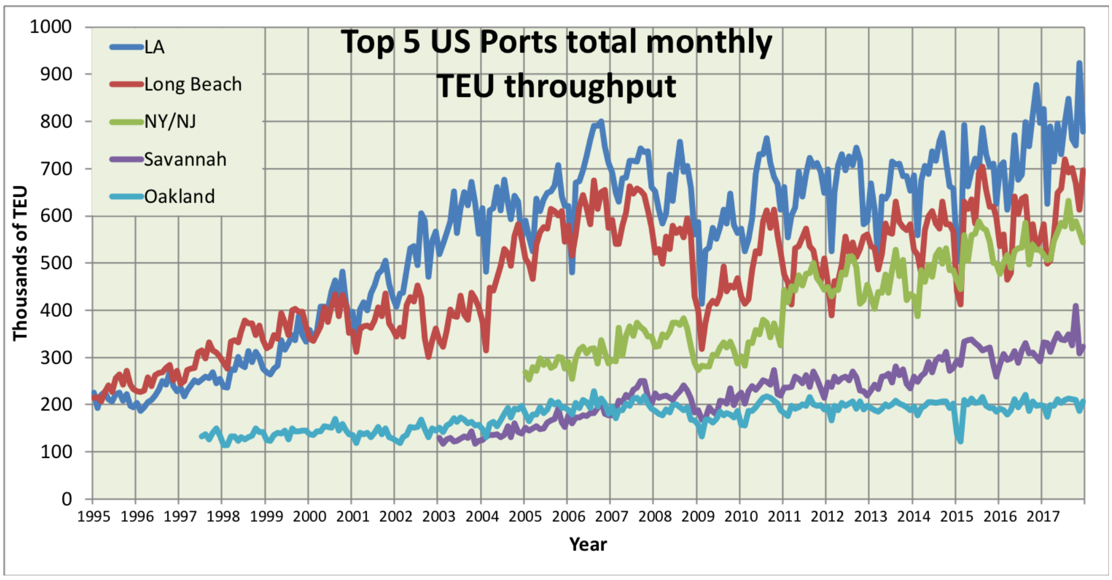


Figure 32 Total monthly TEU equivalent throughput of Top 3 US West Cost ports and Top 2 US East coast ports 1995-2017. Not all ports started providing statistics in 1995. Data compiled by author from individual port websites

The top 3 US West coast ports whose container throughput statistics are used throughout this thesis provide monthly updates of Imported loaded and empty containers and exported loaded and empty containers. Long Beach publishes this data slightly differently by only publishing an aggregated number of empties handled (not categorised into Import and Export). To get around this missing detail in the Long Beach data, an assumption is made that the ratio between empty containers in and empty containers out will be close to that of LA, as the ports are practically geographical neighbours. The ratio between empty in and empty out at the Port of LA is calculated and applied to the Long Beach total empties handled number to differentiate between empty in and empty out container flows.

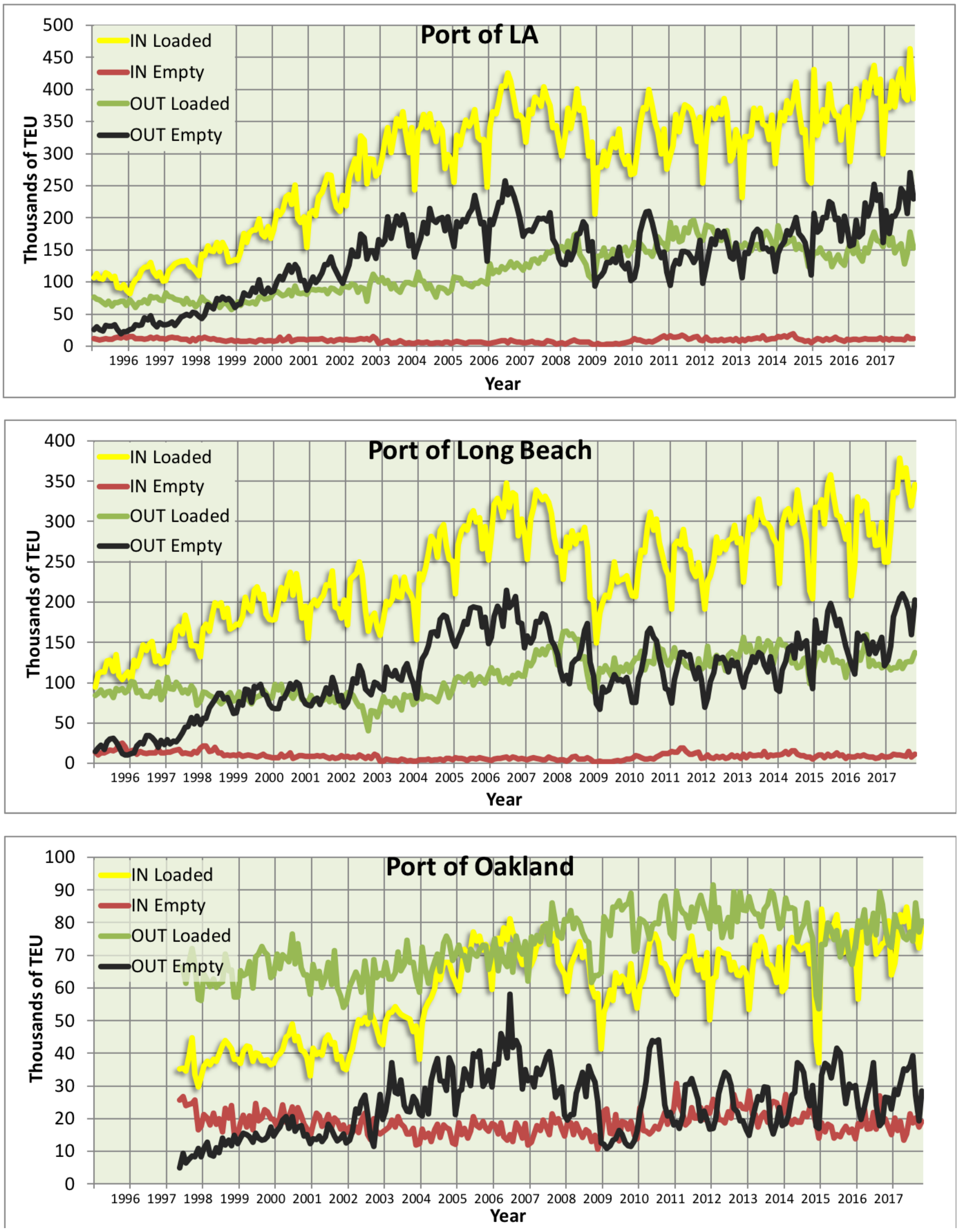


Figure 33 Historic monthly container flows for the top three US West coast ports. Container flows are broken down into Inbound Loaded and Empty containers and Outbound Loaded and Empty. Data compiled by author from individual port websites.

Figure 33 shows a port specific breakdown of the four different container flows (Loaded In, Empty In, Loaded Out, Empty Out) for the three US West coast ports. One can see that for all three ports the loaded Inbound containers and Empty outbound containers display a strong seasonal component, whereas the loaded outbound containers, which represent US exports to Asia, display far less seasonal fluctuations.

When the delta between total inbound and total outbound containers is examined (Figure 34), one can clearly see Oakland consistently exporting more containers monthly than it imports. This is due to Oakland often being the last port of call for transpacific routes. The 2018 Ocean Alliance schedule has Oakland as its last stop for all its transpacific routes (CMA CGM, 2018) and it could well be that this routing is similar for the other 2 main carrier alliances ('The Alliance' and '2M Alliance) considering that LA and Long Beach have such different Empty versus Loaded out ratios. As a consequence, any US shipper looking to minimise transport time to Asia will opt to ship their container from Oakland instead of LA or Long Beach as any container loaded at these two ports will have to take at least 2-3 days longer while the vessel passes through the port of Oakland.

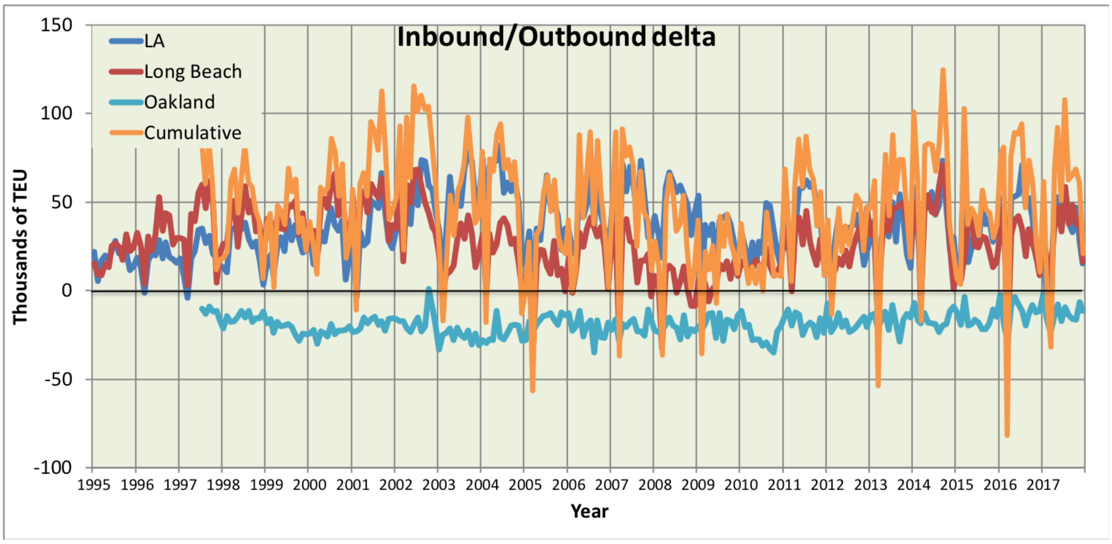


Figure 34 Historic monthly delta between total inbound and total outbound TEU for the top three US West coast ports. Orange line is the total difference of the three ports.

When looking at the total inbound and total outbound delta for all three ports in Figure 34, one can observe that there has nearly always been an overall surplus of containers coming into the US West coast over the past 20 years. This is due to those surplus containers making their way across the US to the East coast (by road or rail) and getting mixed into the transatlantic trades or making their way back to Asia via an East coast port.

The intermodal transport of containers eastwards is down to the population demographics of the United States, which are skewed towards the East coast (see Figure 35). This means that often it will be quickest to ship a container from Asia to the West coast and then use truck or rail transport to get it to arrive (quicker) at a distribution hub for the East coast. For the route back, the container will then take the shortest (and cheaper) route to an East coast port. This skew towards the East coast can also be seen in port distribution: out of the top 25 US TEU handling ports listed in Figure 31, eight are located on the West coast and 17 on the East coast. All West coast ports combined, handled around 20.8 million TEU in 2016 and East coast ports handled 22.8 million, which accounts for the discrepancy between in- and outbound containers on the West coast.

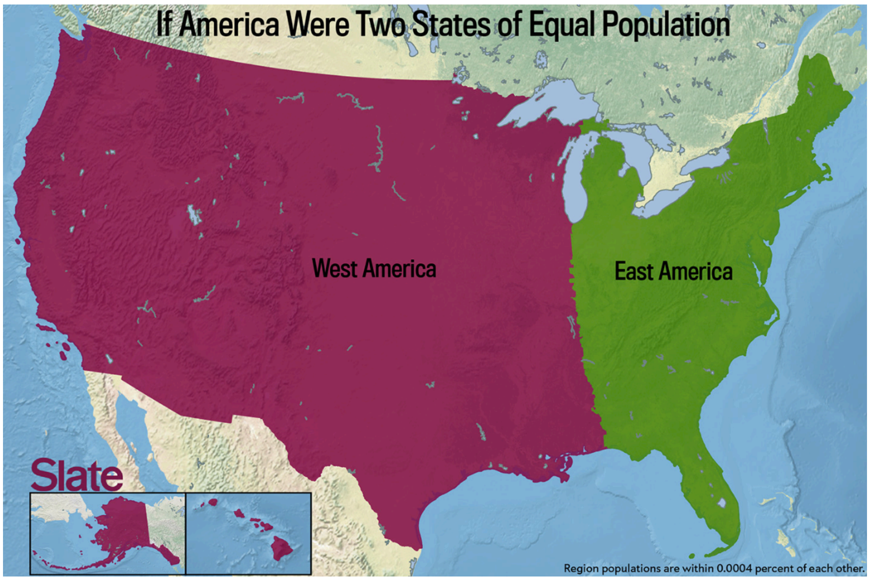


Figure 35 North America divided longitudinally into equal parts by population. It can clearly be seen that the majority of the population is located towards the East coast, which would also mean most (retail) distribution hubs will be located towards the East coast as well. Source: (Blatt, 2014)

As mentioned at the start of this section, not all containers that arrive via the West coast make their way back to Asia via the same West coast ports (empty or loaded). This means the outbound empty and loaded flows do not represent the absolute numbers of containers travelling back to Asia from the transpacific route. This does not present an issue for the objective of this thesis in using these flows to predict economic activity, as the importance lies more in observing inflection points and rates of change in the data rather than absolute numbers.

There is a risk though, that inflection points and rates of change of West coast flows could possibly be 'falsely' affected. There are two main causes that could lead to a 'false' shift in West coast container flows: a major change in long distance rail and truck (intermodal) freight rates and/or a large change in ship scheduling (possible due to the 2016 Panama Canal expansion). Both these events would not alter the total container flow in and out of the US as a whole but, could alter the distribution of container flows between the East and West coast.

For intermodal rates changes this risk is assumed low, as to create an inflection point, there would need to be a large (and rapid) change in intermodal freight rates and when examining the historic volatility of these rates (see chapter 3.3) this does not seem likely. The panama canal expansion on the other hand is leading to East coast ports making big infrastructure investments to accommodate the larger ‘post-Panamax’ vessels that can now make it through the new Panama canal (McCahill, 2018). This could affect ship scheduling significantly with a possible shift in balance between East and West coast TEU volumes. (Van Hassel, Meersman, Van de Voorde, & Vanelslander, 2016) found that if larger post Panamax vessels could dock in US East coast ports, the seaborne transport share of total generalised chain costs (seaborne transport, port and hinterland transport costs combined) decreased and hinterland transport costs made up a larger share of the generalised chain cost (Figure 36).

This was calculated for the transatlantic route, but a similar effect could be assumed for the larger vessels that can pass through the Panama Canal since 2016. This would bring down the seaborne transport share and raise the hinterland share of the total generalised chain costs thereby affecting the decision of when to ship directly to US East coast ports from Asia or via the West coast with a large intermodal leg. This could affect the balance of container flows between the East and West coast.

As the opening of the larger Panama Canal in 2016 is a fairly recent development, this has not affected the majority of historic data used for analysis in this thesis. Looking to the future, it would be advisable to monitor updates to shipping schedules to identify any significant changes in TEU import/export capacity balance between the East and West coast.

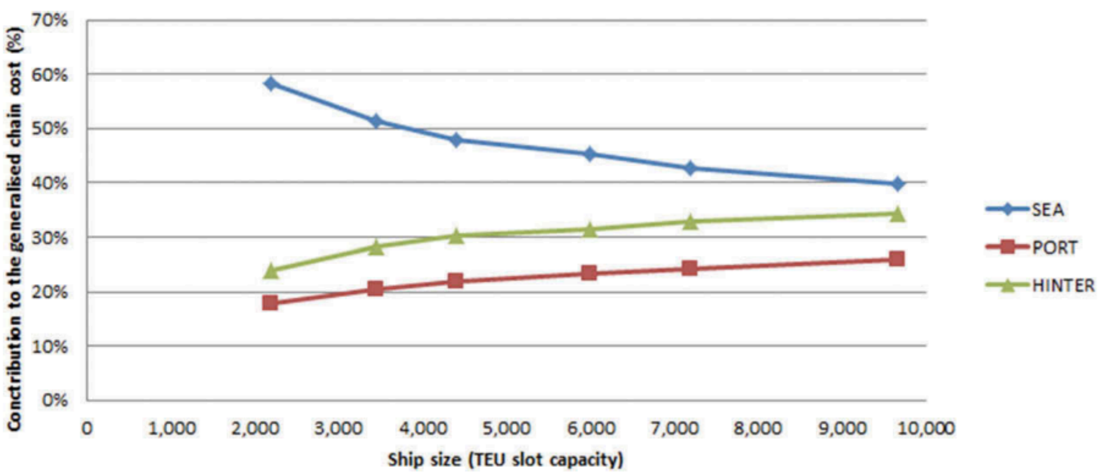


Figure 36 Composition of generalised chain cost for US East coast – Europe trade route for different size vessels. Source: (Van Hassel et al., 2016).

For the final base dataset of historic container flows that will be used throughout the rest of this thesis, the loaded inbound, loaded outbound and empty outbound monthly container flows of the LA, Long Beach and Oakland are combined into one total TEU count (Figure 37). Empty inbound container flows have a non-significant size and are therefore omitted from this dataset. The dataset ranges from July 1997 (the first month Oakland started recording its TEU throughput numbers) to December 2017

As mentioned earlier in the chapter, container flows are highly seasonal. The main reason for the usual annual peak is retailers building up stock for the

Christmas season. The annual low point usually coincides with Chinese New Year, the precise date ranges from around the last week in January to the middle of February. Often Chinese factories shut down for one or two weeks, which causes a lull in Asia – US container traffic.

This seasonal element makes the container flow data a little harder to use for predictions, as a trend could be starting to turn downwards, whilst in absolute numbers the container flow numbers could actually be higher than the previous months due to it being 'container high season'. One way to overcome this is to consider year on year growth (YoY), which is often done in shipping reports. This can lead to misinterpretation of the of the underlying trend though, as YoY growth can be skewed by a range of factors including differing Chinese New Year holiday dates or shipments being brought forward by to avoid General Rate Increases (GRI's) or port labour issues (Maritime Executive, 2014). Another method is using the 12-month moving average, thereby flattening out the YoY differences and revealing the trend. The downside to this method is that the exact timing of peaks and troughs is distorted to later dates, an undesirable feature when the timing element of changes in flows could be essential for prediction purposes.

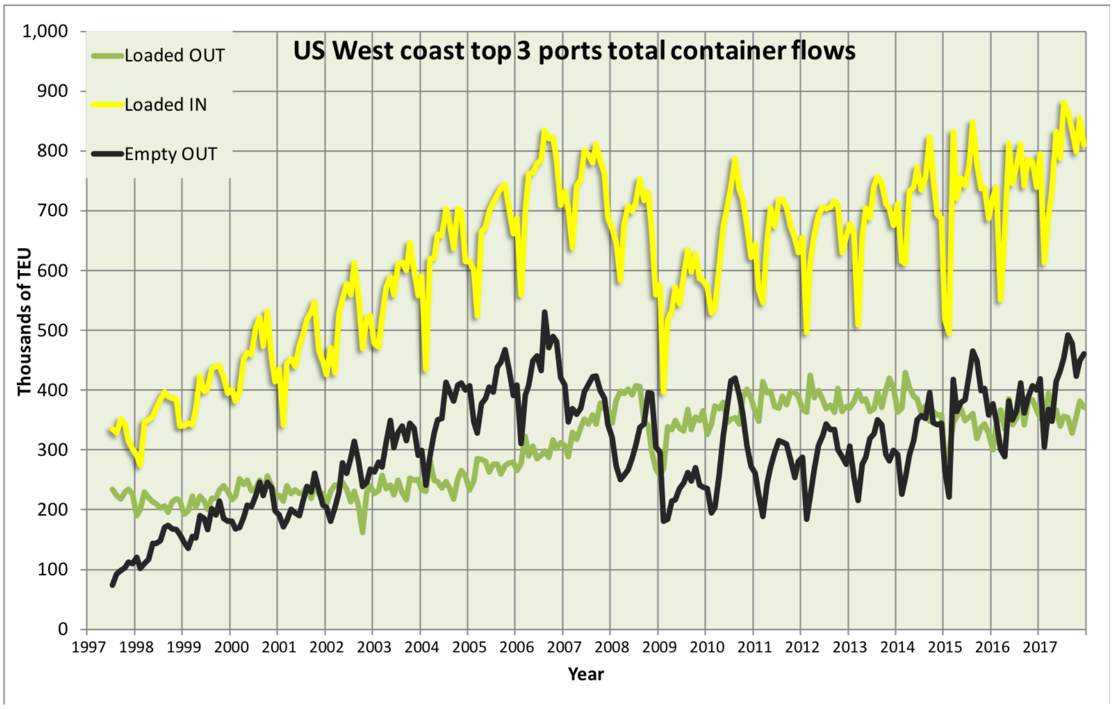


Figure 37 Combined container flows of the top 3 US West coast ports. Data calculated by author from individual port websites.

For the purpose of this thesis a choice was made to 'de-seasonalise' the data by decomposing it into its three constituents in the form of a multiplicative model:

$$y_t = T_t * S_t * I_t \tag{1.3}$$

Whereby:

T_t = The trend-cycle component (as this can be split into a trend and a longer-term cyclical component)
S_t = The seasonal component
I_t = The irregular or error component
y_t = The monthly raw container flow

The container flow time series (y_t) is considered a multiplicative combination of the above three components, i.e. if the number of containers increases, so does the size of the seasonal fluctuation (as opposed to an additive model, where the seasonal fluctuations stay the same irrespective of the amount of container flow). The ratio to moving average seasonal decomposition method also known as the Census I method is used to decompose the container flow data into their various components (Makridakis, Wheelwright, & Hyndman, 1997, p. 110). Figure 38 shows the container flow time series with the seasonal component removed (Seasonally Adjusted Series (SAS)). The trends are now clearer to observe and outliers are also easier to recognise. The SAS is simply the trend component and the irregular component, i.e. equation 1.4 rewritten into:

$$SAS_t = \frac{y_t}{S_t} = T_t * I_t \tag{1.4}$$

An example of the decomposition of the container flow data into its various constituents is given in Figure 39 using the loaded imports container data. Here the trend-cycle component is valuable for identifying fundamental changes in the flow and the irregular component makes it simple to spot short-term outliers in the data.

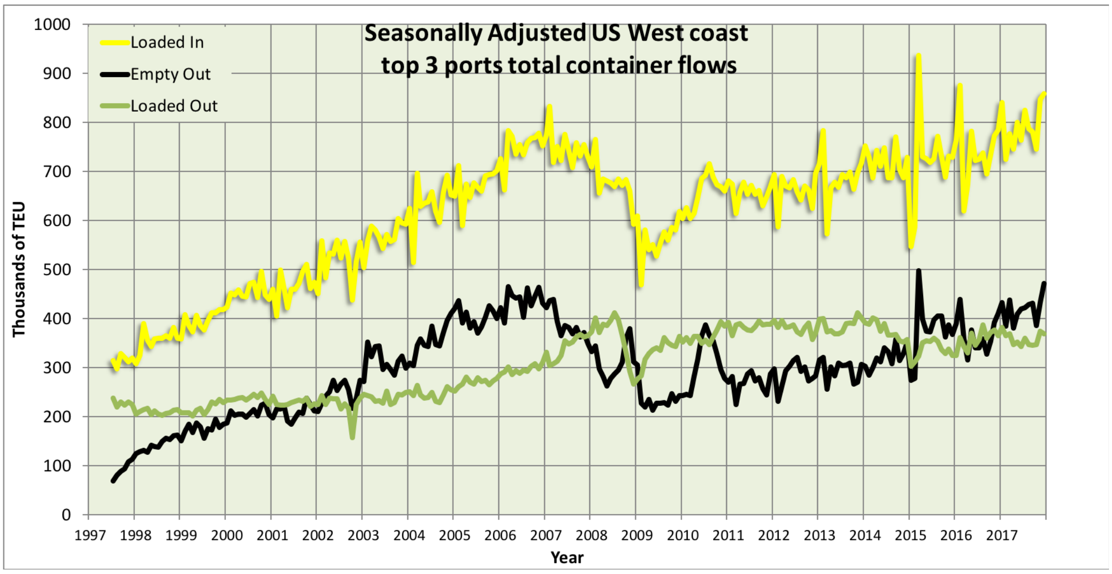


Figure 38 Seasonally Adjusted Series (SAS) for the three individual container flows considered in this thesis. A multiplicative ratio to moving average model was used.

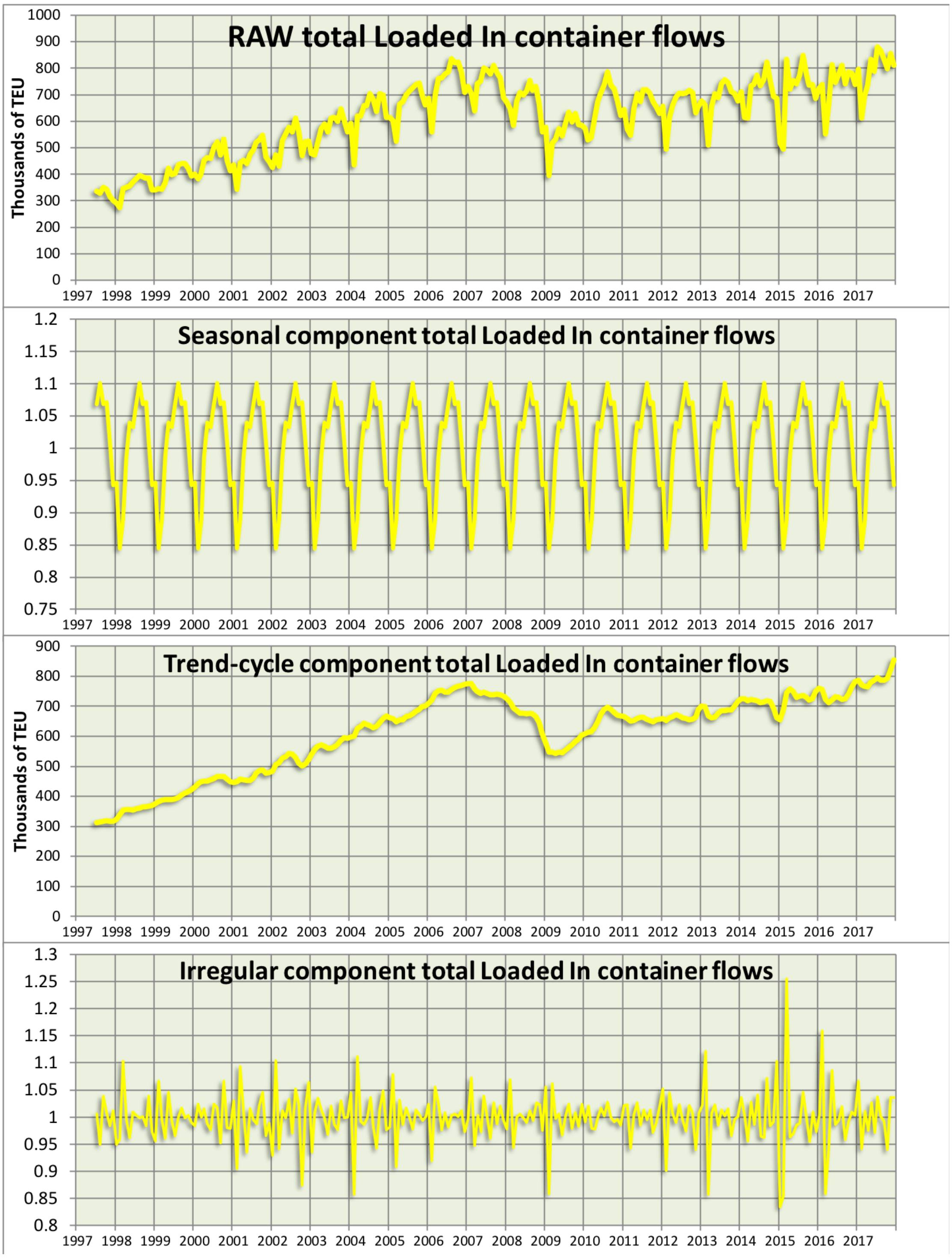


Figure 39 Decomposition plot of historic total US West coast ports Loaded TEU Imports.

When glancing at Figure 37, it seems that the seasonal fluctuations were generally smaller before the 2008 financial crisis and larger in the period afterwards (2011-2017). The SAS in Figure 38 and the decomposition plot in Figure 39 make use of a Seasonal Adjustment Factor (SAF) that is constant for each month over the complete time series. A check is done to see whether using this single set of SAF's over the whole time series is sufficiently accurate for the purpose of this thesis, or whether recalculating the SAF's after the 2008 financial crisis is more accurate (which would mean there would be less fluctuations in the SAS).

Individual seasonal components were calculated for the time periods [January 1997 – December 2006] and [January 2011 – December 2017]. The SAS's obtained from these time periods are plotted over the original SAS in Figure 40 and visually compared. It can be clearly seen that there is no significant difference in reducing the larger fluctuations in the SAS and therefore the choice is made to use the single set of SAF's calculated over the entire time series.

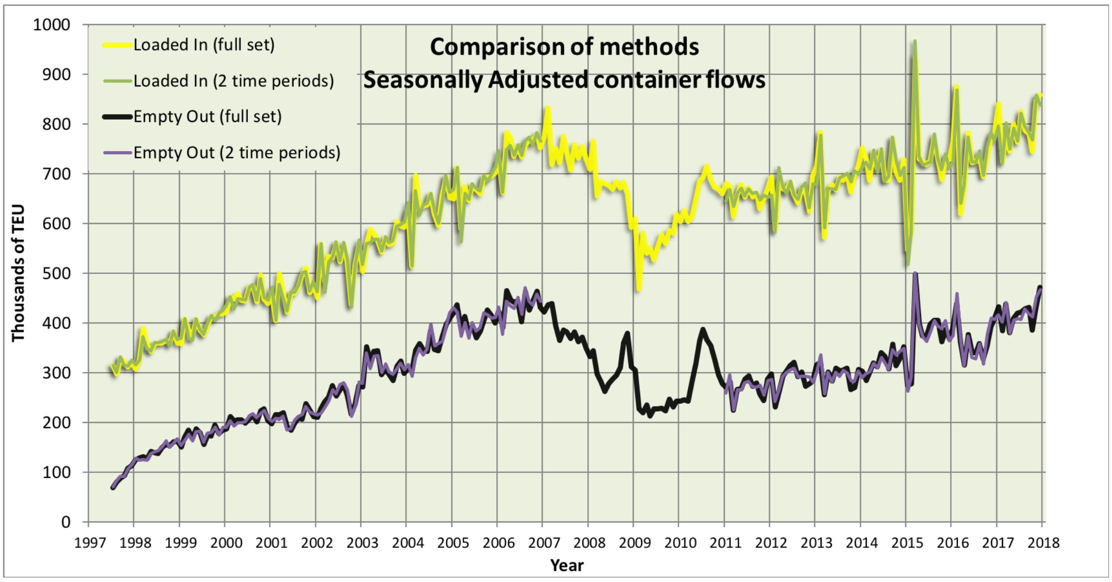


Figure 40 Comparing impact of using different pre- and post-crisis seasonal adjustment factors to calculate the Seasonally adjusted series (purple and green) versus using one constant seasonal adjustment over complete time series (black and yellow). The difference is non-significant.

The final adjusted data series to be used in this thesis is the Smoothed Trend-Cycle Component (STC) presented in Figure 41. It is the SAS smoothed using a 3x3 moving average method. This centre weighted moving average method is shown in equation 1.5 below.

$$STC_t = \frac{1}{9}[(SAS)_{t-2} + 2(SAS)_{t-1} + 3(SAS)_t + 2(SAS)_{t+1} + (SAS)_{t+2}]$$

for $t = 2, \dots, n-2$

and for the two points at the beginning and end of the series:

$$(STC)_1 = (STC)_2 + \frac{1}{2}[(STC)_2 - (STC)_3]$$

$$(STC)_2 = \frac{1}{3}[(SAS)_1 + (SAS)_2 + (SAS)_3]$$

$$(STC)_{n-1} = \frac{1}{3}[(SAS)_{n-2} + (SAS)_{n-1} + (SAS)_n]$$

$$(STC)_n = (STC)_{n-1} + \frac{1}{2}[(STC)_{n-1} - (STC)_{n-2}]$$

(1.5)

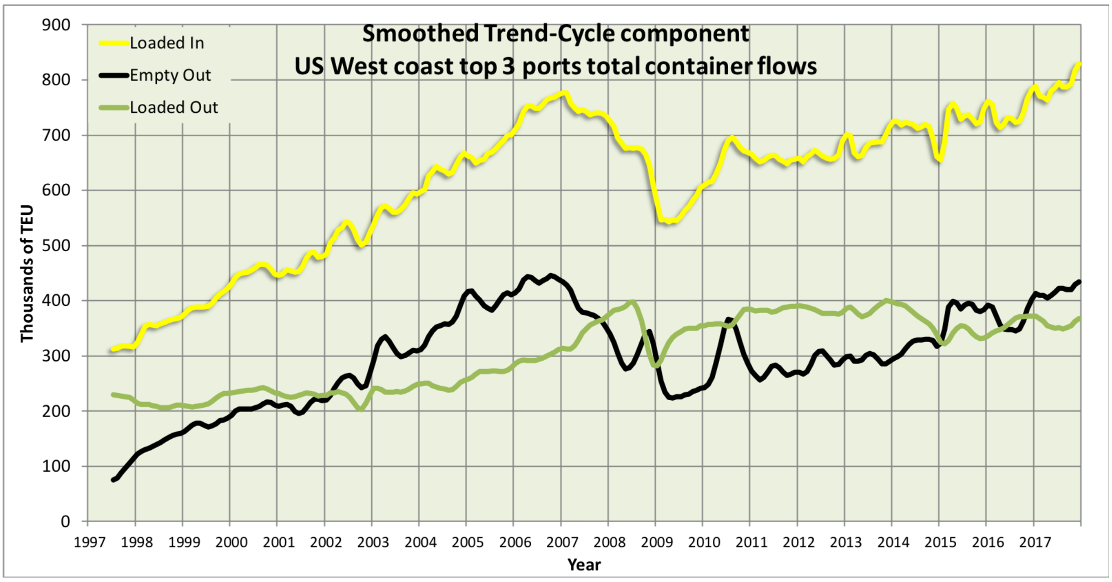


Figure 41 Smoothed trend-cycle component data of total container flow time series

At first sight of Figure 41, Loaded in and Empty out container seems to track each other quite closely in terms of growth, whereas US exports in the form of Loaded out containers have different timing of inflection points and growth rates. The 2008 financial crisis downturn is clearly featured in all three flows, although interestingly, this downturn does not happen at the same time for US exports. Further interpretation of the data discussed in this chapter will be done in chapter 4.

3.2 Non-recurring events

Over the 20-year time period that the container flow data spans, there have unquestionably been events that have caused large fluctuations in flows to occur over the short-term. In this section outliers in the data are highlighted and using historic news reporting, labelled by what caused them. This will help build a picture as to what type of events may significantly affect monthly container flow data in the future and therefore give unreliable data points as a forward indicator.

In Figure 42 the irregular component of the three relevant container flow decompositions is displayed (described in 3.1) along with a shaded band indicating one standard deviation above and below neutral (the irregular component is a multiplication factor (equation 1.3), so 1.00 means it is neutral). This makes it simple to spot outliers in the data and red arrows are used to indicate them.

After examining the main outliers and labelling them in Figure 42, there seem to be four main types of non-recurrent events that cause a short-term peak or trough in the monthly container throughput of US West coast ports:

- Financial events
- Labour Union Disputes
- Chinese New Year disruptions
- Natural disasters

Chinese New Year is of course a recurring event, but the date on which it occurs is different every year. Even though the date is known well ahead of time, it still seems that on numerous occasions the factory shutdowns that go hand in hand with Chinese New Year cause disruption in container flows that show up using the above described methodology of finding outliers. Due to the intermittent nature of these outliers, discussion of Chinese New Year effects has been placed in the non-recurring events section.

What follows is a description of these non-recurrent events, how they have impacted container flows and how to deal with these types of events in the future with regards to interpretation of the data.

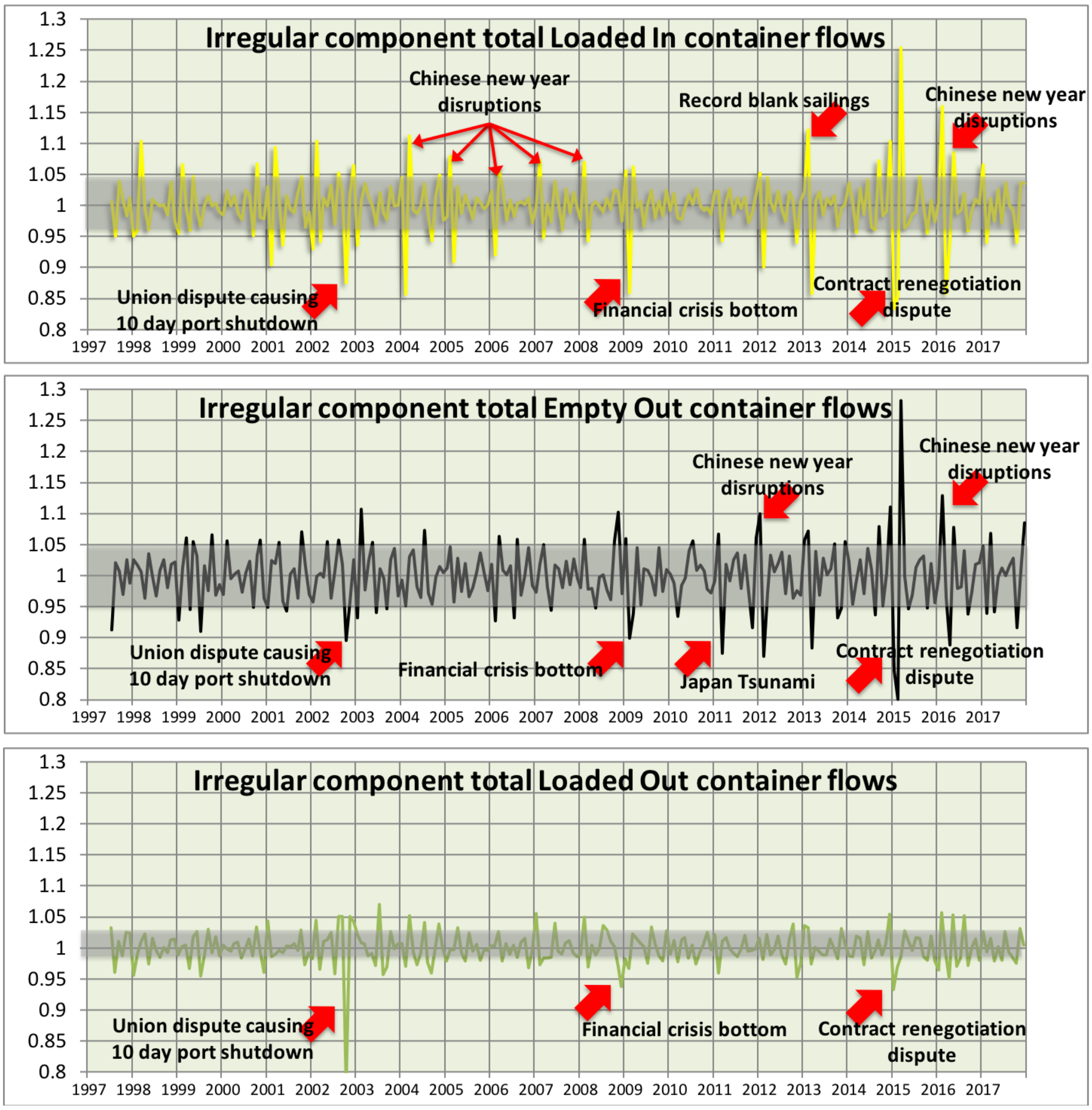


Figure 42 Irregular component of Loaded In, Empty Out and Loaded Out flows. Grey bands indicate one standard deviation above and below neutral (1.00) Standard deviations from top to bottom respectively are: 0.047, 0.05, 0.028.

Financial events

Throughout the 20-year time series used in this thesis, the S&P500 has had two major bear markets (a bear market becomes 'official' after a 20% decline from previous highs). This occurred during the 'dotcom' crisis in the early

2000's and during the Great financial crisis in 2008. Container flows were not affected by the bursting of the dotcom bubble as the companies that lost the most values were the internet companies, that had little to no exposure to physical container shipping. The 2008 crisis affected the whole breadth of the economy and the effect on container flows can clearly be seen in Figure 41. Looking at the decomposition of container flows irregular components in Figure 42, the low point of the crisis is marked almost to the month by the dip in all three flows.

The effect of the 2008 financial crisis played out over a longer term (visible in Figure 41), but the most extreme deterioration does show up in the irregular component data. Another event that dropped markets was the 2001 September 11 attacks, which show up in the form of a few months' sharp deterioration in the loaded imports and loaded exports, but nothing far beyond one standard deviation. Therefore, it can be concluded that (global) financial events mostly have a longer-term effect on container flows and any short-term shocks are not significant in affecting container flows.

Labour Union Disputes

The largest outlier that can be spotted in all three flows is around December 2014 until March 2015. This coincides with a dispute over contract renegotiations between the International Longshore Workers Union (ILWU) and the Pacific Maritime Association (PMA), which resulted in work slowdowns reducing West coast port productivity by 40 to 60% and causing large scale congestion (of containers) in the ports (Laing, 2014; Sanctis, 2015). Negotiations started in mid-May 2014 and were finally resolved in the second half of February. Work slowdowns were reported to have commenced from October onwards. This explains the higher peaks in Loaded Imports and Empty Exports from July 2014, as shippers were most likely trying to get more containers through before negotiations started further breaking down. The work slowdowns that led to large port productivity decreases and port congestion can be seen in the big dip in December 2014. The peak afterwards in February and March is the backlog of containers being processed after a new contract was agreed upon. The contract comes up for renegotiation every five years, with the last contract expiry date being July 2014 meaning that 2019 might see more disruptions.

Another port workers union dispute led to a 10-day port shutdown on the West coast in October 2002, the effects of which are visible in Figure 42 with loaded exports being affected the most by this in the 20-year time series.

The West coast port workers (longshoremen) are highly unionized and have a history of disputes. Because they directly affect port productivity, any type of work slowdown or strike has a large impact on container flow data from these ports. When using monthly container flow data as a forward indicator, it will be clear when a dispute or strike is happening and so the abnormal data can be either discarded or at least interpreted with caution.

Chinese New Year disruptions

The irregular component charts in Figure 42 reveal a common occurrence of outliers around the December to February time period, always starting with a rise and then a sharp drop. This is nearly always caused by Chinese New Year celebrations, whereby factories are shut down for 1 to 3 weeks as workers take holidays and travel to see their families. As this is an annual event, one would expect this to be captured in the seasonal component displayed in Figure 39. The issue with Chinese New Year though, is that the exact date it happens varies every year between the last week in January to the middle of February. This translates into disruptions showing up more in the irregular component than other years. Regardless of this quirk, some years the disruptions caused by Chinese New Year are larger than others. Carriers often 'blank' sailings, which means they adjust capacity by cancelling a service for the weeks that Chinese factories are shut down. 2013 was a notable year, with a record amount of services blanked creating a large short-term impact on container flows. With the trend of larger container ships continuing throughout the 20-year time series, blanking a service nowadays has a larger impact on container flows than when smaller ships could be more flexibly blanked (Baker, 2015) and this could explain the larger spikes from 2012 onwards.

Again, with regards to interpreting container flow data as a forward indicator; knowledge of the exact date for Chinese New Year and if it coincides with the seasonal component's fixed low or not would allow one to have an idea whether there will be large outliers that year. General caution when interpreting the January and February data points would be advised.

Natural Disasters

Natural disasters that can affect transpacific shipping could include typhoons, earthquakes or tsunamis. Although Chinese and Japanese ports have been shut down multiple times in the past due to a passing typhoon, these closures have only been for a day or two before operations were resumed. These kinds of short delays can be made up by container vessels and after comparing the dates of pacific typhoons against the container flow data, the impact of even the largest pacific typhoons of the past 20-years cannot be detected in the container flow data. The same goes for East Pacific hurricanes (that could potentially affect US West coast ports, although most are too far south).

The tsunami of March 11, 2011 in Japan heavily disrupted some Japanese ports, putting them out of action for weeks to months and causing ships to 'skip' these ports in their port of call schedules. The main ports were operating normally fairly quickly, but the effects of the earthquake and subsequent tsunami on the factories producing goods for the supply chain was disrupted far longer and therefore impacting the amount of container for export. With the Chinese New Year falling on the 3rd of February that year, the expected March dip in container flows might have been deepened by the Japanese port disruption. A red arrow has been speculatively placed marking the date in Figure 42.

It seems in general that natural disasters do not significantly affect container flows at US West coast ports and when using the data as a forward indicator one should be aware of any such event, but not discount the value of that data point too much.

3.3 Other influencing variables

Having discussed the singular events that could have affected historic container flows and how to deal with similar future events, the focus now shifts to identifying systemic variables that can affect transpacific container flows. The number of containers traversing the pacific at any one point in time is not a perfect representation of supply and demand between the US and China. There are many variables not directly related with the supply and demand of the goods in containers that influence these container flows and therefore they fall under ‘other’ variables and will be covered in this chapter.

The goal of this section is to identify these influencing variables and understand how they affect transpacific and also often global container movements. Variables which are backed by monthly data can then be used quantitatively in chapter 4 to help build an economic activity prediction model. Variables of which no data was obtainable or are more qualitative in nature, are also briefly discussed, as they could prove helpful when identifying discrepancies in the model and/or qualitatively explaining possible outliers in the container flow data.

If what affects transpacific container flow dynamics can be understood, one will be in a stronger position to identify anomalies and/or key turning points in these flows. An anomaly being a change in the trend of container flows that is not due to a fundamental shift of economic activity but instead due to a large change of one (or multiple) of the influencing variables.

Variable categories

The process of selecting the variables to be used in this thesis was started by making an inventory of all possible influencing factors mentioned in the literature that was studied when compiling chapter 1 and 2. The most insightful work with regards to other influencing variables was found to be in (Theofanis & Boile, 2009) and (Boile, 2006).

Two criteria were used to select variables for further statistical analysis. The first was a practical one: the variable must have data available in monthly time intervals and the data series must span at least the past 10 years. The second criterion was based on the variable’s time-scale, whereby variables that change slowly over a period of years (and thereby also influencing container flows slowly) were disregarded versus variables that can have quick changes within a matter of months.

To structure the variables that were remaining, they were grouped into macroeconomic, commodity and shipping specific categories as can be seen in Table 3. Variables whereby data could not be obtained, that are qualitative in nature or affect container flows on a longer time-scale are discussed more briefly in the 'Missing and omitted variables' section at the end of 3.3.

Table 3 Selected data based variables. All variables have publicly available, monthly data.

Category:	Variable:
Macroeconomic	Consumer confidence
	Interest rates
	Exchange rates
Commodity specific	Oil price
	Steel price
	Baltic Dry Index
Shipping specific	Equipment availability
	Intermodal transport costs
	Freight rates

Methodology for assessing the influencing variables

For each data based variable listed in Table 3 a section will be written. The section will start with a discussion on the relationship the variable has with container flows and the variable data will be plotted against the container flow data found in chapter 3.1.

The annualised volatility of the variable is then calculated as an indication of how much the variable in question moves on a yearly basis. This will enable one to identify moments when changes in a variable are of large or abnormal proportions compared to its historic volatility. Volatility is inherently linked to the standard deviation, therefore the standard deviation of monthly change over the complete time series is calculated. To arrive at an annualised value, the square root of 12 (months per year) is multiplied with the standard deviation:

$$Annual\ Volatility = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2\right) * tp} \tag{1.6}$$

Whereby:
tp = Amount of time periods in a year
N = Total number of time periods
x_i = Monthly change at time period i
μ = Mean of monthly changes of all time periods

Also, a cross correlation test is performed between each variable and the three individual container flows (Loaded In, Empty Out and Loaded Out) to see at which lead or lag the highest correlation lies for each flow. This will indicate whether the variable leads, lags or is in sync with each container flow.

Variables that lead or are in sync can be of value later in chapter 4 when building a model to predict economic activity.

The output of the cross correlation test will be displayed in a table indicating the correlation at zero lag and the maximum correlation and at which time lag it occurs (example shown in Table 4). A negative lag number indicates that the variable leads the container flow.

As an example in terms of timing: the release date of the May container numbers for West coast ports is assumed to be at the start of June. The start of the June data point (or closest to the start of June) of the other variable in the cross correlation is used as the 0 lag in the cross correlation.

Table 4 Example table

Oil Price	0 lag correlation	Max correlation	Lag
Loaded In	0.017	0.119	-2
Empty Out	-0.018	0.125	-3
Loaded Out	0.047	0.073	1

When performing cross correlation testing, both time series being used must be stationary to avoid finding a spurious correlation. To test whether the time series are stationary (and therefore have no unit root), the Augmented Dickey-Fuller (ADF) unit root test (Pindyck & Rubinfeld, 1998) is used. Hereby the null hypothesis (H_0) stating that the variable has a unit root can be rejected when the observed t-statistic is more negative than the 95% confidence level t-critical value (i.e. 5% probability of being wrong). To select the lag length, the Akaike Information Criterion (AIC) is minimised. The lag length indicates how many steps back in the autoregressive process testing is done for serial correlation.

Unit root testing using the ADF method is also the first step towards testing for co-integration between variables. With co-integration demonstrated (i.e. proving the variables follow a long-run stochastic trend), Error Correction Models (ECM) can be produced. However, the scope of this thesis does not extend to such econometric models and unit root testing is purely being used to test for stationarity of the individual variable time series for the purpose of cross correlation testing.

All of the time series used for correlation testing are differenced time series, i.e. showing the Month-on-Month change. Testing these MoM change time series for stationarity using the above-described method shows that all differenced series are stationary and can therefore be used in cross correlation testing. Results of the testing are displayed in Table 5. The software package used to implement the ADF testing was the Real Statistics Resource Pack Microsoft Excel add-on (release 5.7) and IBM's SPSS (version 24) was used for the cross correlation analysis.

Table 5 Stationarity testing results of the differenced time series. The variable Freight rates is expressed by 3 variables (Headhaul, Backhaul and CCFI). The variable Intermodal transport is expressed by the Truck PPI and Rail PPI variables.

Time series:	t-stat	t-critical (5%)	AIC lag	Stationary?
Loaded In containers	-4.124	-1.941	7	y
Empty Out containers	-4.572	-1.941	10	y
Loaded Out containers	-4.923	-1.941	10	y
Consumer confidence	-11.446	-1.941	2	y
Interest rates	-10.923	-1.941	0	y
Exchange rate	-2.593	-1.941	5	y
Oil Price	-12.098	-1.941	0	y
Steel Price	-7.125	-1.941	1	y
Baltic Dry Index	-8.642	-1.941	3	y
Equipment availability	-8.923	-1.946	0	y
Freight rate Headhaul	-10.103	-1.945	0	y
Freight rate Backhaul	-5.453	-1.945	3	y
CCFI	-3.331	-1.941	0	y
Truck PPI	-6.432	-1.941	1	y
Rail PPI	-7.976	-1.941	0	y

Data based variables

This section individually discusses the data based variables listed in Table 3 in more detail. The goal of this is to get a better understanding of each variable's possible effect on container flows and if the effect on flows occurs immediately or with a lag. Chapter 4 will then use these variables together with the container flow data in a multiple regression and then test how well they can predict economic activity.

Consumer Confidence

Nearly all retail related products that are imported by the US get shipped in containers. Therefore, the demand for these goods is driven by how much the US consumer is willing to spend and is influential on the number of loaded containers entering the states from Asia. A way to measure this 'willingness to spend' by the US consumer is captured in the monthly reported University of Michigan Consumer Sentiment Index (UMCSI). The monthly index is obtained from a questionnaire with questions based around three areas of consumer sentiment: business conditions, personal finances and buying conditions and is not seasonally adjusted. To calculate the index, the percentage of negative responses is subtracted from the positive responses to each question and 100 is added to this (University of Michigan, 2018a). The sum of all the questions is then divided by the base number that was obtained in 1966. So the index is always comparing to the base month response taken in 1966, which is not particularly insightful. Looking at the long-term average of the UMSCI though, one can see that it lies around 85 points. The corresponding long-term average US GDP growth for this period is around 3%. When comparing US GDP growth to the UMCSI, 0% GDP growth roughly equates to around 75 points on the UMCSI. So in terms of what the UMCSI signifies with regards to economic activity, it can be looked at zonally:

- 60-70 points ➔ Things are (getting) pretty bad
- 70-80 points ➔ Neutral
- 80+ points ➔ Positive outlook for economy

When comparing the UMCSI to the smoothed trend-cycle (STC) US West coast container flow dataset visually (Figure 43), one can clearly see UMCSI declining along with loaded inbound and empty outbound container flows just before and throughout the financial crisis (2007/2008). The after-crisis years show UMCSI trending together with the abovementioned flows, whereas pre-crisis the trends seem less correlated.

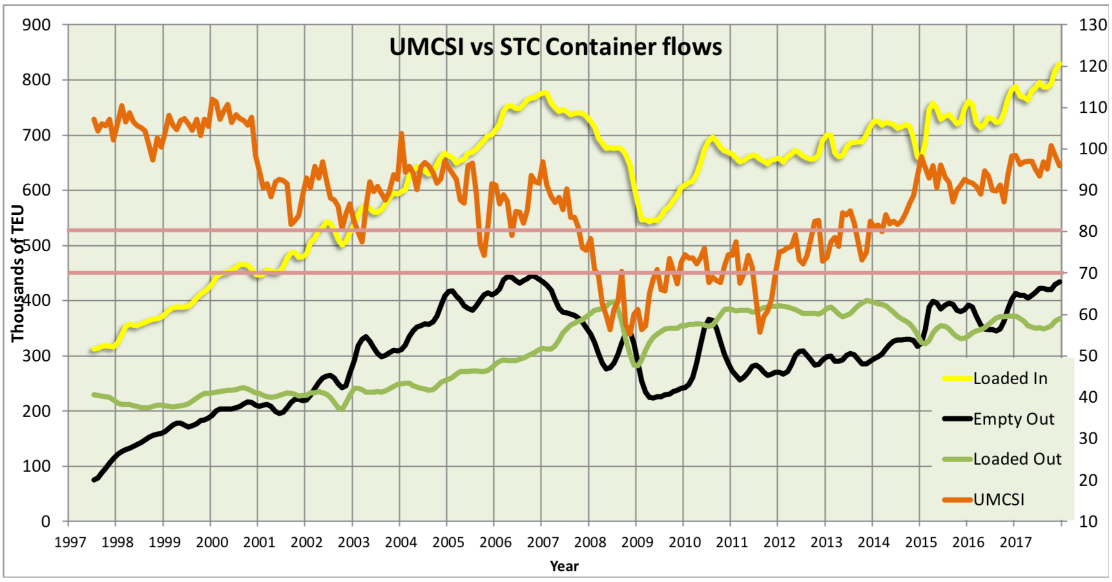


Figure 43 University of Michigan Consumer Sentiment Index (right-axis) compared to STC US West coast historic container flow data. The red horizontal lines indicate the zones of the UMCSI described in the text. UMCSI historic data obtained from (University of Michigan, 2018b).

Annualised volatility of the UMCSI since 1997 is 17.3% and the cross correlation results are given in Table 6 below. At the maximum correlation, the UMCSI leads Loaded In and Empty Out flows by 2-3 months. For Loaded Out flows the connection does not seem very meaningful.

Table 6 Cross correlation results of UMCSI versus container flows.

UMCSI	0 lag correlation	Max correlation	Lag
Loaded In	0.017	0.119	-2
Empty Out	-0.018	0.125	-3
Loaded Out	0.047	0.073	1

Interest rates

The main task of a central bank is to manage a country's money supply and interest rates with the goal of stabilising its currency and preventing high inflation. Central banks use the interest rate as a tool to stimulate or cool off the economy. In a period of high inflation, raising the interest rate tends to slow spending as there is more incentive to save. This works vice versa as lowering the interest rate stimulates spending and therefore hopefully the economy. The central bank is an independent national authority and in the US is called the Federal Reserve Bank. The interest rate policy that they decide to implement affects US spending, part of which goes towards goods that are imported via container, so their actions would be expected to have an influence on container flows (Struyven, 2016).

The tool by which the Federal Reserve enacts interest rate policies is by setting a target interest rate for the so-called Federal funds rate. The federal funds rate is the rate at which banks lend each other reserve balances overnight, which the Federal Reserve can influence by controlling the supply of money available. The effects of this interest rate ripple throughout the global economy as most regard this rate as the so-called ‘risk-free’ rate. Mortgage repayments, option derivatives, financial models, interest paid on consumer bank accounts, bond prices, etc. are all based in some way or another upon this rate.

Figure 44 shows the effective federal funds rate (right axis) versus the STC container flow data. As can be seen, the Federal Reserve started pursuing a zero interest-rate policy (ZIRP) at the end of 2008, a never before seen policy lasting for over 7 years. During this period three rounds of ‘Quantitative Easing’ (QE) were also implemented. In these periods the Federal Reserve purchased large amounts of government bonds and other assets in an attempt to stimulate the economy. The dark green areas in Figure 44 indicate the timing of the three rounds of QE.

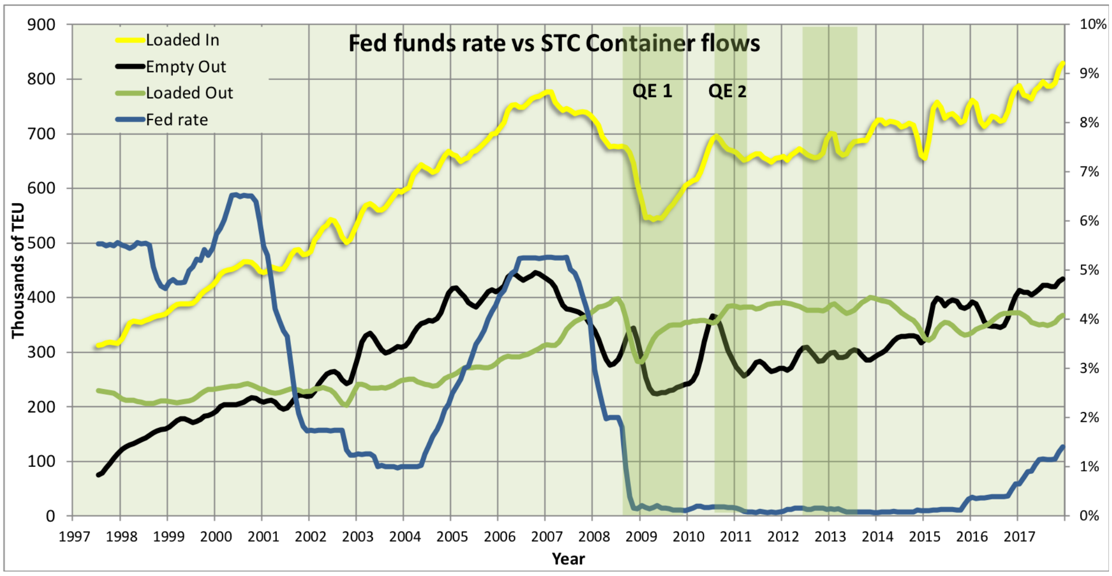


Figure 44 Effective federal fund rate (right-axis) compared to STC US West coast historic container flows. Dark green bands indicate Quantitative Easing stimulus periods. Rate data from (US Federal Reserve, 2018).

ZIRP and the three rounds of QE have led to a bull (stock) market that at the time of writing is the second longest in modern history (Lima, Vasconcelos, Simão, & de Mendonça, 2016). It also seems ZIRP contributed to stabilising a big downtrend in container flows (and the economy) at the end of 2008 and has led to a steady uptrend ever since. When interest rates stopped being raised mid 2006, it wasn't long before loaded inbound and empty outbound container flows peaked. Interest rate policy did not seem to influence container flows in a big way before 2006, but in a world nowadays that has become used to ZIRP and other accommodative monetary policies from the Federal Reserve, one cannot help but wonder what will happen now that the Federal Reserve has started raising rates again.

Annualised interest rate volatility over the period 1997-2017 is 48.1%. This is slightly misleading, as there have been periods of relatively stable interest rates and then large rate hikes and even more rapid interest rate declines. Quite significant maximum correlations with all three flows can be observed in Table 7. What stands out is that the interest rate leads empty flows by 2 months.

Table 7 Cross correlation results of the federal funds rate versus container flows.

Interest Rate	0 lag correlation	Max correlation	Lag
Loaded In	0.146	0.146	0
Empty Out	0.071	0.195	-2
Loaded Out	0.208	0.208	0

Exchange rates

Exchange rates affect international trade by directly affecting the cost of goods and services one must purchase in a foreign currency (Hayakawa & Kimura, 2009; Nicita, 2013). In the transpacific case, the majority of goods come from China, so the most important currency pair is the US dollar against the Chinese Yuan (USD/CNY) pictured in Figure 45.

Exchange rates can also have an effect on freight rates for shippers as most carriers employ currency adjustment factors in their pricing. The overall effect this has on freight rates is small in comparison to the swings the freight rate makes due to changes in supply and demand, which can be seen later in the section '*Freight rates*'.

The USD-CNY is a special currency pair in that the Chinese do not let its value completely be determined by market forces. From 1994 until 2005 the Yuan was 'pegged' at 8.28 Yuan to the dollar. This was done to keep Chinese exports competitive in the worldwide marketplace. In 2005, under pressure from its trading partners, China moved away from a pegged currency to what one would call a 'managed' floating currency. This entailed that the currency could move in a restricted manner against a basket of other currencies including the dollar. Over the next 3 years the Yuan was allowed to appreciate by over 20% before being pegged again in July 2008 as demand for Chinese products drastically ebbed due to the developing great financial crisis (Picardo, 2014). The effect this had on US imports can be seen in the Loaded In container flow data halting its decline for nearly 6-months before things started getting a lot worse towards the end of 2008. It is interesting to note that the peg was removed again at the same time US container imports had started to reach levels that were the same as when the peg was first implemented in 2008. As soon as the Yuan started appreciating again this coincided with loaded inbound container numbers starting to fall again.

As discussed in the example above, an appreciating Yuan affects US imports negatively. The opposite is true for US Exports to Asia, with US products and commodities becoming cheaper for China to purchase. This fact can also be seen when comparing the Loaded Out container numbers against the USD-CNY currency movements.

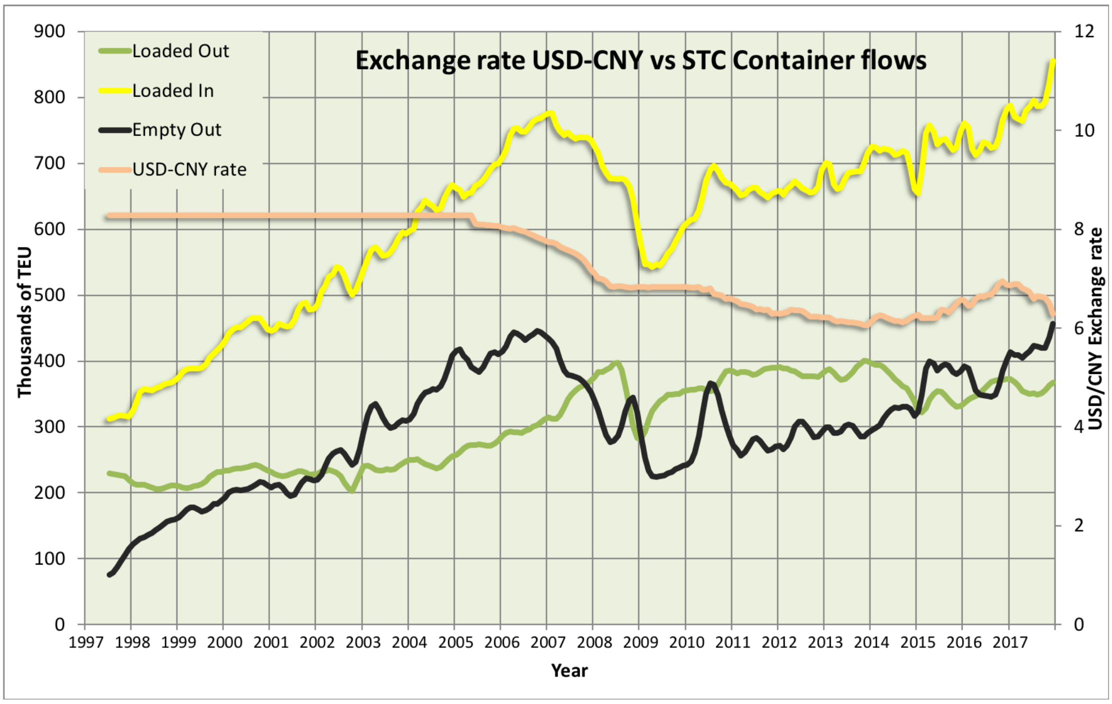


Figure 45 USD-CNY exchange rate. When Yuan depreciates the salmon-coloured line rises. Exchange rate data obtained from (Investing.com, 2018b)

With the wide consensus view that the Yuan is grossly undervalued, the question then remains why the Yuan started depreciating against the dollar from 2014 to 2017? The answer to this lies not in one of President Trump's favourite accusations: China is manipulating rates purposefully by devaluing their currency to boost exports. The real reason this happened was due to the fact that the dollar appreciated a lot against the Euro in the same time period. As the Chinese want to manage the appreciation of the Yuan against a trade-weighted basket of currencies (not just the dollar), they had to let the Yuan depreciate a bit against the dollar to have a more gradual appreciation against the Euro (Cendrowski, 2015). The impact the depreciation of the Yuan against the dollar had can be seen in the drop off of loaded export containers (green line, Figure 45).

It seems that the USD-CNY exchange rate affects longer-term trends of loaded outbound container flows and to a lesser extent, loaded inbound flows. Turning points and pegs of the exchange rate do seem to coincide with turning points in container flows. Therefore, when observing changes in trend of container flows, one must check for turning points in the value of the Yuan against the dollar to see whether they may explain a move away from the trend.

Due to the pegged and regulated nature of the Yuan in the time period since 1997, it is unsurprising to see a low annualised volatility of 2.1%. This does not mean the influence of the USD-CNY exchange rate should be underestimated though.

The results of the cross correlation in Table 8 indicate a peak of correlation with Empty Out and Loaded Out at a lag of 2 and 0 months respectively. The correlation with Loaded In is not so clear as there is also a correlation of 0.13 at lag 2 (see Figure 46). Note the negative correlation for the Loaded Out container flow. This makes sense as when the exchange rate drops, it becomes cheaper for China to buy US Exports and therefore the amount of Loaded Out container will rise and vice versa.

Table 8 Cross correlation results of the USD-CNY currency pair versus container flows.

Exchange Rate	0 lag correlation	Max correlation	Lag
Loaded In	-0.044	0.15	-4
Empty Out	0.072	0.195	2
Loaded Out	-0.120	-0.120	0

The maximum correlation of the exchange rate with the Empty Out flow could suggest that, companies are repositioning more containers back to Asia in expectation of the dollar appreciating against the Yuan and vice-versa. A simpler reason could be that as more containers leave the US loaded, less will be leaving empty.

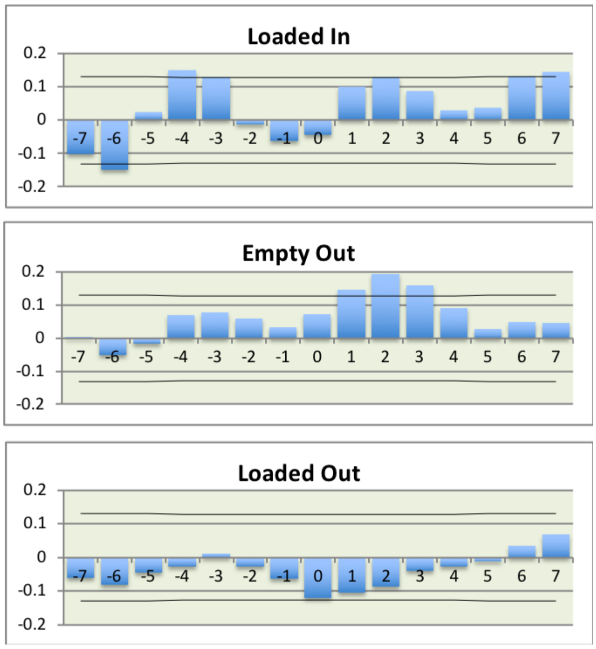


Figure 46 Cross Correlation Function (CCF) of USD-CNY Exchange rate versus the three container flows considered in this thesis. The horizontal axis indicates the lag.

Oil price

The price of crude oil trickles through into the price of many products and services around the world. The way in which it (negatively) affects transpacific container flows is mainly two-fold:

- Bunker rates, which in turn affect freight rates and carrier competitiveness (Ha & Seo, 2017)
- Cost of goods produced that are transported via container

The West Texas Intermediate (WTI) crude price was chosen to represent the crude price (featured in Figure 47). Brent crude is the other main crude oil price traded on international markets and because of its quality for refiners, usually trades at a slightly higher price to WTI. The price variations between WTI and Brent are assumed not to be significant for the purpose of this thesis and therefore WTI prices have been (arbitrarily) chosen.

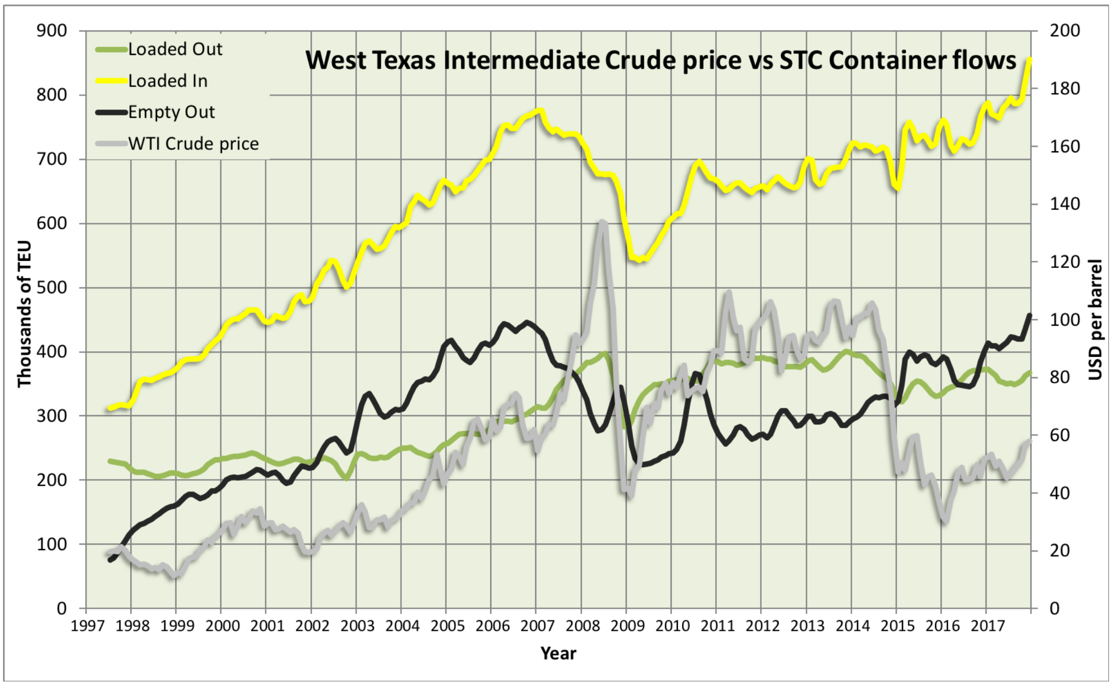


Figure 47 WTI crude price obtained from (Federal Reserve Bank of St. Louis, 2018b)

The annualised WTI oil price volatility since 1997 is 29.7%, but as with the interest rate, the volatility can be a lot higher in years when there have been sharp drops (2008 and 2014).

Looking at the correlations in Table 9, both loaded flows have positive correlations, especially the Loaded Out flow, which goes against the usual arguments that a higher oil price is negative for shipping. This might seem counterintuitive at first, but higher economic productivity needs more oil (energy and base material), which increases the demand for oil and ceteris paribus, therefore the price. This might not necessarily be positive for carriers who also feel the negative effects of a higher oil price (Ha & Seo, 2017), but for loaded container flows it certainly is.

Table 9 Cross correlation results of the West Texas Intermediate oil price versus container flows.

WTI Oil price	0 lag correlation	Max correlation	Lag
Loaded In	0.109	0.145	-2
Empty Out	-0.084	-0.216	3
Loaded Out	0.436	0.436	0

The empty container flow back to Asia has its highest correlation 3 months prior to a change in the oil price. The correlation is negative, implying that a rise in crude oil means less empties going back. This would make sense as repositioning an empty would generally cost more with higher oil prices. A possible explanation why empties are heading back some months before the rise in price could be that carriers are forecasting price rises and therefore want to capitalise by repositioning whilst the price is still low.

Steel price

The price of steel directly affects the container market in two different ways. It affects the cost of producing new containers and affects the demand for steel products transported by container.

Another less direct effect of the steel price on container flows is due to the main ingredient used to produce steel being iron ore. In times of high steel demand and insufficient bulk shipping capacity it can also affect the number of slots available for normal shipping containers as some iron ore transport gets fulfilled with containers. On the transpacific route this is not an issue, but for example, on the Australia-Asia route it is.

To represent the price of steel, the Producer Price Index (PPI) for cold rolled sheet metal is used. This index started in Jun 1982 at 100 and represents the price of cold rolled sheet metal products. As this is a very similar product used to construct containers with, this therefore represents the material cost to produce a new container as well as the general price for steel-based goods. Figure 48 shows the PPI of cold rolled sheet metal charted against the container flows.

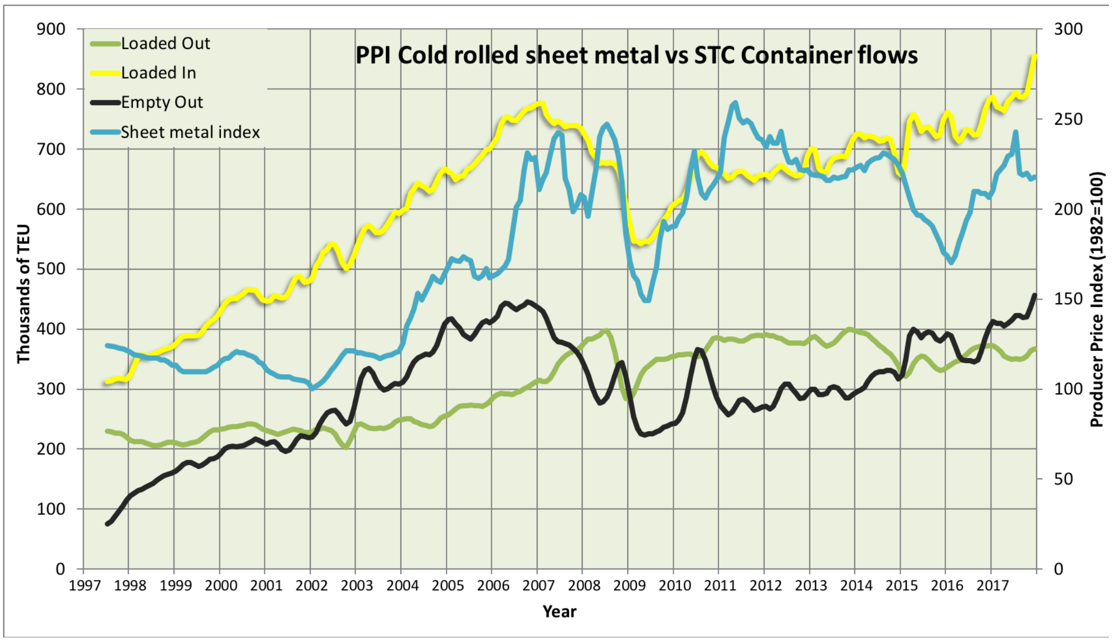


Figure 48 Producer Price Index of cold rolled steel sheet versus STC US West coast historic container flows. PPI data from (US Bureau of Labour Statistics, 2018a).

It is interesting to note that before 2009 the price of iron ore (the main ingredient of steel) was negotiated yearly between buyers and sellers on a fixed yearly contract basis. The annually fixed price changes after contract negotiation can clearly be seen in Figure 49 in purple. With the growth spurt of China in the 2000's and the accompanying growth in the country's steel demand, the traditional suppliers (Australia and Brazil) could not handle the demand. Chinese steel mills started to do more deals with India, which were negotiated per deal and led to the first spot prices of iron ore. When the spot price of iron ore (determined by the China-India trade) sharply dropped during the 2008 financial crisis, some Chinese steel mills defaulted on their yearly contracts with the big Australian (BHP Biliton) and Brazilian (Vale) miners. This led to miners moving to shorter, index linked (based on spot prices) quarterly and monthly contracts (Hume & Sanderson, 2016).

The 2008 spike in sheet metal prices was caused primarily by the annual iron ore price being renegotiated on the basis of the higher steel prices in 2007 (see sheet metal price index in Figure 49). This spike in the price would have most likely not occurred if the prices were based on spot prices and the sheet metal price would have declined more linearly from its 2007 highs.

The abovementioned Chinese growth spurt, led to large shortages of many commodities in the 2000's and the rapid rise in sheet metal prices in January 2002 as well as January 2004. Both these price rises led to a large repositioning of empty containers that had been accumulating in the US (Theofanis & Boile, 2009). This can be seen in Figure 50 where the difference between total containers in and out is pictured.

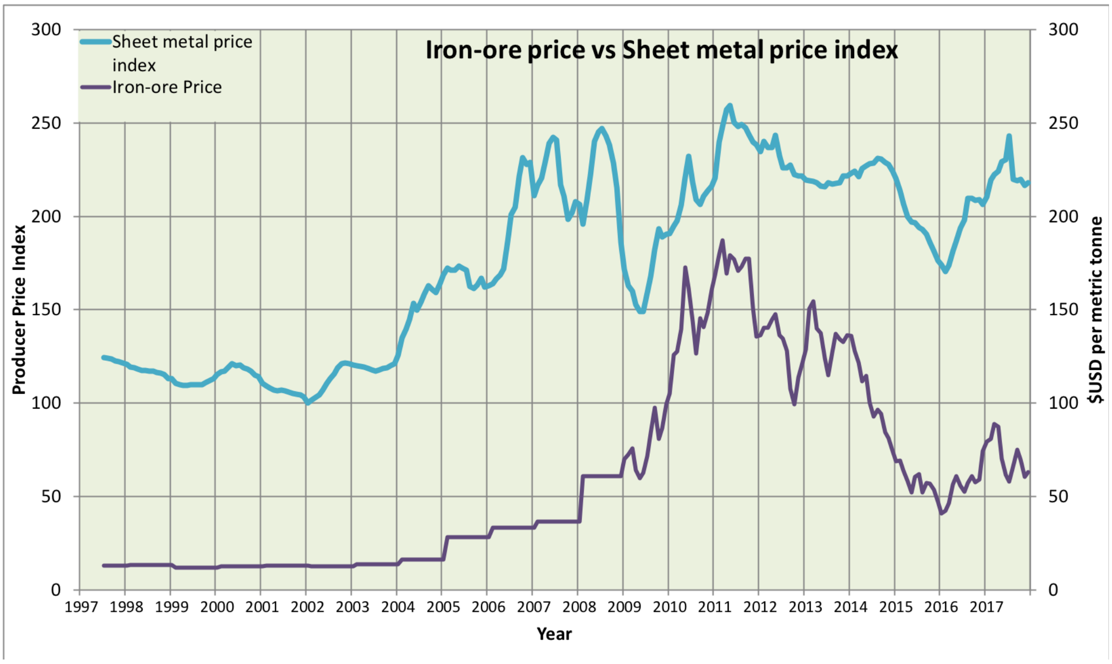


Figure 49 Comparison of Iron ore price (right-axis) and cold rolled sheet metal PPI. Iron ore price only became spot price based from 2009. Iron ore prices from (MarketIndex.com, 2018).

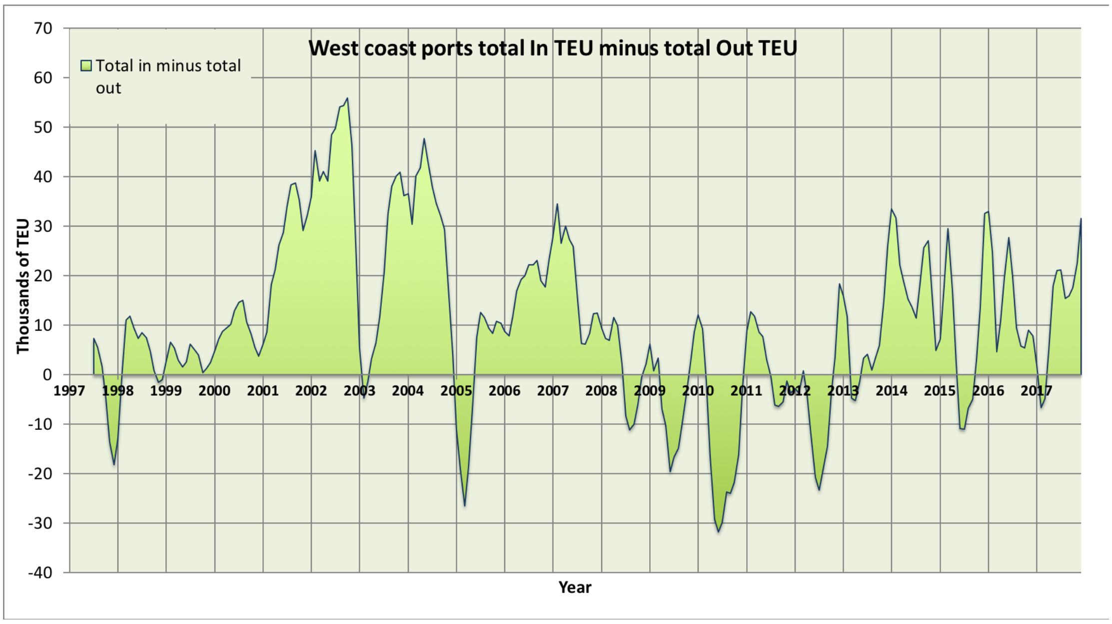


Figure 50 Monthly difference of STC US West coast total containers in and total containers out.

The annualised sheet metal price volatility since 1997 is 10.4%. For Loaded In and Empty Out flows, the highest correlation with the sheet metal price occurs at a lag of -2 (Table 10). This implies that 2 months after the sheet metal price has moved, these container flows react to this in the same direction. The Loaded Out flows have the highest correlation of all, but with the container flow leading the sheet metal price by 4 months. A possible explanation for this is that as demand for US finished products that contain sheet metal increases, containerised exports increase. With this increased demand for sheet metal, its price increases in a lagged manner.

Table 10 Cross correlation results of the Producer Price Index of cold rolled sheet metal versus container flows.

Sheet metal price	0 lag correlation	Max correlation	Lag
Loaded In	0.121	0.198	-2
Empty Out	0.048	0.236	-2
Loaded Out	0.126	0.302	4

Baltic Dry Index

The Baltic Dry Index (BDI) is made up of the average time-charter rates of Capesize, Panamax and Supramax bulk vessels over a selection of 20 global routes. It serves as a proxy for measuring the supply and demand for the shipping of bulk commodities such as iron-ore and grain.

In this thesis the BDI is used to represent the demand for containers from the US to Asia (Loaded Out) in the form of 'backhaul cargo'. Grains and soybeans are one of the largest commodity exports from the US to Asia (apart from US Oil due to the recent fracking revolution) and are mainly transported the usual way by bulk carrier. However, when demand for grains and soybeans increases and bulk carrier supply becomes saturated, these commodities can also be transported by container, by adding a simple plastic liner to the inside of a container. As an example, on average 5-7% of the US soybean crop is exported by container (Clott, Hartman, Ogard, & Gatto, 2015).

Bulk carrier supply is naturally quite inelastic, as it takes up to 2 years to build new ships to react to increased demand. This is the reason why the BDI can quickly become quite volatile to the upside when supply capacity is reached or to the downside when demand decreases (see Figure 51).

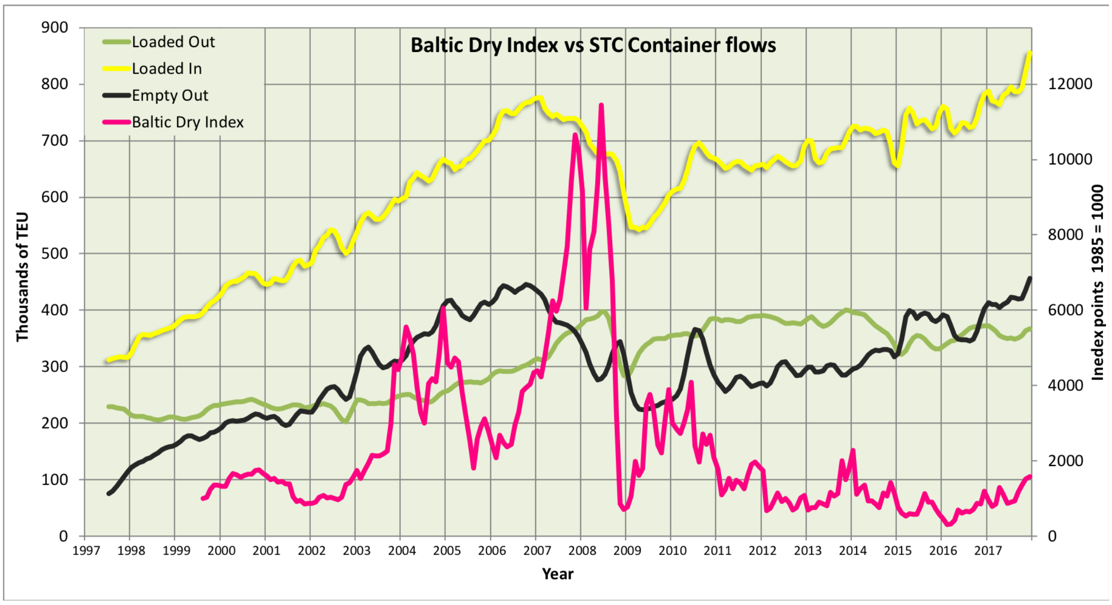


Figure 51 Baltic Dry Index data from (Investing.com, 2018a).

The annualised volatility of the BDI since 1997 lies at 77%, indicating the time-charter price volatility due to the inelasticity of bulk carrier supply. As will be seen in the section about freight rates, carriers drop their backhaul freight rate to encourage lower-priced goods into containers, thereby reducing empty containers. Carriers aim to lower their prices just enough, so that the price becomes competitive with bulk shipping prices (Prentice & Hemmes, 2015). This is done down to a certain price level, below which it is not worthwhile to be competing with bulk carriers. So, when the BDI rises, transpacific carriers can match their US-Asia backhaul prices to compete with bulk shipping and when the BDI really rises due to supply saturation, excess bulk shipping demand from grains and soybeans can spill over into containers. This correlation is seen for the Loaded Out flow at 0 lag (Table 11).

Table 11 Cross correlation results of the Baltic Dry Index versus container flows.

Baltic Dry Index	0 lag correlation	Max correlation	Lag
Loaded In	0.042	-0.155	-2
Empty Out	-0.088	-0.194	-2
Loaded Out	0.309	0.309	0

The Empty Out flow is negatively correlated with a 2-month lag, which is due to more empties being filled with grains to become ‘Loaded Out’ containers instead. The negative correlation of Loaded In containers is expected to be caused by the price impact a higher BDI has on many goods around the world: because the BDI consists of bulk commodities, which are used as the raw inputs to produce intermediate and finished products, higher raw input prices result in higher final goods prices which act as a damper on demand and therefore affect Loaded In container flows in a negative way.

Equipment availability

The United States Department of Agriculture (USDA) provides weekly reports on the availability of containers to provide US (agricultural) exporters with information on container export opportunities. The data is provided for 18 ports and intermodal distribution hubs anonymously by the main shipping alliances. These so-called Ocean Shipping Container Availability Reports (OSCAR) were started early in 2012.

The weekly historic data of container availability for the ports of LA, Long Beach and Oakland is displayed in Figure 52. An additional complexity to container flows, which has not been discussed yet, is the fact that there is more than one container type. This entails that there could be a larger imbalance in a certain container type than another. Changes in these individual imbalances could affect empty repositioning flows, but these changes are not expected to be large enough to be significant for the purpose of this thesis. This becomes apparent when one examines Figure 52, as there appears to be a reasonably stable ratio between the various container types over time.

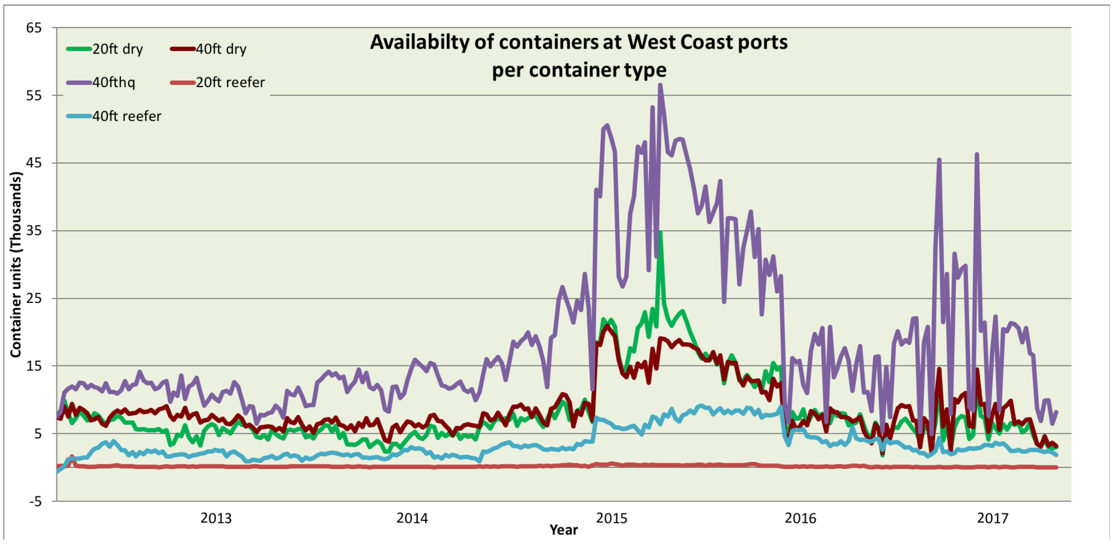


Figure 52 Weekly container availability at US West coast ports. Data compiled by author from weekly availability reports (USDA, 2017).

It is clear from Figure 52 that the largest component of available capacity comes in the form of the 40ft high cube container type (40ft hq). This makes sense as most shipments from Asia are volume constrained (i.e. relatively lightweight) in which case a high cube container will provide maximum volume to shipping cost efficiency. On the other hand, most exports to Asia from the US are commodity based (such as grain) and these types of cargoes are weight constrained, meaning a 20ft or 40ft standard container is more desirable.

The total of the three most popular container types (20ft, 40ft and 40ft hq) have been converted to TEU capacity and are compared with the STC container flow data in Figure 53.

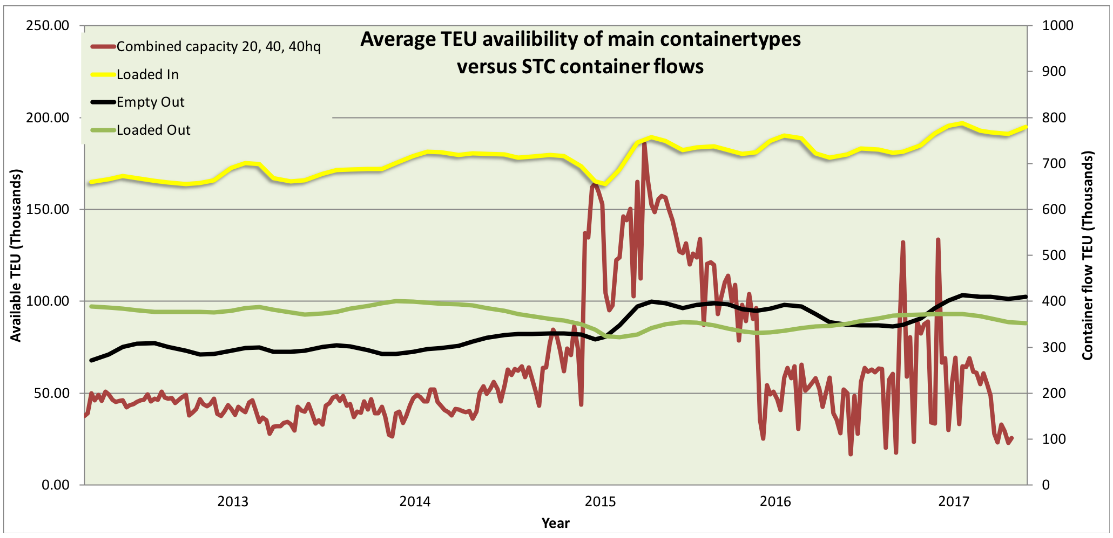


Figure 53 20ft, 40ft and 40ft high cube container availability (converted to TEU) versus STC container flows.

There is clear spike around the start of 2015, which coincides with the labour union work slowdowns in West coast ports discussed in chapter 3.2. Freight rates dropped strongly throughout 2015, which could explain tightening capacity through that year with a big drawdown at the end when Westbound rates had their steepest decline (see Figure 57 and Figure 58 for freight rates). The Hanjin bankruptcy that became official at the start of September 2016 could explain the rise in availability around the same time as well as carriers planning new schedules for new alliance formations that started in April 2017.

Annualised volatility for equipment availability using the aggregated data from Figure 53 comes in at 83.2% since OSCAR measurements began in 2012. The maximum correlations between Loaded In and Empty Out are relatively high, with container availability leading these flows by two months (Table 12). This relationship seems logical, as Loaded In containers lead to more containers becoming available in the US slightly later. The correlation also indicates that a higher container availability leads to more empties travelling back to Asia, which is probably caused by carriers avoiding too much empty container build-up in the US.

Table 12 Cross correlation results of aggregated OSCAR equipment availability data versus container flows.

Equipment availability	0 lag correlation	Max correlation	Lag
Loaded In	-0.181	0.372	-2
Empty Out	-0.065	0.383	-2
Loaded Out	-0.089	-0.217	-6

So it seems container availability does provide some insight into imbalance developments, although these seem more event driven. The data is also noisy with it being published on a weekly basis and having the highest annualised volatility of all the variables from Table 3 (giving it big weekly swings, especially since 2015). The effect this 'noise' has on the results when incorporating this variable into an equation to predict economic activity (chapter 4) is that it leads to the prediction also being volatile or that the variable gets such a small coefficient to 'dampen' out the volatility it becomes useless to incorporate. The USDA announced just recently that they have suspended providing the OSCAR data because there are now only three alliances and they are concerned that the anonymity of the data would be compromised. This makes the data source unavailable to use in future models

Intermodal transport costs

Intermodal transport in the US is nearly always operated by a third-party and therefore carriers, shippers or container leasing companies will incur a cost when transporting an empty container back to a container deficit area. To represent the costs of intermodal repositioning, the Producer Price Indices (PPI) of long distance truck and rail freight transportation are used (Figure 54). These are compiled by the US Bureau of Labour Statistics (BLS) by indexing a basket of quoted prices from US trucking and rail companies.

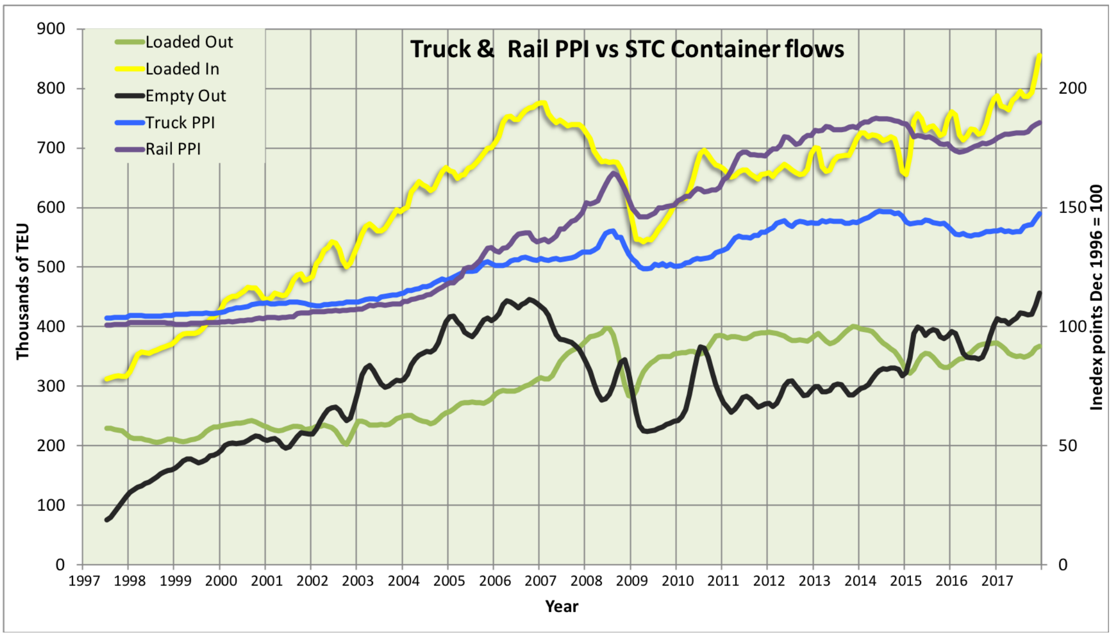


Figure 54 Producer Price Index of Rail transportation and Truck transportation versus STC container flows. Data from (US Bureau of Labour Statistics, 2018c, 2018b).

These PPI's are partially correlated to the price of fuel, so to get an idea of what is the pure supply and demand related cost of intermodal transport, the Cass Linehaul Truckload index is introduced in Figure 55. This index separates out fuel and accessorial costs to indicate the changes in the baseline truckload prices. Figure 55 also includes the WTI oil price to show just how the PPI index is affected by swings in the oil price. Because the influence of the oil price is not extreme in the Truck PPI and the fact that its historic data reaches further back than the Cass Linehaul index, the Truck PPI index will be used for correlation analysis with the container flows.

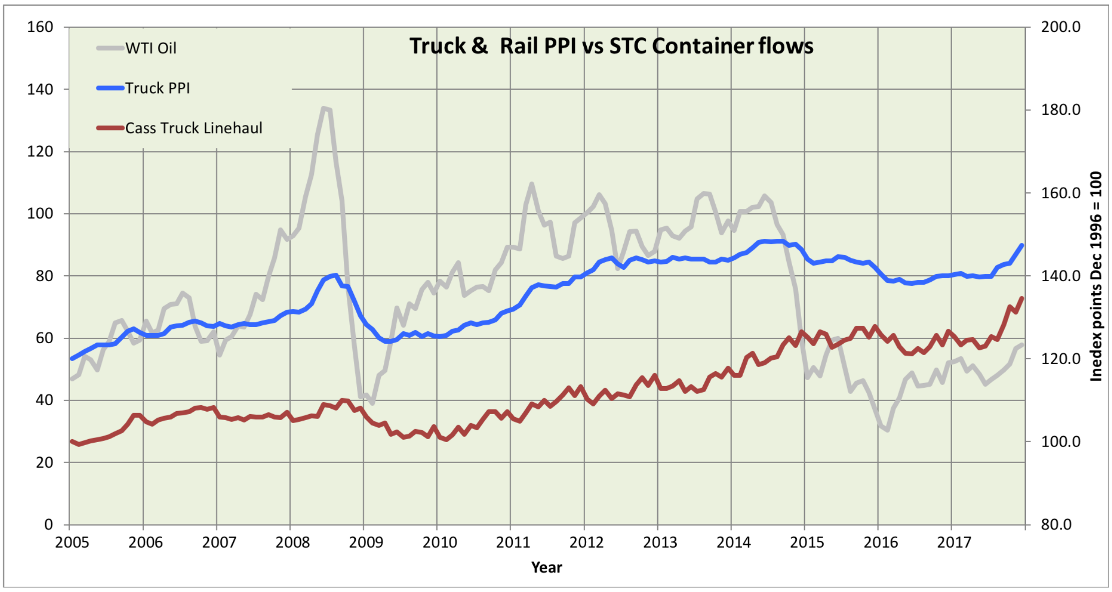


Figure 55 Cass Truckload linehaul index in red indicating the evolution of the baseline intermodal trucking prices. In blue it is clear to see the effect of the oil price (grey) on PPI for long distance trucking. Data from (Cass Information Systems, 2018).

Annualised volatility of Truck and Rail PPI's works out at 2.6% and 2.1% respectively.

Assuming a constant supply of intermodal transportation, it seems that in general, intermodal transport prices follow the demand for transportation of goods. This is most likely the reason why Loaded out containers lead intermodal prices by 2-3 months. And when loaded out containers are rising, that means things are improving with the US Export economy and therefore a few months later Loaded In container flows also rise (lag-1). Looking at the cross-correlation function chart (Figure 56), Empty Out flows seem to just mirror the Loaded Out flows (more Loaded Out means less Empty Out and vice versa).

Table 13 Cross correlation results of the long distance truck Producer Price Index data versus container flows.

Truck PPI	0 lag correlation	Max correlation	Lag
Loaded In	0.162	0.207	-1
Empty Out	0.074	0.248	-3
Loaded Out	0.223	0.348	3

Table 14 Cross correlation results of the rail freight transportation Producer Price Index data versus container flows.

Rail PPI	0 lag correlation	Max correlation	Lag
Loaded In	0.141	0.166	-1
Empty Out	0.068	-0.26	4
Loaded Out	0.207	0.391	2

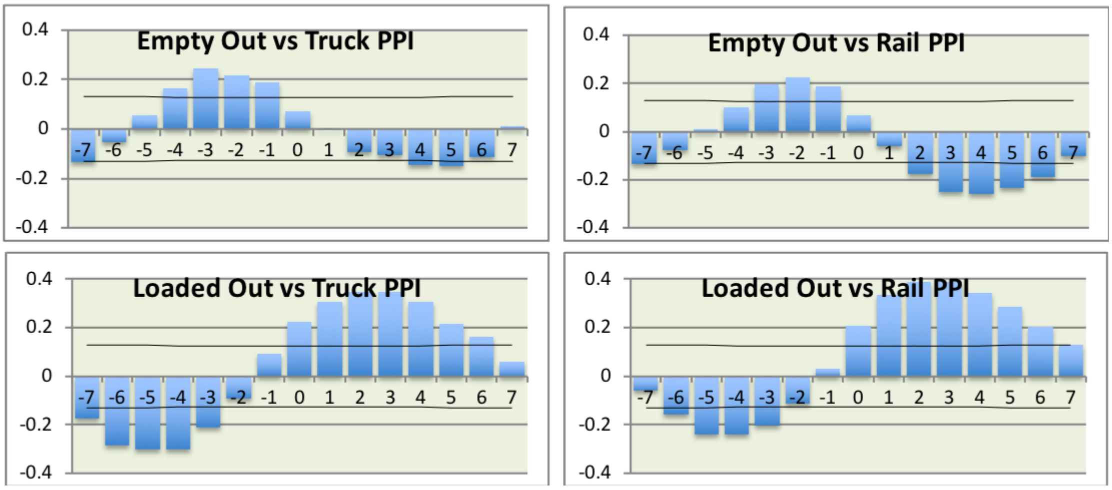


Figure 56 Cross Correlation Function (CCF) of Truck and Rail PPI's versus the three container flows considered in this thesis. Note how Empty Out correlation direction is inverse to the Loaded Out flow.

Freight Rates

Freight rates link together supply and demand like any other market. For containerised transport this is achieved by rates influencing the actions taken by carriers and shippers. And just like any other market, container freight rates have their own intricacies. On the supply side, there is the inelasticity over the short-term due to the time it takes to construct and deliver new vessels, whereas on the demand side, demand for container transport can change far quicker. This phenomenon generally leads to irregular freight(rate) cycles (Stopford, 2009, p. 173). Specific to the liner industry is the need to operate a scheduled service and the relatively high fixed overhead (due to the deployment and handling costs per container). Market sentiment, speculation and random shocks add to the complexity of understanding where freight rates are heading in the future.

For the purpose of this thesis, it is not necessary to dive any deeper into how and why the freight rate fluctuates. It is sufficient to understand that it influences the decisions made by carriers and shippers and therefore can affect container flows.

In Figure 57 the main freight rate time series used in this thesis is charted: the China Containerised Freight Index (CCFI). It is made up of a selection of 12 shipping lines that depart from 10 Chinese ports with data starting in 2000 (Shanghai Shipping Exchange, 2018). The selected shipping lines have destinations across the globe, making the index not completely specific for the transpacific trade route. However, the other available freight rate time series start in 2011 and because this index is from 2000, the decision was made to use the CCFI as a proxy for transpacific freight rates.

The other time series are the Drewry World Container Index (WCI) East- and Westbound rates for the transpacific (Shanghai-LA and LA-Shanghai respectively, measured in in USD per Forty-foot Equivalent Unit (FEU)). These are more specific to transpacific trade than the CCFI, and the three are compared in Figure 58. When looking at this figure, it can be seen that the CCFI tracks the movements of the East- and Westbound Drewry rates quite well and validates the choice to use the CCFI as a proxy for transpacific rates.

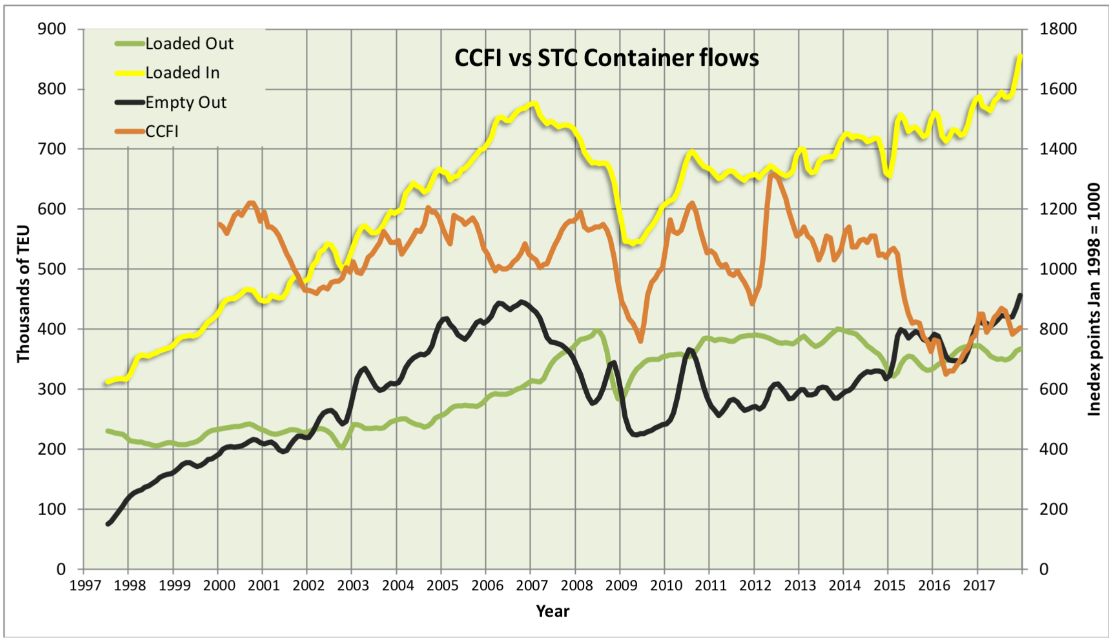


Figure 57 China Containerised Freight Index (CCFI) versus STC container flows. CCFI data from (Bloomberg, 2018)

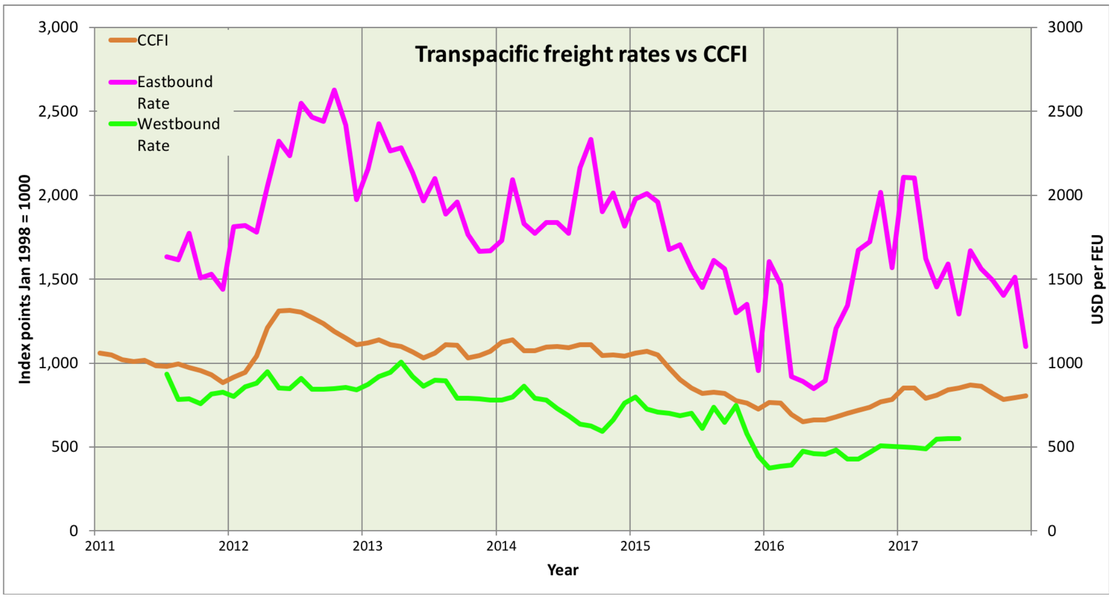


Figure 58 Comparison of CCFI (left axis) versus transpacific freight rates (right axis) in the form of the Drewry WCI Shanghai-Los Angeles (Eastbound) and Los-Angeles-Shanghai (Westbound) rates. Drewry WCI data from (Bloomberg, 2018)

Another interesting characteristic of container freight rates that can be seen in Figure 58 is that of rate cross subsidisation. The Eastbound headhaul rate is usually more than double the Westbound backhaul rate. The level of backhaul rates does not just reflect a lower demand for containerised transport in this direction, but rates are lowered enough for it to make sense to transport certain commodities via container. This allows carriers to reach a larger market and fill more containers. It might not make a profit for carriers, but it covers the marginal cost of repositioning a container back to Asia. This marginal cost is the cost of lifting and handling a container since the ship is already scheduled to make the journey.

The level of annualised freight rate volatility for the Drewry Eastbound and Westbound rates lies at 55% and 29%, whereas the CCFI's annualised volatility is 12%. This lower value makes sense as the CCFI consists of many rates on different routes around the globe, therefore 'damping out' freight rate jumps on one specific trade lane. Because of this, there is a possibility that the CCFI will miss a fluctuation in rates specific to transpacific trade and if a longer time series is available, using the Drewry rates would be recommended.

The results of the cross correlation testing are displayed in Table 15 to Table 17. Both the CCFI and Eastbound rates have maximum correlation at 0 or positive lags, meaning that they are in sync with the flows or lag behind them. Correlation is lowest with Eastbound rates. As mentioned above, the results from the CCFI cross correlation (Table 15) will be used for further analysis in chapter 4.

Table 15 Cross correlation results of the China Containerised Freight Index versus container flows.

CCFI	0 lag correlation	Max correlation	Lag
Loaded In	0.277	0.277	0
Empty Out	0.251	0.251	0
Loaded Out	0.04	0.323	5

Table 16 Cross correlation results of the Drewry transpacific Eastbound (headhaul) freight rate versus container flows. The coloured row indicates which container flow is directly affected by the freight rate.

Eastbound rate	0 lag correlation	Max correlation	Lag
Loaded In	0.115	-0.138	3
Empty Out	0.183	-0.201	3
Loaded Out	0.046	0.154	5

Table 17 Cross correlation results of the Drewry transpacific Westbound (backhaul) freight rate versus container flows. The coloured row indicates which container flow is directly affected by the freight rate.

Westbound rate	0 lag correlation	Max correlation	Lag
Loaded In	-0.269	0.283	-3
Empty Out	-0.15	0.33	-3
Loaded Out	-0.178	-0.23	-1

Missing and omitted variables

This section addresses variables whereby either data was not available or that are less suited to being described by a monthly dataset.

There were two shipping specific variables that would have made it into the data based variable section of this thesis, were it not for access to them being restricted. These variables have to do with the supply of container capacity on a local and global basis. A variable that affects local capacity is the capacity utilisation numbers of US West coast container storage depots, whose location within the supply chain was discussed in Figure 22 in chapter 2. The other variable affecting container supply on a more global level is the number of new containers being built together with the number of containers being scrapped. Changes in these variables are expected to influence transpacific container flows even if economic activity stays the same, although by how much is unknown.

There are many other variables not mentioned in the previous section that could influence containers as well. Many of these are thought to affect container flows slowly, over longer time periods (years), that are not deemed relevant for the shorter-term (less than 6-months) predictions aiming to be made in chapter 4. For those wishing to research this subject further, Table 18 provides a list of variables that possibly influence container flows over longer time horizons and/or in ways they are more difficult to measure.

Table 18 Possible variables for further research that are longer-term or harder to measure on a monthly basis.

Category:	**Variable:**
Macroeconomic	Asian economic policies (One belt, one road)
	Political sanctions / Trade wars
	Demographic or wealth distribution shifts
Shipping specific	Container pooling (grey boxes)
	Container cabotage opportunities
	Per diem penalties
	Dwell time restrictions

4. LOADED AND EMPTY CONTAINER FLOWS AS A POTENTIAL FORWARD INDICATOR OF ECONOMIC ACTIVITY

The previous chapters have provided an understanding of how container flows are connected with economic activity, the dynamics of container flows and what other factors influence the transpacific flow of containers. Chapter 4 combines this knowledge to construct and test models with the aim of predicting US GDP.

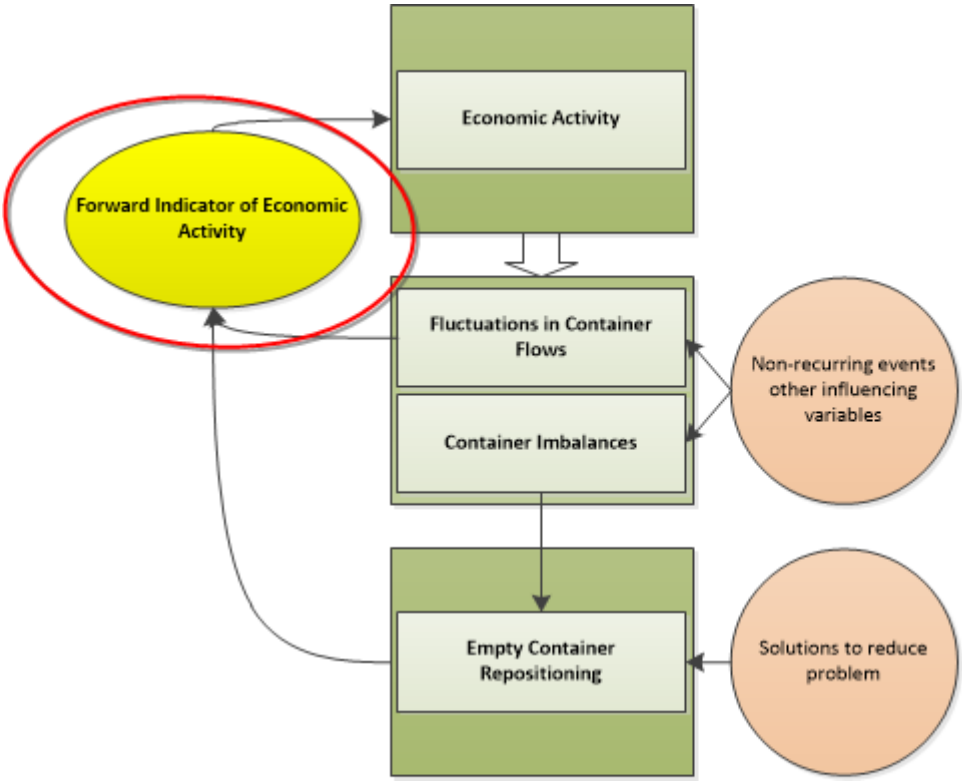


Figure 59 The area covered in chapter 4.

4.1 Existing indicator introduction and benchmarking

One of the most well-known forward indicators of GDP is the Purchasing Managers Index. The Institute for Supply Management (ISM) monthly Manufacturing Report on Business is released on the first business day of each month and the main figure it contains is the Purchasing Managers Index. This is a composite of 5 equally weighted diffusion indices consisting of:

- New Orders
- Production
- Employment
- Deliveries
- Inventories

Each month over 300 purchase and supply executives from across the US respond to a questionnaire about conditions within their business compared with last month in each of the above categories. Answers can be either: Improved, deteriorated or stayed the same. The diffusion indices are then calculated by the ISM using:

$$PMI = (P_1 * 1) + (P_2 * 0.5) + (P_3 * 0) \quad (1.7)$$

Whereby:
P_1 = Percentage number of answers that reported an improvement
P_2 = Percentage number of answers that reported no change
P_3 = Percentage number of answers that reported a deterioration

The composite of the equally weighted average of these indices is the PMI figure. This means of calculation, can lead to the same output given different distributions of answers, but the nature of any diffusion index is to measure the proportion of components that contribute positively to the index. The interpretation of this is that a number above 50 indicates improving business conditions and a number below 50 indicates deteriorating business conditions. The more extreme the number diverges from 50, the larger the change from the previous month.

A considerable amount of research has already been done on the correlation between the PMI and US GDP (Kauffman, 1999; Klein & Moore, 1988) and personal experience shows that many macro analysts use the PMI as a forward indicator. Therefore, the PMI will be used as a benchmark to test the predictive qualities of various container flow metrics with regards to economic activity against.

The results of a cross correlation between GDP and the PMI number are presented in Table 19 (for the time period of August 1997 until December 2017). To convert the quarterly GDP number to a monthly number, the assumption is made that GDP growth between quarters is linear. In this time period, the PMI has the highest correlation with GDP when it is leading by 3 months (see Figure 60).

The same procedure is done for four container flow metrics: Loaded In, Empty Out, Loaded Out and the ratio Loaded In/Empty Out (from the chart in Figure 50). The latter metric is included to see if this ratio reveals any information with regards to GDP. The results in Figure 60 show that the LI/EO ratio does not provide any information as to GDP (non-significant correlations) and will no longer be used for statistical testing in this chapter.

The Loaded Out container flow CCF looks the most similar to the PMI CCF (top left and top right of Figure 60) and more interestingly shows a slightly higher correlation. This similar time lag would make sense as Loaded Out flows can be viewed as an expression of US manufacturing output, which is pretty much what the PMI expresses as well. Looking at Table 19, both Loaded In and Empty Out flows show a maximum correlation well above 0.3, although these maximum correlations are at a 0 and 1-month lag, which is not useful for predictive purposes. Looking at the same 3-month lead that PMI has over GDP, the Loaded in and Loaded Out container flows actually still have higher correlations of 0.268 and 0.277 respectively than the PMI does.

For the testing of GDP predictions later in this chapter, PMI, Loaded In and Loaded Out at a lead of 3-months will be used as well as Empty Out at a lead of 1-month. This keeps the correlations of the container flows with GDP higher than the maximum of the PMI-GDP correlation (>0.24) and still provides a lead on the actual GDP announcement, as the goal is prediction.

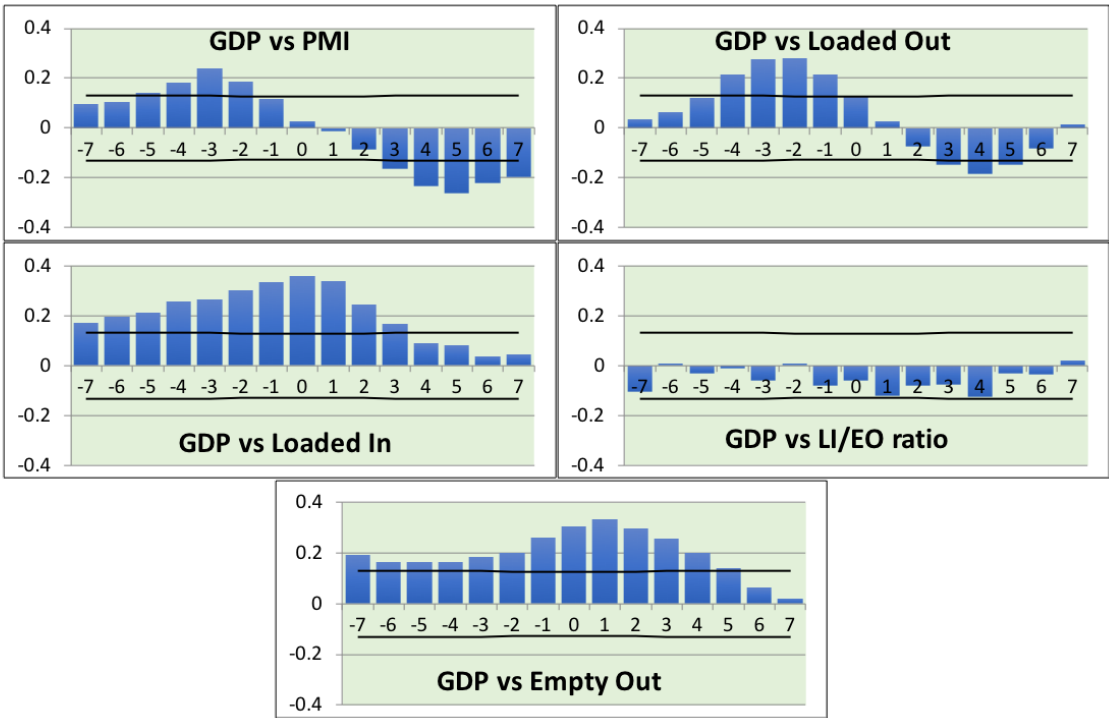


Figure 60 CCF plots of GDP against PMI, the three container flows and the container flow metric 'Loaded In/Empty Out ratio.

Table 19 Data from Figure 60 with yellow indicating the highest correlation and green indicating the correlation at the selected lead to be used for further testing (-3-months for LI and LO,- 1-month for EO)

Lag	-4	-3	-2	-1	0	1	2	3	4
PMI	0.183	0.24	0.189	0.118	0.03	-0.012	-0.086	-0.162	-0.234
LI	0.257	0.268	0.303	0.337	0.361	0.339	0.248	0.168	0.09
EO	0.166	0.187	0.202	0.264	0.307	0.335	0.298	0.26	0.202
LO	0.218	0.277	0.28	0.215	0.125	0.028	-0.072	-0.148	-0.182
LI/EO	-0.01	-0.059	0.009	-0.08	-0.058	-0.122	-0.082	-0.077	-0.124

4.2 (Simple) regression analysis of container flows

The next step is to see how well container flows and PMI predict GDP based on a simple linear regression, without taking any other variables into account. The regression equation used is:

$$CF_i = \beta_0 + \beta_1 GDP_i + \varepsilon_i \tag{1.8}$$

Whereby β_0 and β_1 are (unknown) constants and GDP_i is GDP growth at month i ($i = 1, \dots, n$). ε_i is the error term. When using the PMI, replace CF_i by PMI_i.

Using an Ordinary Least Squares (OLS) regression, the coefficients are found (Table 20).

Table 20 Coefficients, standard error of the estimate and adjusted R-squared found for OLS regression of the individual container flows and the PMI against GDP growth.

	LI	EO	LO	PMI
β_0	-0.0002	-0.0004	-0.0026	-0.0068
β_1	2.2955	4.2098	2.5144	4.1713
σ_{est}	0.0168	0.0332	0.0177	0.0339
R^2 adj.	0.069	0.059	0.074	0.056

To compare these regressions, one can look at the standard error of the estimate as well as the adjusted R^2. The standard error of the estimate (σ_{est}) is the standard deviation of the prediction errors of a linear regression. Since all series represent MoM growth, the results in Table 20 represent the standard deviation error of the container flow or PMI (not GDP) growth prediction by each regression.

To compare how well these regressions fit, the adjusted R^2 is used. The R^2 adjusted takes the number of variables into account used in a (multiple) regression using:

$$R^2_{adj} = 1 - \left[\frac{(1 - R^2)(n - 1)}{n - k - 1}\right] \tag{1.9}$$

Whereby n is the number of points in the data sample used and k is the number of independent regressors (variables) excluding the constant (β_0). Even though there is only 1 variable used in these first regressions, the R^2 adjusted is used for comparison, so as to be able to compare directly to the R^2 adjusted of the multiple regressions later.

An example of how to interpret these two metrics from Table 20 for the LI container flow would be that the standard error estimate of 0.017 means that one standard deviation of error in the PMI forecast using GDP growth will be 1.7% (up or down). The R^2 adjusted of 0.069 means that GDP growth explains 6.9% of the LI flow growth.

The constants β_0, β_1 and the metrics can only be found with hindsight as the regression is being done with GDP data brought forward 3-months for the LI, LO and PMI time series and 1-month for the EO series as explained at the end of 4.1.

With the constants in Table 20 found over the time period 1997 to 2017, equation 1.8 is then rearranged to express GDP as a function of container flows (or PMI):

$$GDP_i = \frac{CF_i - \beta_0}{\beta_1} \tag{1.10}$$

Using equation 1.10 together with the coefficients from Table 20, the various monthly container flow growth rates are filled in to get a predicted GDP growth rate for 3-months ahead (or 1 month ahead in the case of EO flows). Using this model and the announcement of Q3 1997 GDP ($11124 Billion), the predicted GDP by each container flow and the PMI can be calculated. The results are shown in Figure 61. The predictions have been synchronised to the same month as the actual GDP number is released to give a better indication if the predictions are capturing the turning points of actual GDP. As the predictions evolve from the Q3 1997 starting point, their prediction error is cumulative.

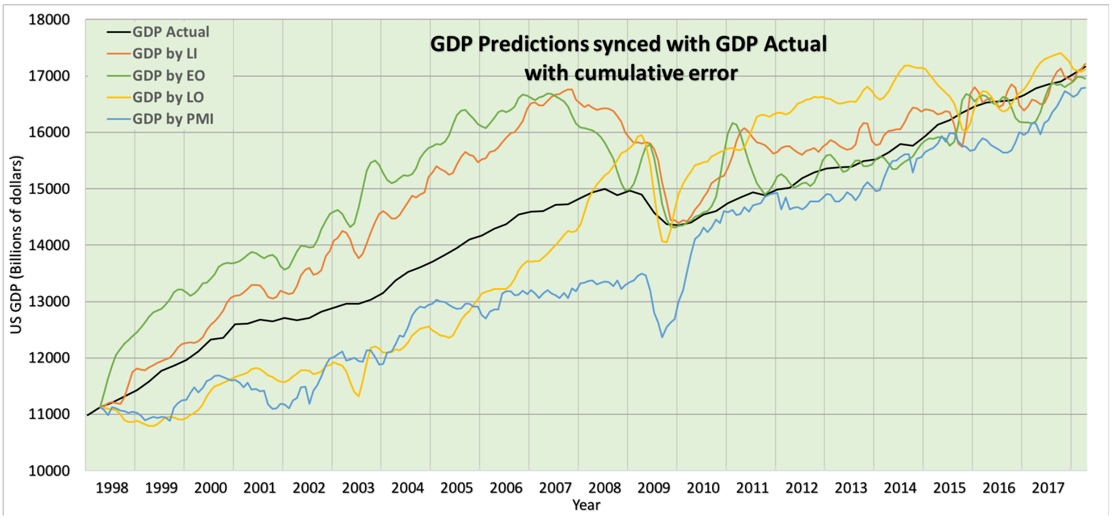


Figure 61 Actual US GDP versus predictions made based upon the individual container flows and the PMI.

To avoid a cumulative prediction error, the predictions can be improved upon by recalibrating every quarter when a new GDP announcement is released. The resulting predictions are shown in Figure 62. As with Figure 61, the prediction results are synchronised with the same month as actual GDP to be able to better compare the predictions versus the actual GDP. In reality, these predictions would have been known 3 months before (or 1 month before in the case of Empty Out flows).

Chapter 4.5 will measure and interpret the predictive performance of the models described in this section as well as 4.3 to help answer the research question.

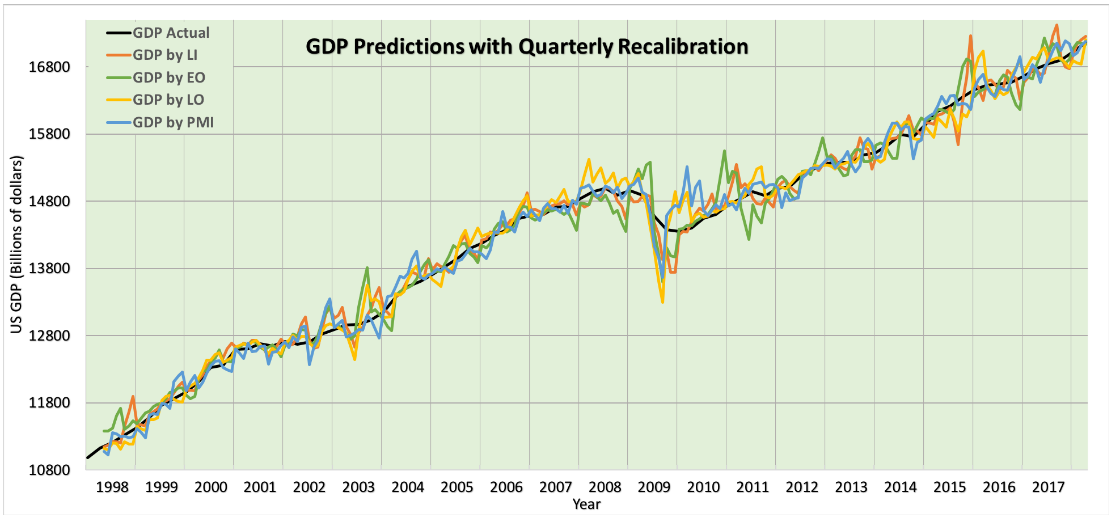


Figure 62 Actual US GDP versus predictions made based upon the individual container flows and the PMI, which are recalibrated every quarter to avoid making a cumulative prediction error.

4.3 Multiple regression analysis of container flows

The question now remains whether the accuracy of GDP prediction by the three container flows can be improved. Taking the knowledge built up in chapter 3.3, the data-based variables are added systematically to the regression in an attempt to improve its fit to US GDP.

The multiple regression equation is a more generalised version of equation 1.8:

$$CF_i = \beta_0 + \beta_1 GDP_i + \beta_2 X_{i1} + \beta_3 X_{i2} + \cdots + \beta_p X_{i,p-1} + \varepsilon_i \tag{1.11}$$

Whereby X_{i1} represents the first variable listed in Table 21, X_{i2} represents the second and so on, with $i = 1, \dots, n$ denoting the months of the time series, $p = 0, \dots, v$ (v is number of extra variables) and ε_i is the error term.

In a stepwise procedure, one variable will be added at a time, upon which a regression will be done. The order in which the variables are added differs between the three container flows and is decided by the maximum (absolute) correlation score with the specific container flow (Table 21). Absolute correlations below 0.1 are dropped. The other criterium is that the variable spans from at least the year 2000 so that most of the date range of the container flow data can be utilised (1997 to 2017).

Variables will stop being added to the regression when the P-value of any of the variables in the regression exceeds 0.05 (5%). The P-value signifies the probability of obtaining a result as extreme as the one that was obtained in a collection of random data in which the variable has no effect. In other words, there is a 95% probability of being correct in saying that the variable has some effect. The t-statistic is inherently linked to the P-value. The t-statistic is the value of the variable's coefficient divided by its standard error. To then obtain the P-value one must calculate the percentage of the t-distribution that is further from the mean than the t-statistic of the variable. If 5% of the t-distribution is further from the mean than the variables t-statistic, the P-value will be 0.05. The t-distribution is a distribution describing how the mean of a sample with n observations is expected to behave and with a large n it is very similar to a normal distribution. For the amount of observations in the data used in this thesis a P-value of 0.05 corresponds to a t-statistic needing to be roughly larger than 2.

Using the criteria described above (adding variables in the order listed in Table 21 until the P-value exceeds 0.05 and/or t-statistic drops below 2), it was possible to add the first extra variable to the Loaded In regression and the first two to the Empty Out regression. The Loaded regression did not meet the criteria when adding its first extra variable. The multiple regression results of Loaded In and Empty out flows can be found in Table 22.

Table 21 List of variables per container flow to be systematically added to regression until P-value and t-statistic criteria reached.

Order to be added:	**LI**	Max Corr.	Lag	**EO**	Max Corr.	Lag	**LO**	Max Corr.	Lag
1	CCFI	0.277	0	CCFI	0.251	0	Oil Price	0.436	0
2	Truck	0.207	-1	Truck	0.248	-3	Baltic Dry Index	0.309	0
3	Steel Price	0.198	-2	Steel Price	0.236	-2	Truck	0.223	0
4	Rail	0.166	-1	Interest rates	0.195	-2	Interest rates	0.208	0
5	Baltic Dry Index	-0.155	-2	Baltic Dry Index	-0.194	-2	Rail	0.207	0
6	Exchange rate	0.15	-4	Consumer confidence	0.125	-3	Steel Price	0.126	0
7	Interest rates	0.146	0				Exchange rate	0.12	0
8	Oil Price	0.145	-2						

Table 22 Multiple regression results of Loaded In and Empty Out flows. Loaded in has the CCFI variable added to it and Empty out has the CCFI and Truck PPI variables added. Note the improved R-squared adjusted metrics compared to the regressions from 4.2.

	Coefficient	σ_{est}	**t-statistic**	**P-value**	**R^2 adj.**
Loaded In					0.1575
β_0	-0.0009	0.0015	-0.6665	0.5058	
β_1 **(GDP)**	2.7815	0.5997	4.6383	0.0000	
β_2 **(CCFI)**	0.1054	0.0343	3.0719	0.0024	
Empty Out					0.1364
β_0	2.9640	1.1467	2.5849	0.0104	
β_1 **(GDP)**	0.1601	0.0661	2.4196	0.0164	
β_2 **(CCFI)**	1.1477	0.3559	3.2252	0.0015	
β_3 **(Truck)**	2.9640	1.1467	2.5849	0.0104	

Just like in 4.2, equation 1.11 is rearranged to express GDP as a function of container flow, the CCFI and the Truck PPI (in the case of Empty Out flow). The coefficients from Table 22 are then used with the historic container flow growth rates to calculate the GDP growth rate predictions.

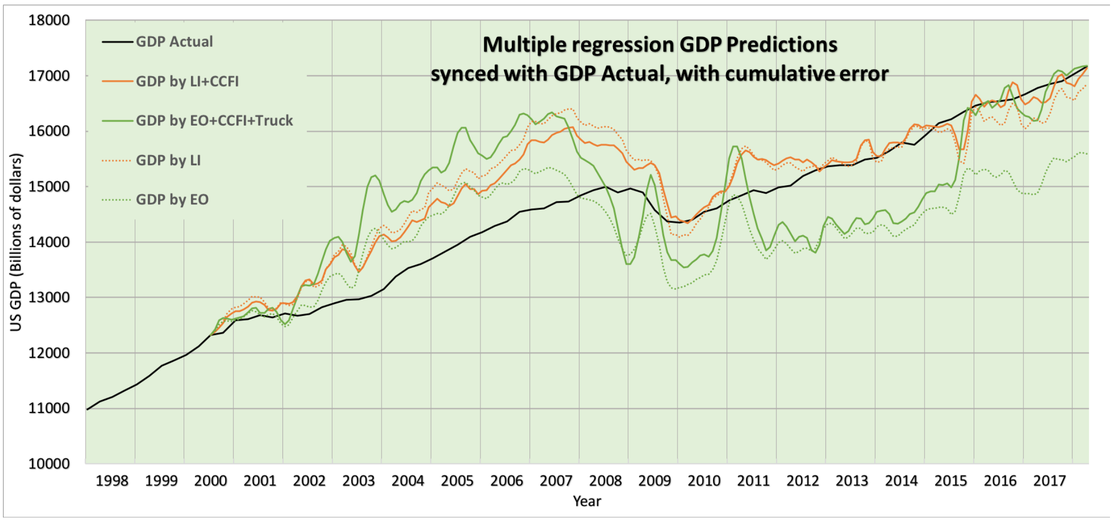


Figure 63 Actual US GDP versus predictions made based upon multiple regressions of the individual container flows combined with CCFI and Truck PPI variables. Dotted lines represent prediction made based upon the simple regression model from 4.2.

Again, to avoid a cumulative error, the predictions are recalibrated on a quarterly basis. The results are displayed in Figure 64. Comparing this figure to Figure 62 it seems the GDP prediction using Loaded In flows with the CCFI (red line) has become slightly more accurate, but that the GDP prediction using Empty Out flows with the CCFI and Truck PPI variables (green line) has become less accurate.

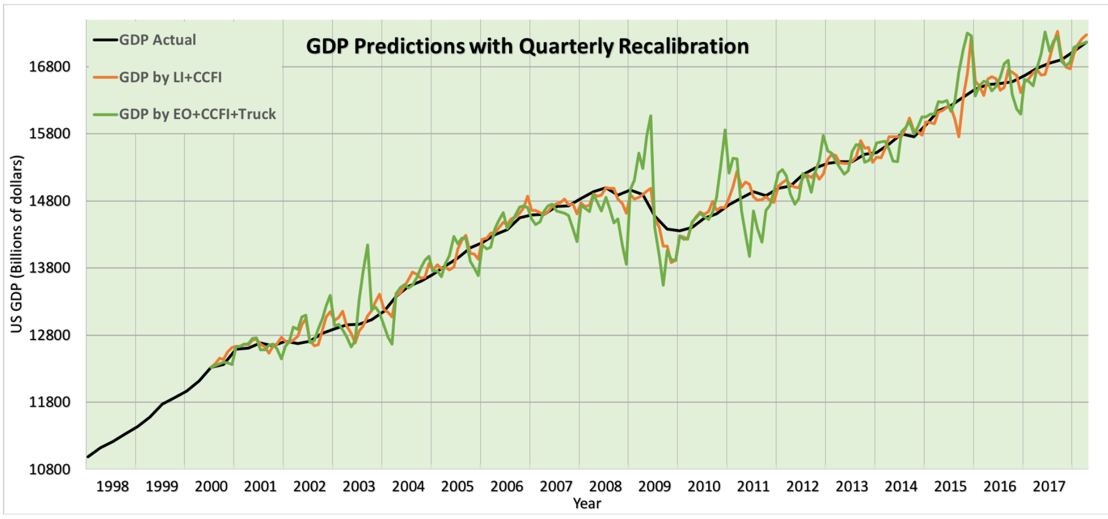


Figure 64 GDP prediction results from the best combination of variables for each container flow. GDP prediction number is synchronised with the actual GDP date.

The final prediction models that will be tested for their performance in the next section will be:

- Loaded In (**LI**)
- Loaded In with the CCFI (**LI+**)
- Empty Out (**EO**)
- Empty Out with the CCFI and Truck PPI (**EO++**)
- Loaded Out (**LO**)
- PMI (**PMI**)

All these models are smoothed using the same process described by equation 1.5 in chapter 3.1. The smoothed versions of all these models are shown in Figure 65. In this figure the predictions are shown on the date that they become known (as opposed to the date of the GDP announcement release they are actually predicting), thereby showing if they are making the correct prediction before the actual GDP is announced. This is the final dataset that will be used for predictive performance testing in 4.4.

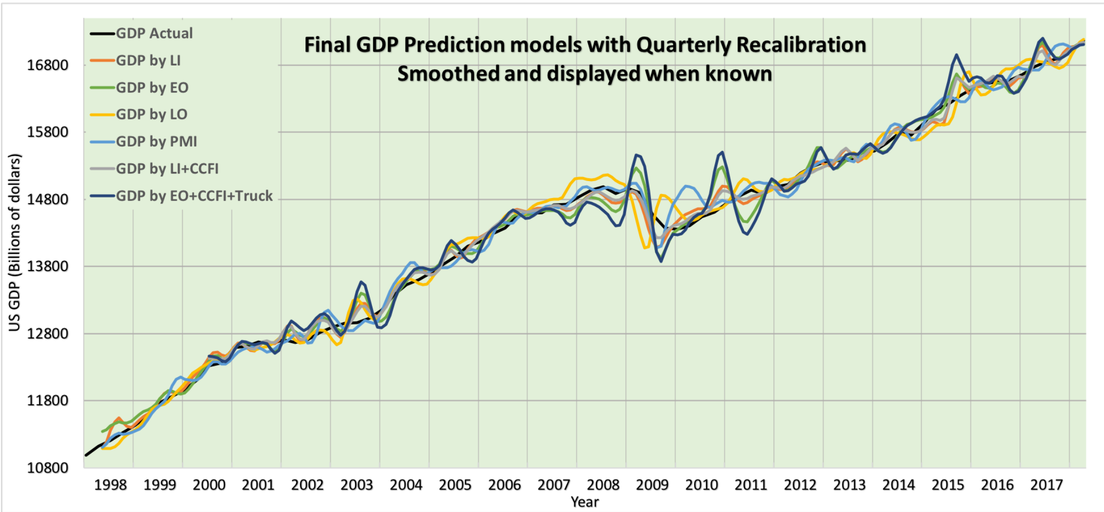


Figure 65 Smoothed GDP prediction model results displayed on the date that they become known.

4.4 Predictive performance results of regressions

To help answer the research question of if loaded and/or empty container flows be used to predict economic activity and how precise they are, this section is dedicated to quantifying the predictive performance of the six models introduced in 4.2 and 4.3.

As US GDP is announced quarterly, but the container data allows for predictions at a monthly timescale, the sum of the last three monthly GDP growth predictions from each model is used as the predicted quarterly GDP growth rate.

Using the historical data, the quarterly GDP growth predictions made by the models are compared with the actual announced quarterly GDP growth. The LI, LO, PMI and LI+CCFI models make this prediction three months ahead of time and the EO and EO+CCFI+Truck models predict one month ahead. Testing was performed from Q1 2000 until Q4 2017, due to the availability of the CCFI data used by two models.

The first metric for quantifying the performance of the models, is obtained from a binary test aiming to quantify in how many instances a model's quarterly GDP prediction was correct and how often it was wrong. This test has four outcomes:

- GDP growth is negative and predicted growth is negative
- GDP growth is positive and predicted growth is positive
- GDP growth is negative and predicted growth is positive
- GDP growth is positive and predicted growth is negative

For the 70 US GDP announcements tested from 2000, the binary prediction results are listed in Table 23. The first four rows show the amount of times the model had a certain outcome. The coloured rows at the bottom of the table show the percentage of times each model made correct and wrong predictions. The highest percentage of correct predictions is made by the LI+CCFI model with 69%, followed by the LI and LO model with 66% and 64% correct respectively. These three models also outperformed the PMI benchmark model, which made correct predictions 61% of the time. For comparison, a random coin toss would score 50% in this test given enough cases. So, these models certainly seem to have an edge as well as outperform the PMI benchmark. Figure 66 visualises the results from Table 23.

Table 23 Binary test results for the six models.

	LI	EO	LO	PMI	LI+	EO++
GDP- Pred. -	7	4	3	5	7	4
GDP+ Pred. +	39	37	42	38	41	34
GDP- Pred. +	2	5	6	4	2	5
GDP+ Pred. -	22	24	19	23	20	27
%Correct	66%	59%	64%	61%	69%	54%
%Wrong	34%	41%	36%	39%	31%	46%

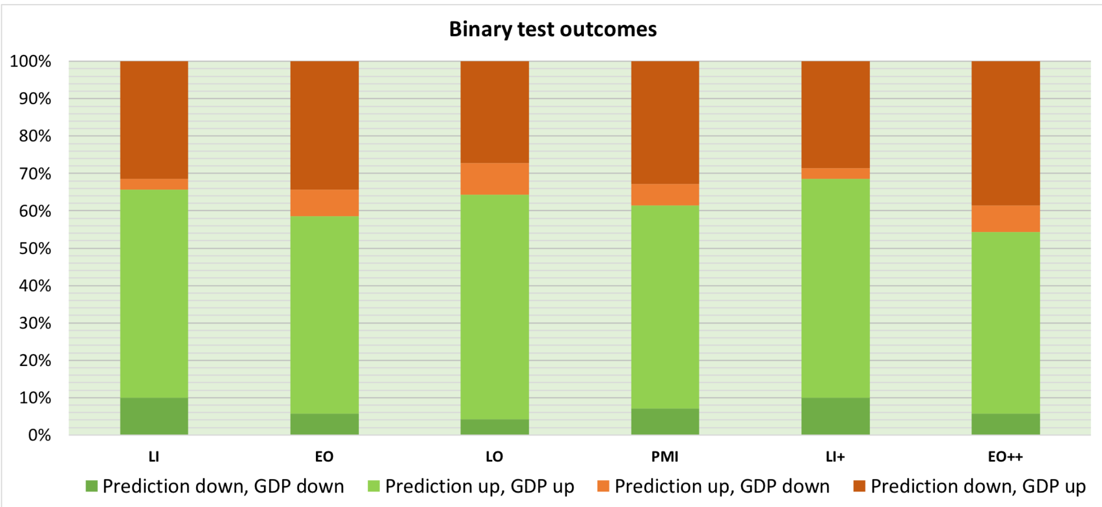


Figure 66 Percentage distribution of the binary outcomes. Green colours indicate instances whereby the GDP growth prediction was correct and red vice versa.

Binary outcomes do not paint the complete picture, as they do not indicate how right or wrong the prediction was. For this, a second metric is calculated to see how precise the predictions are. The quarterly prediction errors of each model (the difference between predicted growth and actual GDP growth) are calculated and the distribution of the errors is visualised in the histograms of Figure 67. The standard deviation of these errors is listed per model in Table 24. This captures the visual results from Figure 67 in the form of a number.

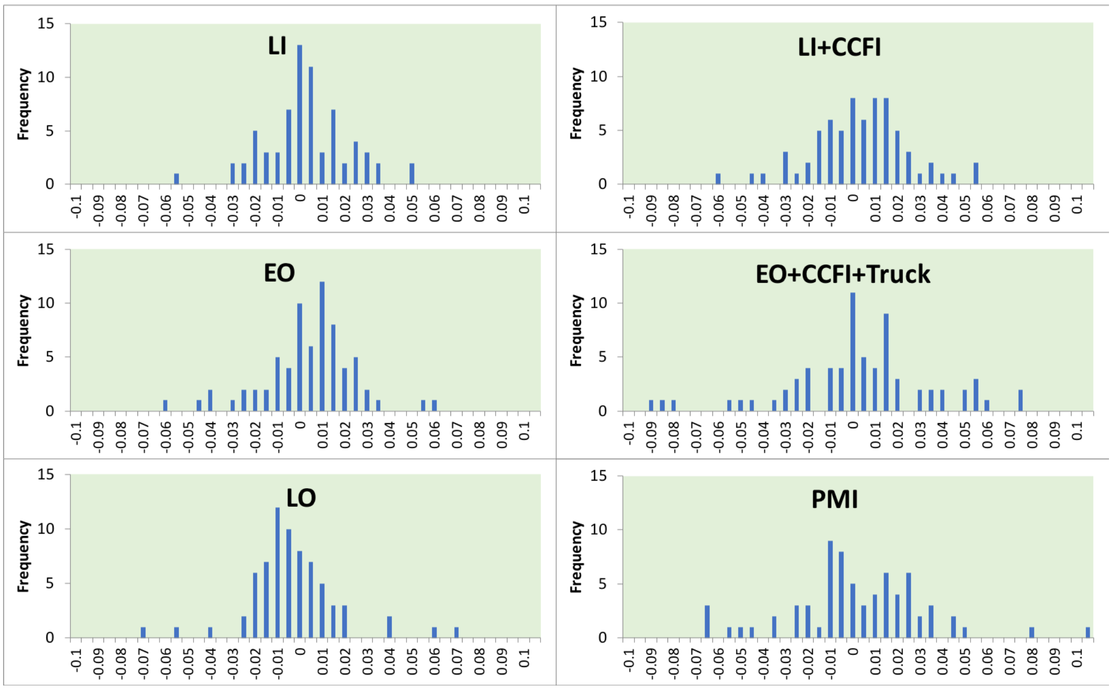


Figure 67 Histograms of each model showing the distribution of the prediction errors. A negative error indicates instances where the predicted GDP growth rate was too large and a positive error indicates instances where the prediction was too small.

Table 24 Standard deviation of prediction errors per model.

	LI	EO	LO	PMI	LI+	EO++
Std.dev σ	1.89%	2.04%	2.09%	3.05%	2.18%	3.34%

The prediction errors were calculated by subtracting the predicted GDP growth from the actual GDP growth. This means that when looking at the histograms in Figure 67, that negative numbers (left-hand side of the horizontal axis) indicate an instance where the predicted growth rate was too large and positive numbers indicate instances where the prediction was too small. Using this information, it seems the LO model has a tendency to make too large predictions, whereas the EO model has the tendency to underestimate GDP growth.

A small standard deviation number of the prediction error distribution of a model, indicates that model is making only small mistakes (Table 24). The models with larger prediction error distribution standard deviations make larger errors when predicting GDP growth. It is interesting to see the EO++ model making the largest prediction errors, as it was hoped that the extra variables it uses would make it more accurate. This could be to both CCFI and Truck PPI variables being positively correlated with the Empty Out container flow and thereby increasing its swings when all three rise at the same time.

Looking at the top three models from the binary test (LI+, LI and LO), their standard deviations are 2.18%, 1.89% and 2.09% respectively. This means that even though the LI+ model got slightly more predictions correct, the amount its prediction was off of the actual GDP growth number, was larger, i.e. it is less accurate than the LI model that has a smaller standard deviation. This can also be seen visually in Figure 65, with the LI model tracking closer to actual GDP.

It is a slightly subjective choice as to which model of the three that outperform the PMI benchmark is the best. This is because it is at the discretion of the model user whether they want to make a correct prediction in the sense of direction more often, or whether they prefer to be more accurate in their prediction in the (fewer) cases the prediction is correct.

Looking at this with a trader's point of view, for predicting a recession (definition: a fall in GDP for two or more quarters), the LI and LI+ model pick up these declining GDP situations the best (first row of Table 23). The LI model has a greater probability of making a smaller error though, which makes it slightly superior. For predicting the upside, the LO model turns out to be the best, predicting the most amount of positive GDP announcement of all models. As already stated, the LO model does have a probability to overestimate its prediction of GDP. The analysis of the models is concluded here with Table 25 (subjectively) ranking the models.

Table 25 Models ranked from 1 to 6 by author.

	Model	**% Correct**	**Std.dev σ**	**Prediction time**
1	**LI**	66%	1.89%	3-months
2	**LI+**	69%	2.18%	3-months
3	**LO**	64%	2.09%	3-months
4	**PMI**	61%	3.05%	3-months
5	**EO**	59%	2.04%	1-month
6	**EO++**	54%	3.34%	1-month

5. CONCLUSION AND RECOMMENDATIONS

Chapter 1 made the link between maritime transport and economic activity. It concluded that containerised transport has rapidly grown in the last 60 years to becoming the main way most products are shipped globally. Because so many goods travel via container nowadays, economic activity expressed in the form of GDP is inherently connected with container flows.

Chapter 2 looked into the imbalances seen in global container flows, the problems they cause and the solutions proposed and implemented to minimise the issue. In this chapter it was concluded that:

- Empty repositioning will be a problem so long as there exist trade imbalances
- ECR optimising strategies likely do not have a big influence on transpacific empty container flows to be significant for the purpose of predicting economic activity on the short-term (<6-months)

It was suggested at the end of this chapter that if carriers make ECR decisions on the basis of customer demand, the LI/EO ratio would be a good metric for picking this up. When doing cross correlation testing in chapter 4 it was concluded that this ratio has little to no correlation with historic US GDP data and the metric was disregarded from further analysis.

This thesis mainly considered academic literature when researching ECR. It was found that there is little written about the how carriers react to changes in demand or even influence capacity (supply) with regards to their ECR strategies. Further research into this, possibly by conducting interviews with various stakeholders in the ECR logistics chain would certainly fill a gap in the literature.

Chapter 3 discussed and prepared the data for further analysis. It then identified outliers in the data and finally identified and analysed possible influencing variables that could affect the number of containers crossing the pacific in ways that are not directly linked with economic activity. The idea being that if other influencing variables on container flows are known, one can have a better idea when changes in flows are because of actual changes in economic activity.

In this chapter it was concluded that container data is seasonal and needs to be de-seasonalised to reveal the trend. Also, Chinese New Year and labour union strikes (of US port workers) affect flows on a short-term basis. When interpreting future data, care must therefore be taken when any of these events is known to be occurring. It would seem worthwhile exploring the increase in performance of the prediction models by incorporating the use of so-called ‘dummy variables’ to model Chinese new-year and labour strikes when performing the multiple regressions.

There proved to be many data based drivers identified in the literature that could influence loaded and empty container flows, but in more than a few cases data was difficult to obtain. Container storage depot utilisation numbers and container newbuild and scrapping numbers are variables that would have been included in the analysis if they were obtainable. It is recommended that, by collaborating with companies involved in using this data or larger companies who are able to purchase this type of data, future research in this area can be facilitated.

Chapter 4 introduced the PMI as benchmark forward indicator to be used as comparison. Cross correlation analysis identified the monthly time lags with the highest correlations of the container flows and PMI with US GDP. This led to LI, LO and PMI having the greatest correlation at 3-months ahead of US GDP announcements and EO flows 1-month ahead.

The possible influencing variables were then ranked in order of highest correlation with each individual container flow. These variables were then added in this order in a stepwise manner to regressions until the t-statistic and/or P-value reached a threshold. For LI flows this led to 1 extra variable able to be added to the regression (the CCFI) and for EO flows, 2 extra variables were able to be added (CCFI and Truck PPI).

For future work, it would be recommended to experiment with which variables are combined with container flows to improve their predictive performance. Further research into statistical methods to transform the variable data in such a way that more variables can be added to the prediction models is warranted. The effects of multicollinearity within the multivariate prediction models would be a suggested starting point as to why this thesis was only able to add 1 or 2 variables to the models.

The 5 models were tested for performance against the PMI model using a binary GDP ‘up or down’ test. To be able to draw conclusions about the accuracy of the predictions, the distributions of the prediction errors were plotted and the standard deviations were calculated. The results of the binary test combined with the prediction error metrics indicated that the LI, LI+ and LO models outperformed the PMI benchmark model, with LI having the highest outperformance and LO the lowest. The EO and EO++ underperformed in comparison to the benchmark.

More insight could be gained in future work by looking at the distributions and standard deviations of the prediction errors individually per binary outcome. This would allow conclusions to be made on how accurate the models are per individual binary outcome, for example, statements could then be made such as ‘when the model predicts GDP growth to be positive, its prediction error standard deviation is smaller than when it predicts negative GDP growth’. It would also be interesting to compare how often the different models agreed with each other on a positive or negative GDP growth prediction. When they agree, this could increase the probability of the prediction being correct.

Since everything in economics and finance should come with the disclaimer 'Past performance does not guarantee future results', another recommended area to explore further is testing the performance of these models on out of sample data.

From the research that was done in this thesis, it can be concluded that the short answer to the research question "*Can loaded and/or empty container flows be used to predict economic activity?*" is yes. The LI, LI+ and LO models all outperformed the benchmark in the testing done in this thesis. It must be noted that these were all loaded container flows, the prediction models using the empty flow underperformed the benchmark.

The other questions posed for this research were "*How precise/reliable are these predictions?*" and "*What is the time horizon of these predictions?*" With regards to accuracy, over the past 17 years, the LI, LI+ and LO models that outperformed the benchmark were able to predict a quarterly rise or fall in US GDP growth 66%,69% and 64% of the time respectively. The PMI benchmark model predicted quarterly GDP growth correctly in 61% of cases. These three models were tested using a 3-month lead on the actual GDP announcement. So, the prediction is made at the start of a quarter and the actual GDP announcement is made 3-months later at the end.

With regards to the value of predicting economic activity to a professional trader described in chapter 1.8, it can be concluded that using the LI, LI+ and LO prediction models can be a valuable addition to his or her macroeconomic 'toolbox'. The PMI is often used by traders to help them determine their bigger picture view of markets and with the three models outperforming the predictive power of the PMI in testing over the past 17 years, container flows as a forward indicator are certainly worth considering incorporating into their market analysis framework. Further research would be recommended into testing the predictive strengths of container flows with regards to US equity markets, especially on specific sectors that are more exposed to containerised trade than others (identified at the end of chapter 1.2).

Even though it was known beforehand, conducting research within the container industry turns out to be tough, with so many aspects that influence each other in different ways. This thesis was a brave attempt to filter out new information from this complex system with some promising initial results. To put this into perspective, we finish this thesis with a quote:

"*When we try to pick out anything by itself, we find it hitched to everything else in the universe*"
--John Muir, Scottish-American naturalist and preservationist

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