Erasmus School of Economics

Master Thesis Urban, Port and Transport Economics: The impact of COVID-19 on European ports an ARIMA approach

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"The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam."

1. Contents

1. Introduction

1.1 Introduction

In December of 2019 the first reports of a new type of virus became public. Within a few months the whole world knew what the virus was; COVID-19 (World Health Organization, n.d.). As of 11th of March 2020 the World Health Organization (WHO) declared it a pandemic. The impact of pandemics on the world economy is generally immense. The COVID pandemic forced whole sectors of the economy to shut down. Other effects of this pandemic were lockdowns of citizens and increased hospitalization (Ministerie van Algemene Zaken, 2021a). What followed was a stock market crash during the first months of 2020, whereby the Dow Jones lost more than 30 percent of its value in one month (figure 1) (Frazier, 2021).

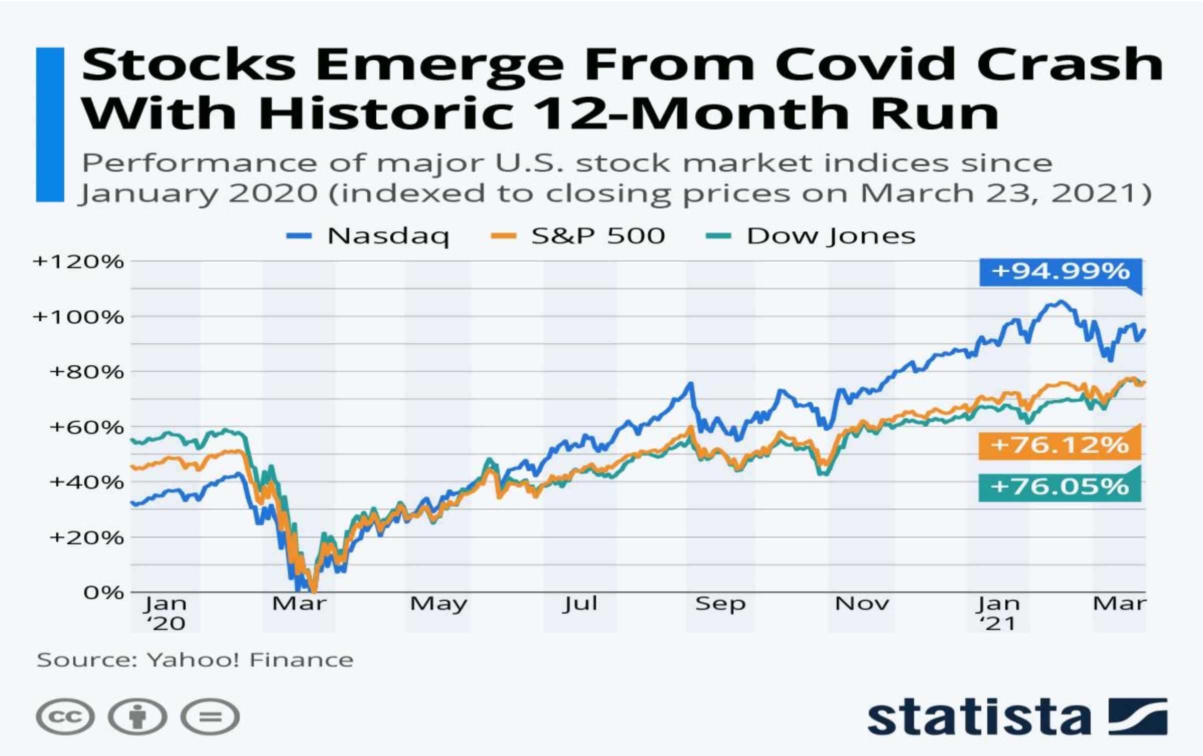

Figure 1, USA Stock market 2020-March 2021 (Yahoo! Finance & Statista, 2021)

The created uncertainty led to hoarding of long-lasting essentials by consumers (Islam et al., 2021). The hospitality industry saw a sharp decline in demand. Employees were forced to work from home. These effects caused a chain reaction in the logistical chain whereby some products or services saw a sharp decrease and other a sudden increase in demand.

The sudden massive shift of demand and supply in goods and services effected the standing supply chains significantly. Over the past two decades Asia has become the world's manufacturing hub. In the past, between 1962 and 2004, Rotterdam was the largest harbour in the world for 42 years, (*A History of the Port of Rotterdam*, 2016). Nowadays seven of the 10 biggest ports in the world by cargo volume are in China. The remaining three are in Singapore, the Netherlands, and South Korea. Modern supply chains rely on production of parts or modules in countries who can produce these as efficiently as possible. The result is that parts are assembled in pieces across the globe, with every component arriving just in time for the final product to be assembled. Resulting in low stockpiles and low risks when the value of their inventory is diminishing in value (e.g., computer chips as a result of Moore's law) (*Encyclopaedia Britannica*, z.d.). These supply chains are highly efficient but have become incredibly fragile as a result of the increased distance and lack of supplies. It takes longer to move goods from A to B, time to market must be considered. A disruption of only six days of the Suez Canal by the mega containership, EVER GIVEN, resulted over $1 billion in damages and losses. German insurer Allianz had said in a recent analysis that the blockage could bring down the annual global trade growth by 0.2 to 0.4% (*The Global Economic Impact of Suez Canal Blockage*, 2021). Of course, companies analyse their customers behaviour and try to predict what the demand is going to be, but when a large shock like a pandemic goes through this system, it takes time for companies to adjust.

1.2 Research question

This research is trying to connect data to an event (Covid Pandemic) and analyse the impact of this event on the economy. This is done by a reflection on the theory and analysing assembled data in that perspective. Lastly it aims to distal possible lessons to further enhance resilience of ports for such events in the future. These objectives have formulated the following overarching research question:

What has been the impact of the COVID-19 pandemic on container throughput of ports in the Northern European region and specifically Rotterdam?

1.3 Methodology and Scope

To try to answer this research question first literature was reviewed over economic shocks, pandemics and forecasting models. Then data was collected from different sources: DataStream, ISL and port authorities, and used in a forecast model SARIMA. The SARIMA model forecasts the container throughput using "historic data" and is used to forecast the expected throughput throughout the pandemic as if there was no pandemic. This is then used to compare the forecasted data to the actual data to determine the impact of the pandemic on the container throughput in those ports. The scope of this research are the container ports in the Hamburg-Le Havre range and the port of Rotterdam. The port of Singapore is used as a reference (transshipment port) outside the investigated area (end ports) to see possible differences. The monthly container throughput data from 2012 till 2020 is used. Because the data from the North Sea ports and Germany is percentual, the outcome of this research is to look if there is a percentual decrease in container throughput during the pandemic.

1.4 Overview of the report

This research starts with an overview of the literature, beginning with what economic shocks are, what kind of shock Covid caused, what kind of shapes shocks can have and the impact of COVID on the economy and ports. Subsequently the issue of container forecasting will be explained to compare the planned container flow with the real container flow to be able to detect the impact of COVID. In the chapter "Methodology" a closer look will be taken into different container forecasting models and why SARIMA has been chosen as the most appropriate model for this research. With the available data in the chapter "Analysis" a comparison can be made between the forecasted throughput and the real throughput. With other supporting facts a conclusion can be drawn with regards to the four different hypothesis which have been formulated at the end of the theoretical framework. Finally, the research question will be answered in the chapter "Conclusion and discussions", where also the limitations of the research and options for follow-on research will presented.

2. Review of the Literature

This chapter captures the research that has been done regarding the different topics with an impact on the research question. The aim of this chapter is to clearly define the underlaying topics and to offer background information. This review will also help to clearly define the hypotheses that will help to answer the main research question.

This review consists of the following topics:

- What is an external economic shock?
- What is the impact of covid on the economy?
- What is the impact of covid on ports?
- What kind of shapes of negative economic shocks can we distinguish?
- What kind of shape of shock has COVID caused on the economy?
- Can container forecasting help to explain the impact of economic shocks on ports?

These questions will be answered by a description or explanation and if possible, with an example. From a holistic perspective, economic shocks have widespread and often lasting effects on the macro economy. They are random, unpredictable events and may form the start of a recession. For this research it is helpful to get a clearer picture of this phenomena.

2.1. External shock.

Economic shocks can come from many different sectors. They can be derived from weather and natural disasters (Hurricane Katrina flooding in 2005), technology (e.g., IT) or politics (trade war). You could summarize it as an unexpected event that dramatically changes an entire economy's direction, either upward (value gains and job creation) or downward (value lost and job destruction).

An external economic shock is an unpredictable sudden event from outside the economy that will highly impact said economy (Weina & Tan, 2020). Examples for these are international conflicts, sharp increases of price of commodities or a pandemic outbreak. Simply said an external shock must be "exogenous", meaning that it comes from outside the economy instead of arising from developments within it.

“Endogenous“ shocks arise from within the economic system. A classic and recent example is India’s demonetization (Nazmi, 2019). Prime Minister Modi shocked Indians in November 2016 when he announced on live television that all 500 and 1000-rupee notes, equivalent to about £6 and £12, would be banned in four hours’ time. People were given several weeks to exchange their demonetized currency for new notes at banks. But new notes could not be printed fast enough, and the policy sparked a months-long currency crunch that left tens of millions of Indians cashless. This shock was caused by an economic policy. Therefore, it was shock from within the economy, including its policy formulation and governance system.

The effects of the Covid pandemic on the economy has been an external factor and is therefore classified as an external economic shock.

External economic shocks can be classified in several ways (Investopedia, 2021):

- Supply shocks
- Demand shocks
- Financial shocks
- Policy shocks
- Technology shocks

Each of these can be distinguished by where the economic shock originates from. Supply shocks can be classified as shocks that increases the price of production, e.g., an increase in the value of commodities used in production. Demand shocks are caused when consumer behavior changes in such a way that certain goods cannot be sold. Financial shocks are caused by the financial sector, the most recent example for that is the stock market crash of 2008 (The Economist, 2015). Policy shocks happen when political policies suddenly change. This can happen, for example, with a change in tax policy, but also with changing subsidies or a change in protectionism policy. Finally, there are technological shocks, where an economic shock can be triggered if technology revolutionizes production or behavior. In the case of the COVID pandemic it created a recession creating negative growth, at least for two consecutive quarters. The negative effects of economic shocks will provoke governments to react to diminish the negative effects. The shape of the shock – the so called “shock geometry” — indicates the damage to the economies and may lay bare its legacy on ports.

2.2 What kind of shapes of negative economic shocks can we distinguish?

Countries are subject to economic shocks; they affect prospects for growth and quality of life. The impact varies between countries as there are differences in economic structures, historical legacies, and policies, and in the resulting levels of vulnerability to economic shocks. Studies have shown that economic shocks produce political unrest in the form of anti-government protests and ethnic riots (Nurmanova, 2004-2019). The effects of an economic shock are specific to each country. The effectiveness of policy responses will depend on several different factors, such as the structure of its economy, its historical legacies and resulting levels of vulnerability. It is obvious that often a combination of measures is necessary to recover from an economic shock.

Downturns following the two banking crises were initially very similar. The difference occurred after about ten months (Eichengreen & O'Rourke, 2010). During the Great Recession there was a relatively quick recovery after ten months. Such a recovery did not occur during the Great Depression. The downturn would continue for another 25 months before a steady recovery set in. It is now generally recognized that the fundamental reason for this sharp contrast between these two crises was the different reactions of monetary and fiscal authorities (De Grauwe & Ji, 2020). In other words, authorities can influence the shape of the gross domestic product (GDP) curve after a shock.

At high level economic shocks can be presented in pictorial terms. The shapes of recessions and recoveries are frequently associated with letters such as V, U, L, and W (figure 2).
V-shaped economic crises are supposed to happen when the recession is large but very short-lived. U-shaped crises are characterized by a prolonged drop followed by a quick recovery.
W-shaped crises have a so-called relapse and an L-shaped crisis shows a permanent loss of output. The shape of the shock — what is called "shock geometry" — may indicate different progressions and recoveries (Carlsson-Szlezak et al., 2021). The most common shock recovery types: V, U and L are explained below using examples from the 2008 recession (Harvard business review, 2020):

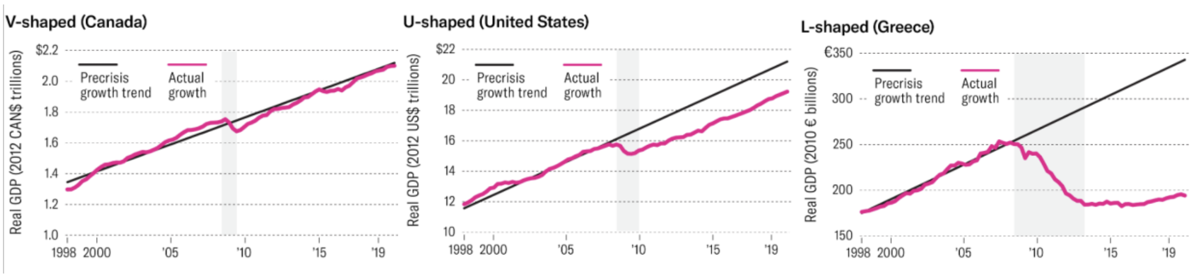

Figure 2. The global crisis in 2008 different shock shapes in terms of shock progression and recovery (Harvard business review, 2020).

A. *V-shape*. In 2008, Canada avoided a banking crisis: Credit continued to flow, and capital formation was not as significantly disrupted. Avoiding a deeper collapse helped keep labor in place and prevented skill atrophy. GDP dropped but substantially climbed back to its pre-crisis path. This is typical of a classic "V-shape" shock, where output is displaced but growth eventually rebounds to its old path.
B. *U-shape*. The U.S. crisis in 2008 showed a classic "U-shape" — a much more costly version than Canada's V-shape. Growth dropped precipitously and never rebounded to its pre-crisis path. Note that the growth rate recovered (the slopes are the same), but the gap between the old and new path remains large, representing a one-off damage to the economy's supply side, and indefinitely lost output. This was driven by a deep banking crisis that disrupted credit intermediation. As the recession dragged on, it did more damage to the labor supply and productivity.
C. *L-shape*. Greece is the third example and by far the worst shape — not only has the country never recovered to its prior output path, but its growth has rate also declined. The distance between old and new path is widening, with lost output continuously growing. This means the crisis has left lasting structural damage to the economy's supply side. Capital inputs, labor inputs, and productivity are repeatedly damaged. Greece can be seen as an example of L-shape, by far the most pernicious shape.

2.3 What kind of shape of shock has COVID caused on the economy?

One way to see what kind of shock Covid creates is by assessing the shocks that different crises create. Table 1 presents a taxonomy of crises and associated shocks, with the latter organized by their mechanism, scope, duration, and certainty.

Types of crises	Characteristics of shocks							
	Mechanism		Scope		Duration		Certainty	
	Supply	Demand	Domestic/ Regional	Global	Short	Long	Uncertain	Very uncertain
Pandemics	X	X	X	X		X		X
Wars	X	X	X			X		X
Macroeconomic crisis (e.g. hyperinflation)		X	X			X		X
International financial crises		X		X	X		X	
Natural hazards	X		X		X		X	

Table 1. Characteristics of economic shocks (Loayza et al., 2020a)

So, what drives "shock geometry" as shown above? The key determinant is the shock's ability to damage an economy's supply side, and more specifically, capital formation (Loayza et al., 2020b). When credit intermediation is disrupted and the capital stock doesn't grow, recovery is slow, workers exit the workforce, skills are lost, productivity is down. The shock becomes structural. V, U, L shocks can come in different intensities. A V-shaped path may be shallow or deep. A U-shape may come with a deep drop to a new growth path or a small one. Where does the coronavirus shock fit in so far? The intensity of the shock will be determined by the underlying virus properties, policy responses, as well as consumer and corporate behavior in the face of adversity. But the shape of the shock is determined by the virus' capacity to damage economies' supply side, particularly capital formation.

Keeping in mind the impact a pandemic had from chapter 2.2 and 2.3, the type of shock a pandemic has is heavily influenced by the policies that governments take. When the pandemic first started in 2020, governments in Europe hosted a large number of policies to alleviate the impact the pandemic will have on the economy.

These policies include support of credit such as guarantees for bank loans, particular for small- and medium-sized businesses (SMEs) (Anderson et al., 2021). Lockdowns were used to limit the spread of the virus. Lockdowns help reduce the spread of the virus but also limits the spending the people can do. This has the effect of a consumption reduction of 13 percent during the first Lockdown beginning from March 2020. Problematic for many companies is that although they cannot produce, they still had to employ their employees and pay them their salaries. This led to an increase of borrowed money, to help alleviate the problems therein European governments provided loan guarantees, tax deferrals, wage subsidies, grants and loan moratoria (Anderson et al., 2021).

Not only countries set funds for the recovery of the economy, but Europe did also. On the 23rd of April 2020, they agreed to establish an EU-recovery fund to help counteract the effects of the pandemic (Council of the EU and the European Council, 2021). The European countries agreed on the 21st of July that the overall budget for the recovery would be €1 824 billion for the years of 2021 to 2027. This was in addition to a safety net of €540 billion to help workers, businesses, and countries (Council of the EU and the European Council, 2021). These funds are intended to support the economy and prepare it for the post pandemic era. These measures are not expected to have an impact on the short term.

The policies mentioned here are for the general benefit of the economy and are mainly aimed at companies and employees but are not aimed at the flow of goods to and from ports. This is because the flow of goods depends not only on the domestic economy but also on the foreign/international economy. In addition, there may be a mock economy that is only kept afloat by political measures and not by its own stability. This has shown itself in the reduction of bankruptcies in the past year (Centraal Bureau voor de Statistiek, 2021). While the number of bankruptcies in the Netherlands stayed relatively stable from 2013 to 2020, it halved after the corona measures came into effect. In 2020 they were record low.

Because policies are so important for the eventual type of shock, it is difficult to forecast the exact shape because of all the supporting measures in the different countries. In my opinion both U and V shape shocks are possible, depending on the region and country, because of the enormous amount of economic aid being given by the individual countries to counteract the negative effects of the pandemic. The L-shape seems unlikely to me as all EU-countries have been supporting business to prevent them going broke and ending up with a high level of unemployment in the pandemic. The EU measures will take some time to have an influence. We can only know for sure which type of shock it is, when we can look back at the crisis and evaluate then.

2.4 Impact covid on the economy

It is obvious that pandemics have an impact on the economy, but what are the exact impacts? Broadly speaking, there will be a major fall in the GDP in the short term. For example, according to the Dutch CBS, GDP in the 2nd quarter of 2020 fell by 8 percentage points compared to a year earlier (CBS, 2021). This will then be compensated for by the adjustment of the economy to the new world position, so that to quarter 3 of 2020 there was only a 3 percent decline in the GDP compared to quarter 3 of 2019. The GDP reduction coincides with the introduction of the lockdown as a measure against the pandemic.

The precise impact of a pandemic on the economy mainly stems from the measures taken by governments, with lockdowns, closing of certain types of businesses and the introduction of health measures as wearing face masks. When people are no longer allowed to go to cafes or restaurants, a drop in the revenue they generate is seen. In the long term, this will partly be absorbed by other sectors such as do-it-yourself, IT, construction, etc. (Smith et al., 2009). However, this transition will take time for people but also for the supply chain to adept. Sectors anticipate a certain number of economic transactions. Changes due to economic shocks take time to catch up. This could be a trap for companies, namely the uncertainty of what the likely economic traffic will be. Since there is hardly any experience in this area, the estimates will be far from optimal. This change consumer behaviour is outlined in figure 3.

Next to the impact a pandemic has on the tangible economy, the pandemic also influences the capital markets. This effect comes from the inability of companies that cannot operate to fulfill their financial duties, like rent, mortgage, or current liabilities. These impacts could be mitigated by policies that governments can make. For example, in the Netherlands there is a nationwide economic aid for companies that face economic difficulties due to the pandemic (Ministerie van Algemene Zaken, 2021b). One problem with this is that the normal flow of the economy cannot be followed and that also businesses that are not economically viable get that economic aid. If a company cannot fulfill the expectations of their investors, then the values of their shares can drop. When this happens to a lot of companies at the same time, a capital crisis can occur, where investors do not want to invest into the economy because they do not feel they are profitable. Either because the returns are not high enough or because there is a high probability that the company, they invest in, will go bankrupt (Kotios et al., 2015).

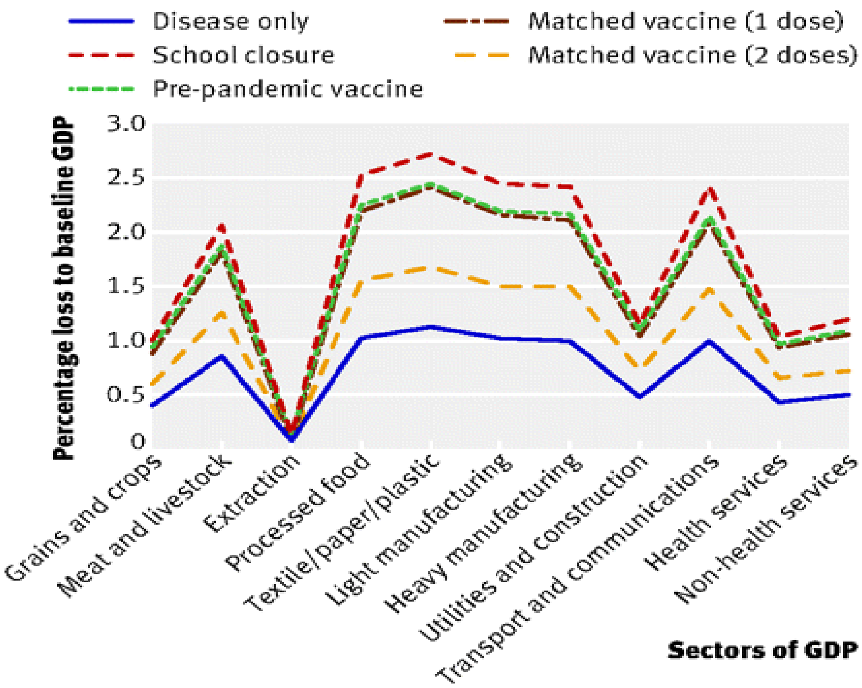

Figure 3, Impact of pandemic influenza on different economic sectors of UK gross domestic product (GDP) Impact of pandemic influenza on different economic sectors of UK gross domestic product (GDP) (Smith et al., 2009)

A supply shock is an economic shock that disrupts the supply side of the economy. With Covid, this is happening because many governments closed stores and discouraged working on location where it was possible to reduce chances of infecting others. There was also a reduction in available workforce because more of them were sick or in quarantine. As a result, many sectors had a decrease in production (Maiello, 2020). These events also disrupted the supply chain, making it difficult for sectors to obtain goods even if they were available.

A health risk that the public faces due to the pandemic is that of mental health. Due to the increased isolation, loss of income and uncertainty of the future, the average mental health has decreased (WHO, 2020). The decrease in mental health influences productivity due to an increase in sick leave. But also, if no extra sick leave is taken, productivity will decrease. This is addictive to the increase in sick leave due to directly corona related complaints.

All in all, when a pandemic hits an economy, it will resemble multiple type of shocks (table 2). There will be a supply and demand shock, due to a decrease in supply and a differentiation of demand. Financially there could be a shock due to the failing of financial obligations by companies and an increase of pessimism by investors. Also, a policy shock could happen due to restrictions or lockdowns, but there could also be policies that lessen the shocks like relief aid.

Crisis	Shock type				
	Supply	Demand	Financial	Policy	Technological
Pandemic	X	X	X	X	
War	X	X			X
Natural hazards	X				
International financial crisis		X	X		
Venezuelan monetary crisis				X	
Introduction of Internet					X

Table 2. Crisis linked to shock types.

2.5 Economic shocks and Ports

When the pandemic first began in 2020 the transport sector was not excluded from its effects, because the transport sector is highly connected to all kinds of other economic sectors. Transport is a derived demand and thus cannot be stored or sold later (Rodrigue, 2020). When stores cannot sell their products, they can lower their prices or wait with selling their products till the market is in a better shape for them. This is not possible with transportation. Also, transportation is not the end goal of a transaction. It is a means to get goods or people from points A to point B. In the transportation sector ports play a big part in transporting goods, since transport over water is relatively cheap and an easy way to move large amounts of goods, with the downside that it takes a lot of time (Union Pacific, 2019).

Countries took unprecedented containment measures, like lockdowns and social distancing, to prevent further outbreak of the Coronavirus disease (COVID-19). Countries introduced national and local restrictions for ports, including (International Chamber of Shipping, 2020):

a. Delayed port clearance.
b. Prevention of crew (or passengers where applicable) from embarking or disembarking (preventing shore leave and crew changes).
c. Prevention of discharging or loading of cargo or stores, or taking on fuel, water, food, and supplies; and
d. Imposition of quarantine or refusal of port entry to ships (in extreme cases).

But ports also introduced measures themself (Port of Antwerp, n.d.), (Port of Rotterdam, n.d.):

a. Working from home if possible.
b. All seagoing vessels are required to submit a Maritime Declaration of Health (MDoH) before arriving.
c. All events, receptions and non-essential training courses have been postponed or cancelled.

Not only affected these measures the economic and social activities in the ports but they also affected the global mobility patterns. Due to a decrease in available employees in the ports and the handling of goods in the hinterland, goods took longer to arrive or where very difficult to ship. This in some cases resulted in big congestions, for example with the Los Angeles port (Goodman & Luxen, 2021).

On average the transport sector saw a decline between 1 and 2.5 percent of its GDP (Smith et al., 2009). For ports specifically this varied but a study published in Nature noted an unprecedented slowdown in global shipping mobility, which was steadily increasing since 2016, and a noticeable activity decrease for all ship categories in 2020, when compared with projections (assuming the average growth rate of past years). The most affected traffic segment is that of passenger ships, followed by container ships. Effects of the pandemic on global ship mobility are observable since March until the end of June 2020, with variations ranging between −5.62 and −13.77% for container ships, between + 2.28 and −3.32% for dry bulks, between −0.22 and −9.27% for wet bulks, and between −19.57 and −42.77% for passenger ships (Millefiori et al., 2021).

As a result, it is no surprise that also the activity of ports is affected. The IAPH-WPSP Port Economic Impact Barometer One year report showed – by means of a survey – that in the period between early April and mid-July 2020 that container vessel calls were down by more than 5%. However, the situation improved considerably by September 2020 (week 36) to reach a much lower 28% (Safety4sea, 2021). The share of ports reporting reductions in other cargo vessel calls of more than 25% gradually decreased from 16% in week 21 to 4% in week 25, which is also far below the 12 to 15% observed throughout weeks 16 to 20. The worst situation was found in the passenger sector: 40% of the ports discontinued this type of operation.

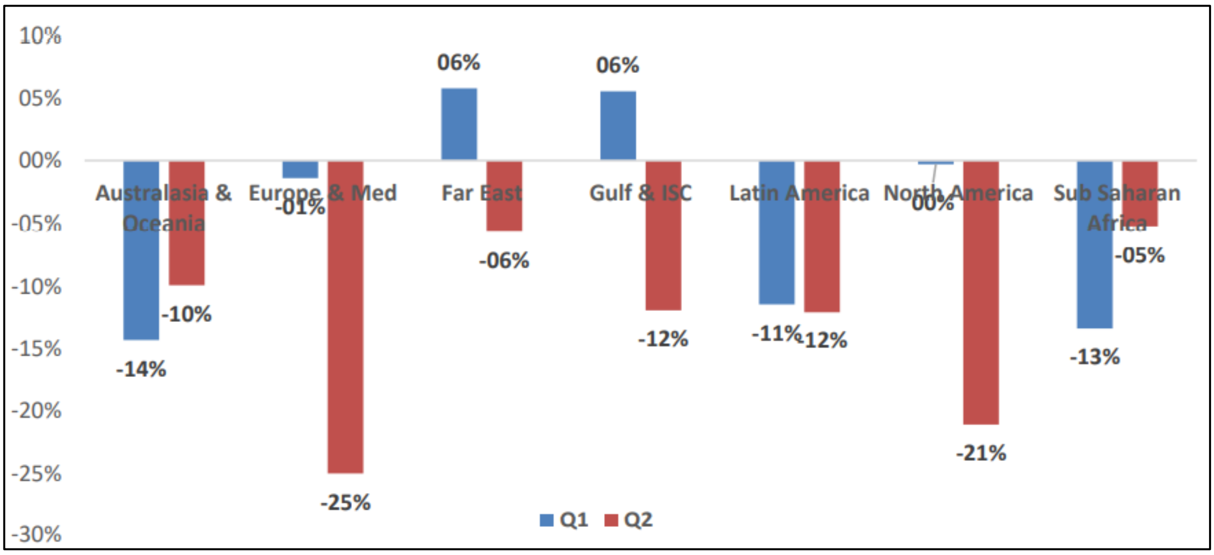

Figure 4, Total number of ship calls by region in 2020 (Percentage change over 2019), (UNCTAD, 2021).

Another good indication comes from the Automatic Identification System (AIS). Automated Identification System (AIS) data tracks and traces ship movements, and provides near real-time information on maritime transport. By tracking ships, AIS data can help identify underlying trends at an early stage (figure 4 and 5). By using AIS data - collected and provided by MarineTraffic – UNCTAD showed the impact of the COVID pandemic in her report: “COVID-19 and maritime transport: Impact and response” (UNCTAD, 2021).

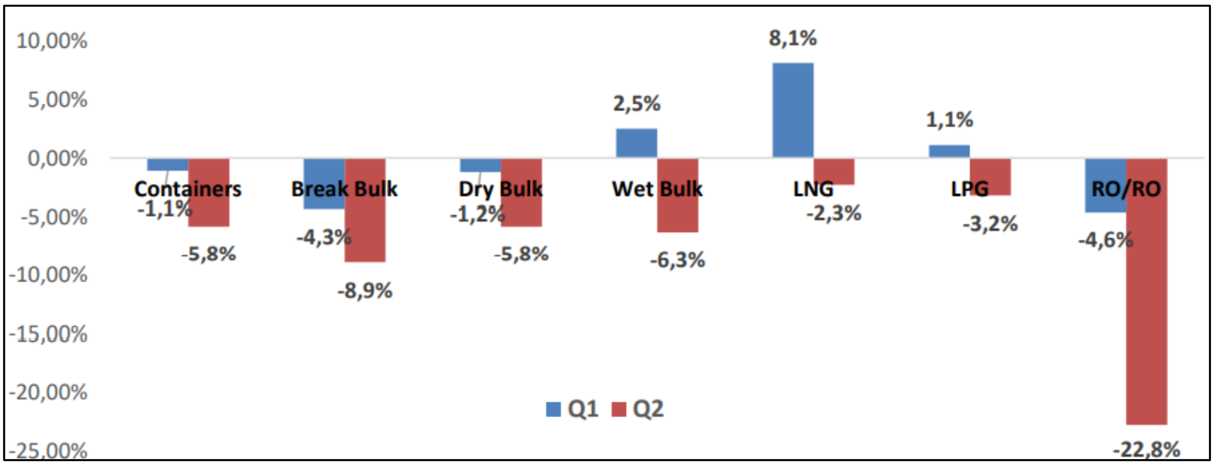

Figure 5: Total number of ship calls worldwide, by ship type in 2020 (Percentage change over 2019), (UNCTAD, 2021).

2.6 Container throughput forecasting

To examine the impact of the Covid pandemic, the actual container flow needs to be compared with the planned container flow if the pandemic had not happened. To know something that has not happened is not possible, therefor a proxy must be used. One possibility for such a proxy is that of container forecasting.

Presently, several container forecasting models are available. These models use data that is currently available to predict future container flow. These models cannot forecast an economic shock, such as caused by a pandemic. If a model can accurately predict the future of container flow in an uninterrupted economic situation, then that model probably will be able to make a good estimation of what would have happened to the container flow if the pandemic had not happened. Forecasting models work well in stable environments and may show only a cyclical or seasonal variance. However, if an external shock appears (COVID or blockage of the SUEZ canal) these models for forecasting will initially show the unaffected predicted flow, which will deviate from the actual flow. With some delay the models will take into account the new trend and should reflect the container flow more accurately again. That is why one of the conclusions of Peter de Langen, when he studied forecasting models, is that companies should be flexible when using container forecasting (de Langen, 2003) as the results may deviate from reality.

Two kinds of forecasting models can be distinguished. The first category uses statistics, such as GDP and current state of the economy to predict future container flow. These types of forecasting models are generally used for longer term planning - with planned data. The IMF for example uses models to estimate the future GDP for countries. This data can be used in regression models with or without dummies for seasonal or cyclical trends to forecast the container throughput for long term.

The second category uses only the current trend of container throughput. It assumes that there is a stationary growth and is more used for short term planning.

2.6.1 Regression models

Regression models are widely used to estimate data. De Langen did extensive research in what parameters influence the amount of container transport flows (de Langen, 2003). He identified 7 different components for this model, 4 economic factors and 3 factors that determine the containerized share of the transport flow. The economic factors included GDP, openness of the economy, the importance of the country as a trade partner and the value density. Containerized share of the transport flow is calculated by the composition of trade, the competitive position of the port and the containerization rate. With the inclusion of GDP, which has seen long term forecasting by the IMF, they try to find a reliable way to forecast long term container throughput. The IMF claims that the short-term volatility of GDP will disappear in the long run. This makes it possible to predict the long-term outcome of this model more accurately. However, this will not benefit the accuracy for short-term container throughput forecasting.

2.6.2 Classical and multiplicative decomposition model

The classical decomposition model is one of the first models used to forecast time models (Bowerman and O'Connel, 1993). This model uses four different components: trend, cyclical, seasonal and irregular. It is one of the simplest models used but also on of the most inconsistent, because of its assumption of keeping parameters constant over time (Dragan et al., 2014). These parameters are used in an additive way to compute the trend. The same model is also possible to be used with a multiplicative approach, this is a variation of the classical model with the assumption that the different components interact in a multiplicative way.

2.6.3 (S)ARIMA model

The SARIMA model is an enhanced version of the ARIMA model. The ARIMA model is a statistical model that tries to fit into a time series and can be used to estimate future data. The ARIMA model was first used by Box-Jenkins to combine a time series variable and a moving average. This method can be enhanced by the addition of seasonal variation which denotes to the SARIMA model. Multiple researchers have already used SARIMA models to forecast future container throughput in different areas of the world (Rashed et al., 2017), (Dragan et al., 2014) and (Zhang, 2021). Dragan et al's research focused on the best way to model container forecasting. Thereby comparing 5 different forecasting models. The conclusion of this report was that SARIMA gave the most accurate forecasts.

2.7 Hypotheses

Because of the impact pandemics have on the total supply chain, it is expected that a pandemic, such as covid, will have an effect on the container throughput. Therefor the following hypotheses are drawn:

- Hypotheses 1:
  - During the Covid-19 pandemic there is less container throughput than was expected in the ports in Northern Europe.
- Hypotheses 2:
  - During the Covid-19 pandemic there is less container throughput than was expected in the German Ports.
- Hypotheses 3:
  - During the Covid-19 pandemic there is less container throughput than was expected in the port of Singapore.
- Hypotheses 4:
  - During the Covid-19 pandemic there is less container throughput than was expected in the port of Rotterdam.

3. Methodology

This chapter first introduces the SARIMA model, why it is chosen to compute the data, how it works and how the results should be interpreted. After that an overview of the data is given, where the data came from, and what the different variables are.

3.1 The SARIMA Model

To understand the impact of the pandemic, it must be clear what the container throughput would have been if there had been no pandemic. The method chosen is to compare the measured data with the forecasted throughput. If a forecast is made over the time period that the pandemic covers, and it is not using the data during the pandemic then this can be seen as the container throughput that would have happened if there had been no pandemic. However, a number of conditions will have to be met. Firstly, the model must be able to make a precise forecast. This is guaranteed by first checking if the model is making a practice prediction in the period just before the pandemic. If this is a good fit, then we can assume that the model should be given the expected throughput during the pandemic. Secondly, the model must be able to take into account the cyclical or seasonal variations in container throughput over the years (e.g., impact of [Chinese] New Year) (Mansurov, 2021).

This research concerns short-term forecasting. Therefor a standard regression model is not suitable. Regression models have to make use of the magnitude and the growth of the economies with which the port is trading. In this case GDP is often used. As the growth of GDP is often unreliable in short-term forecasting, but stable in long-term forecasting, it is not possible to make an accurate prediction in the short term required for this research.

ARIMA is a good alternative for short-term forecasting. It combines autoregressive models (AR) with moving average models (MA) to forecast data (Hyndman & Athanasopoulos, 2021). An AR model is a model that forecast with the usage of its own previous data, while an MA model uses past forecasting errors to predict the future. This combines into an ARIMA (p, d, q) model whereby, p stands for the order of the autoregressive part, d for the degree of first differencing and q for the order of the moving average part. This standard ARIMA model is in this case supplemented with a seasonal component; SARIMA (p, d, q,) (P, D, Q,) m, whereby m is the number of observations there are in a year. Therefor we get an equation as follows:

$$(p - \phi_1 B)\,(P - \phi_1 B^m)(d - \phi_1 B)\,(D - \phi_1 B^m) = (q - \phi_1 B)\,(Q - \phi_1 B^m)$$

The parameters are found as follows (Hyndman & Athanasopoulos, 2021). First d is obtained by looking if the data is stationary, if it is, then d = 0. If this is not the case the data is differentiated and checked again for stationarity if this is the case, then d = 1. This process is repeated until stationarity is found. Then d is found by utilizing partial auto correlation (PACF). When PACF cuts off after x number of lags, then x is equal to d. At last q is obtained by looking at the auto correlation (ACF) of the differenced data. When ACF cuts off that is q. To check the fit of the ARIMA (p, d, q) model, different models are tested in the vicinity of the found p, d and q. Thereafter the received model is checked for seasonality (SARIMA).

To make the process of finding the model that fits best more efficient, it can be automated in “R” with the command; “auto.arima(dataset, seasonal = T)”, (whereby T is the seasonality) (Hyndman & Athanasopoulos, 2021). “R” is used in this research to analyse and process the data that is used (Annex 1).

3.2 Data

The variables used in the SARIMA models are that of “container throughput”. “Container throughput” measures the amount of container handlings of a port or a combination of ports, these include imports, exports, empty containers, and transshipments (Til, n.d.). The container throughput could be in twenty-foot equivalent unit (TEU) or as a chain index, a chain index refers the number of containers to a reference year which is set to 100. The monthly container throughput data from open sources is limited. Monthly data was found from three different regions and data for the port of Rotterdam was provided by the Port authority of Rotterdam (Table 3), (It should be noted that the North-Range data covers monthly data from the 15th to 15th, so January data is from 15 December to 15 January).

Location	Type of data	Data Source
North-Range	Chain index (2015 = 100)	ISL
Germany	Chain index (2015 = 100)	EIKON/DATASTREAM
Singapore	TEU (‘000)	Maritime and Port Authority of Singapore
Rotterdam	TEU	Port authority of Rotterdam

Table 3, Data sources

The different locations used are that of

- North-Range, which are the big container ports in the Hamburg-Le Havre range including Hamburg, Bremer(haven), Rotterdam, Antwerp, Zeebrugge and Le Havre;
- Germany, which include the total container throughput in German ports;
- Singapore;
- Rotterdam.

It is noted that, unlike the others, the data of the port of Rotterdam is not publicly available. While it is used no specific monthly statements will be made. The data used spans the time from 2012 to 2020. 2012 was chosen as the starting year because to form a good forecasting model it is necessary to exclude as many large shocks as possible. It has therefore been decided not to include the container throughput during and shortly after the economic crash of 2008.

For every dataset a yearly plot has been made to compare the graphs of the different years. These can be found in the following figures: Figure 6, Figure 7, Figure 8. The graphs reveal a seasonal trend in the month of February, in which a significant dip occurs in comparison with the months leading and following that month. In addition, there is an annual increasing trend in all 3 data sets. These two trends reinforce the assumption to use a SARIMA model in this study (as discussed in 3.1)

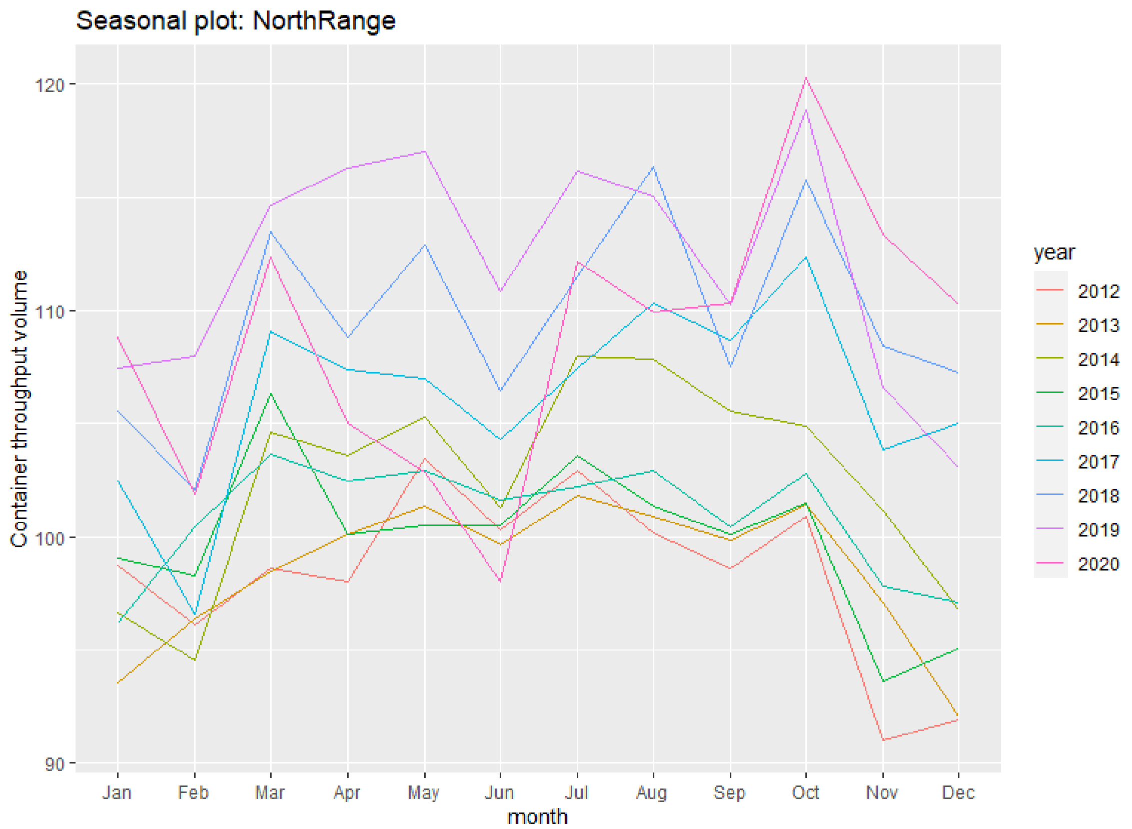

Figure 6, Seasonal plot for the container throughput in the North Range.

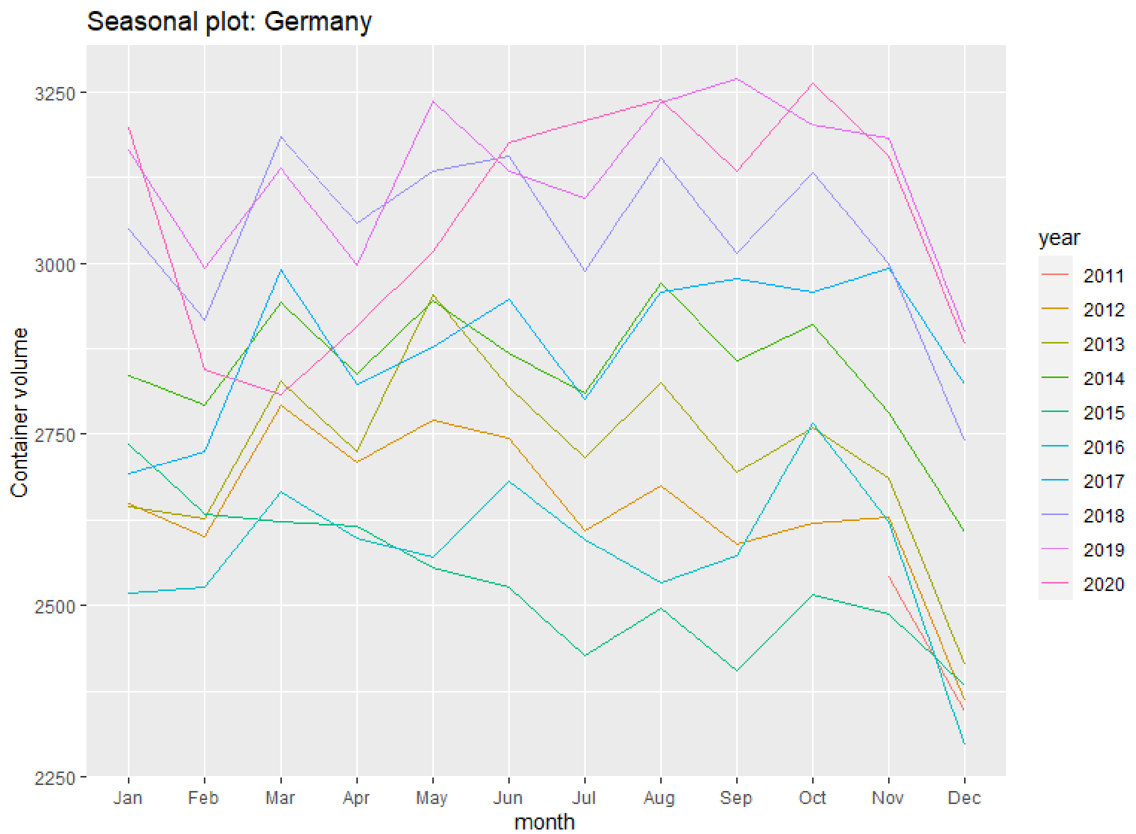

Figure 7, Seasonal plot for the container throughput in Germany.

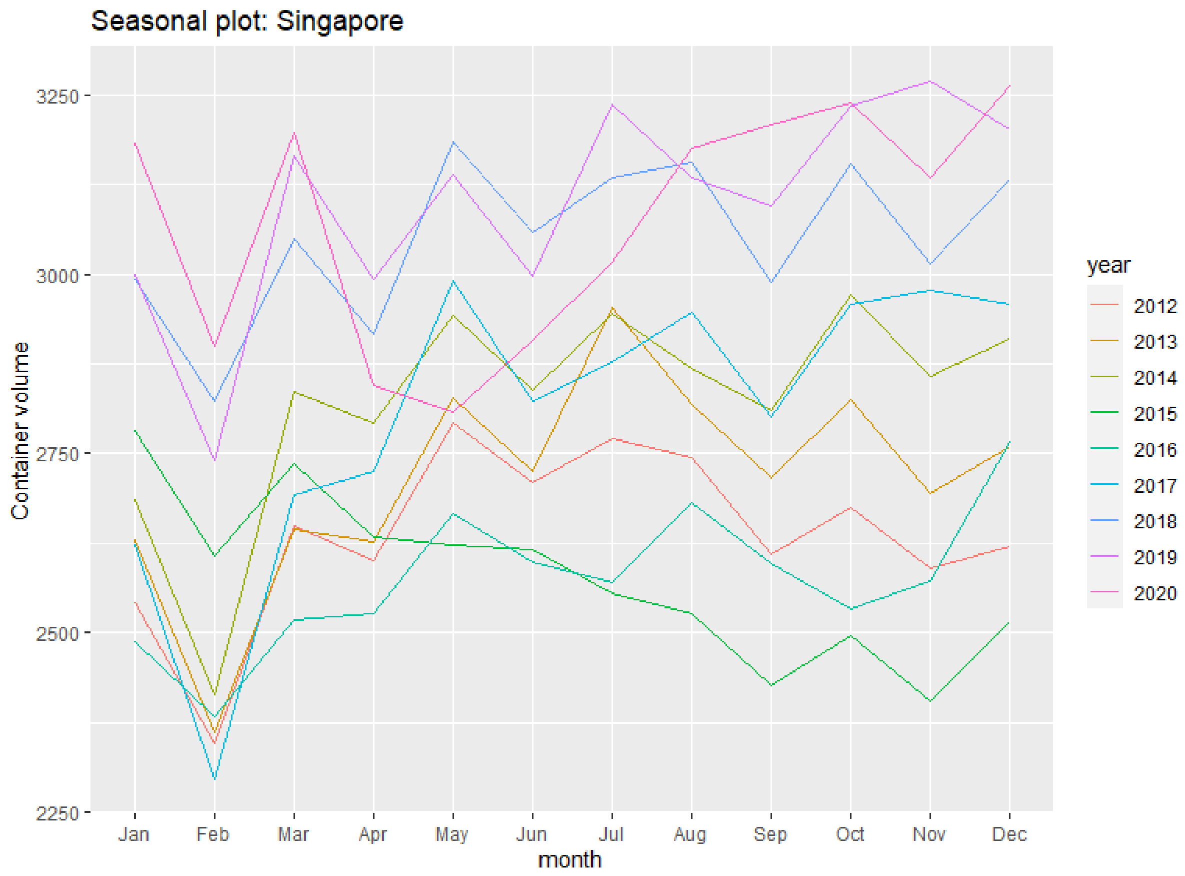

Figure 8, Seasonal plot for the container throughput in Singapore.

Some general observations can be made from these figures.

First of all, that there is a consistent yearly dip in February, when container handling drops to a minimum, this coincides with Chinese New Year, whereby a drop in production is seen in China.

Secondly container throughput reaches its yearly height during September/October, which probably coincides with the stock up of companies before the holidays and festivities in December.

A final concluding remark about the data is that data about container throughput is very difficult to get access to. For a limited number of harbours monthly data was publicly accessible, but weekly data or daily data for container throughput is almost nonexistent in open sources.

4. Data Analysis

To test whether there is an impact of the COVID-19 pandemic on container throughput, a forecasting model has been made for the different data samples. The forecasting model is based on the data from 2012 till 2018 to calculate forecasts for 2019 and 2020. The forecast of 2019 will be compared with the actual throughput from 2019 to see if the model delivers an acceptable fit, this is assessed by the "Mean Average Percentage Error" (MAPE) method. If there is an acceptable fit (MAPE is smaller than 5 percent), the forecasted data will be compared with the actual data from 2019 and 2020 to see if there is a significant impact. It should be noted that the "auto.arima function" in R returns a 0 differentiation (d=0) SARIMA model with chain index data. Due to two reasons the d=0 model was not used and set to an optimized d=1 model. The first reason is that there is a clear upward trend with the result that the data is not stationary and is not ready to be used in a SARIMA model. Secondly because the AIC value (the value that determines how good a model fits) is lower than the forced d=1 SARIMA model. The forced d=1 SARIMA model delivers thus a better fit then the d=0 SARIMA model.

4.1 North-Range ports

For the North-Range ports, as explained before, the time-series to become stationary was calculated with the "ndiffs" function with value 1. The resulting optimal model for this dataset became as follows: SARIMA(0,1,2)(0,1,1). This SARIMA model was used to forecast the throughput for 2019 and 2020 (Annex 2, Figure 9). In figure 9 the actual values and the forecasted data are compared in the same timeline; the blue line states the actual data and the orange line states the forecasted data. At the same time the MAPE value was calculated through measuring the average percentage error of every month in 2019, this came out to 4.1897 percent. This means that on average the fitted value is wrong by 4.2 percent. Therefore, as 4.2 percent is smaller than the 5 percent accepted differentiation. The conclusion can be made that this model is a reasonable fit and can be used for 2020. Using the same approach on the data in January 2020 the MAPE became more than 5 percent. This is also the case for February, April, May, and June. From July onwards, the real data matched the bandwidth of the 2019 forecasted data again. It is observed that the forecasted data was more than 10 percent higher than the actual data during the first half of 2020. This is the same period as the first Covid wave.

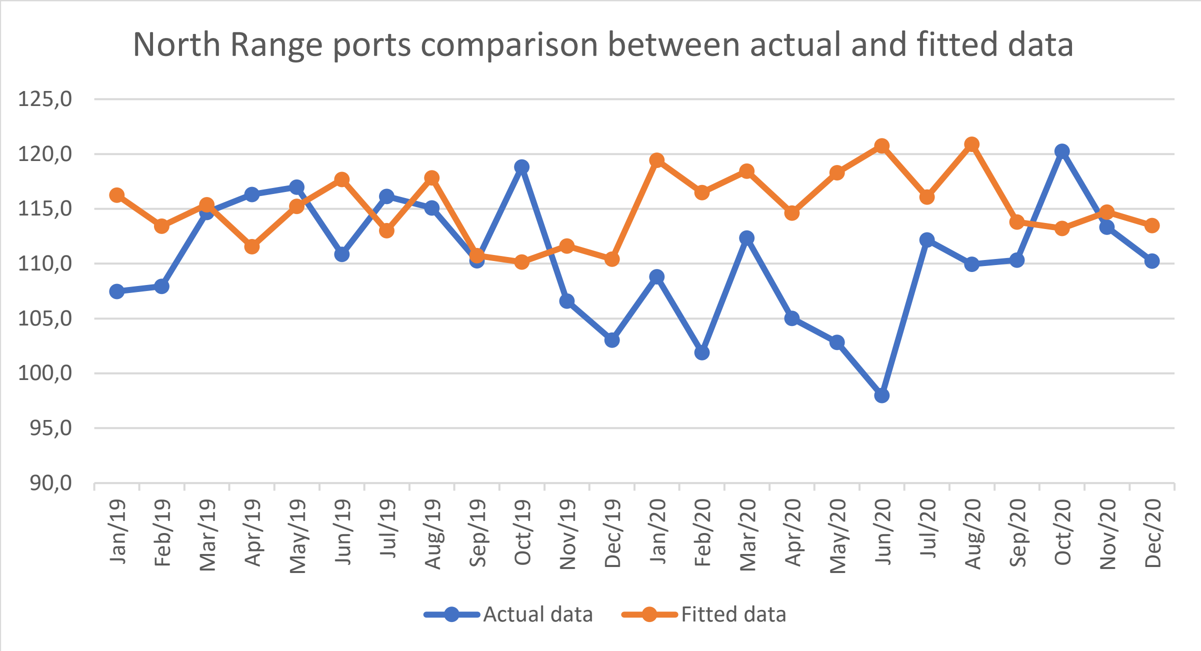

Figure 9, North-Range ports, comparison of the actual and fitted data.

Hypothesis 1: *During the Covid-19 pandemic there is less container throughput than was expected in the ports in Northern Europe.*

Given the following facts:

a. The first outbreak started in Wuhan, Hubei, China in November 2019 and the Chinese government imposed a lockdown on 23 January 2020 in Wuhan and other cities in Hubei in an effort to quarantine the center of an outbreak of COVID-19.
b. The lock down lasted until the beginning of April (Davidson, 2020).
c. The transport time for containers from China to Europe takes - via the maritime route which runs through the South China Sea, the Malacca Strait, the waters of the Indian Ocean and the Suez Canal - usually 30-48 days.
d. There are no other plausible facts for the container throughput dip observed.

The impact has been noted from February until July. The economic shock has a V-shape shock as the container throughput from July onwards seems to follow the predicted throughput again. The hypothesis is confirmed because there is a significant difference (> 5%) of the expected container throughput from February onwards of the throughput whereas this was not the case before the covid pandemic started.

4.2 German Ports

For the German ports, the same method as the North-Range ports has been used. The time-series, that was calculated with the "ndiffs" function, became stationary with a value of 1. The resulting optimal model for this dataset became as follows: SARIMA(2,1,0)(2,1,0). This SARIMA model was used to forecast the throughput for 2019 and 2020 (Annex 3, Figure 10). In figure 10 the actual values and the forecasted data are compared in the same timeline, the blue line states the actual data and the orange line states the forecasted data. At the same time the MAPE value came out to 2.5251 percent. This means that on average the fitted value is wrong by 2.5 percent. Therefore, the conclusion can be made that this model is a reasonable fit and can be used for 2020. Using the same approach on the data in 2020 the MAPE became more than 10 percent from February till June. It was observed that the fitted value was more than 10 percent higher than the actual value of the container throughput. This is the same period as the first covid wave.

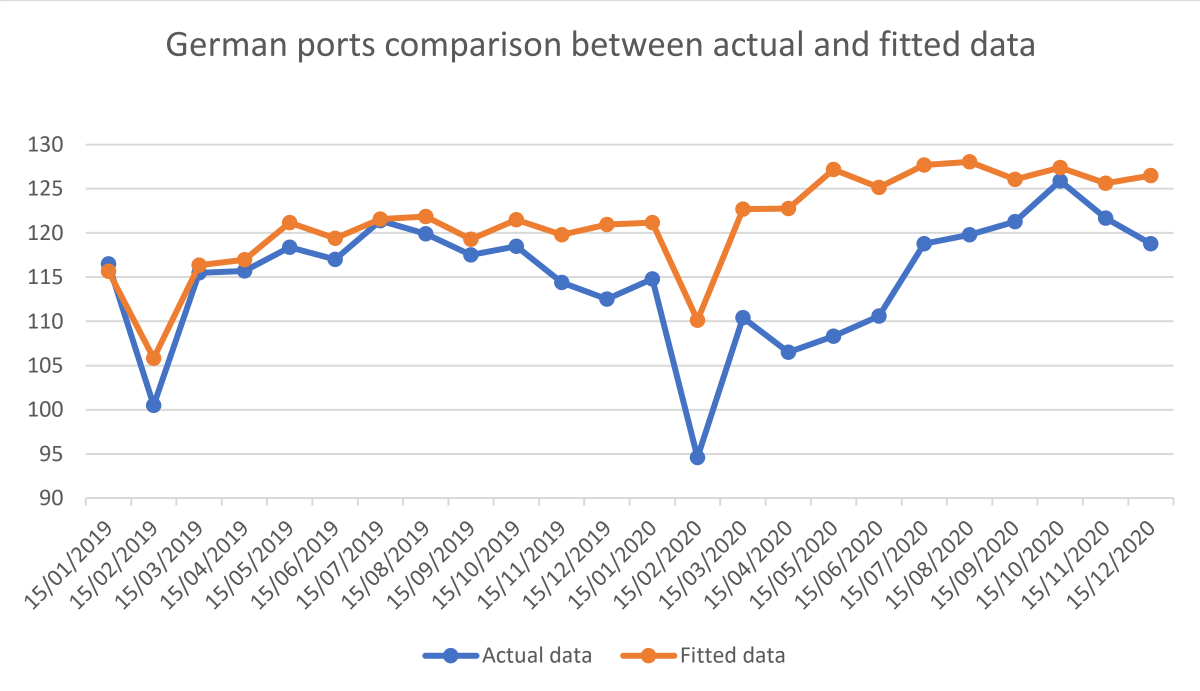

Figure 10. German ports, comparison of the actual and fitted data.

Hypothesis 2: *During the Covid-19 pandemic there is less container throughput than was expected in Germany.*

Given the following facts:

a. The first outbreak started in Wuhan, Hubei, China in November 2019 and the Chinese government imposed a lockdown on 23 January 2020 in Wuhan and other cities in Hubei in an effort to quarantine the center of an outbreak of COVID-19.

b. The lock down lasted until the beginning of April (Davidson, 2020).

c. The transport time for containers from China to Europe takes - via the maritime route which runs through the South China Sea, the Malacca Strait, the waters of the Indian Ocean and the Suez Canal - usually 30-48 days.

d. There are no other plausible facts for the container throughput dip observed.

The impact has been noted from February until July. The economic shock has a V-shape shock as the container throughput from July onwards seems to follow the predicted throughput again. The hypothesis is confirmed because there is a significant difference (> 5%) during the pandemic of the expected container throughput whereas this was not the case before the covid pandemic started.

4.3 Port of Singapore

For the port of Singapore, the time-series calculated with the “ndiffs” function, became stationary with a value of 1. The resulting optimal model for this dataset became as follows: SARIMA(0,1,1)(2,1,0). This SARIMA model was used to forecast the throughput for 2019 and 2020 (Annex 4, Figure 11). In figure 11 the actual values and the forecasted data are compared in the same timeline; the blue line states the actual data and the orange line states the forecasted data. At the same time the MAPE came out to 3.737 percent. Which means that on average the fitted value is wrong by 3.7 percent. Therefore, it is concluded that this model is a reasonable fit and can be used for 2020. Using the same approach on the data in 2020 the MAPE became more than 10 percent from April till August. It was observed that the fitted value was more than 10 percent higher than the actual value of the container throughput. This is the same period as the first covid wave.

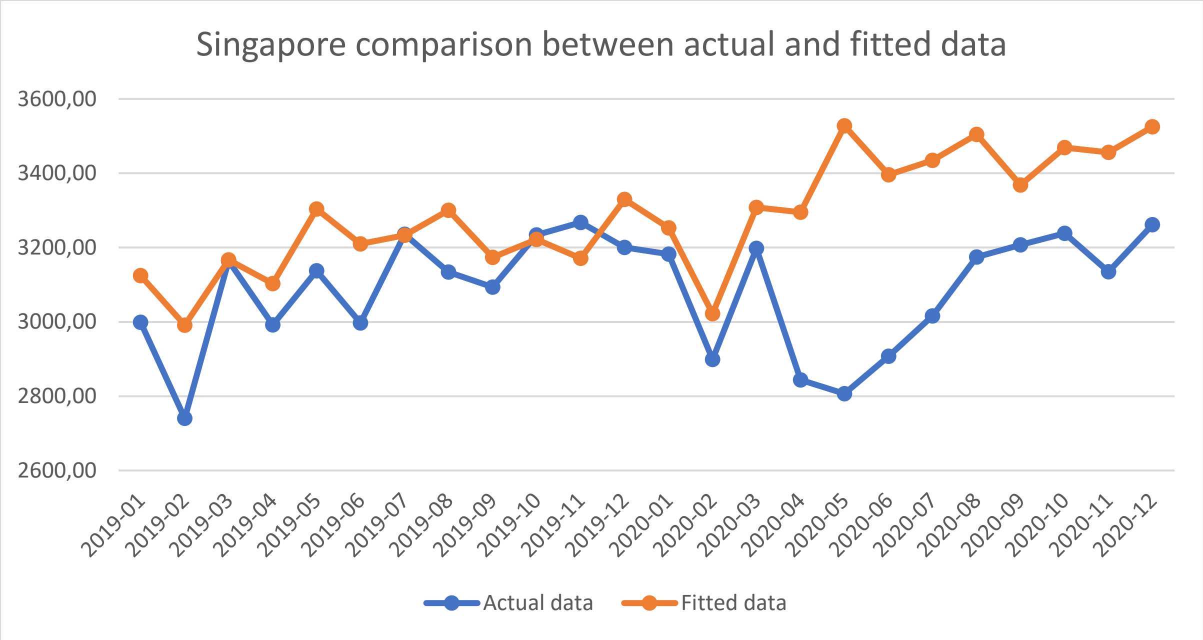

Figure 11. Singapore, comparison of the actual and fitted data.

Hypothesis 3: *During the Covid-19 pandemic there is less container throughput than was expected in the port of Singapore.*

Given the following facts:

a. The first outbreak started in Wuhan, Hubei, China in November 2019 and the Chinese government imposed a lockdown on 23 January 2020 in Wuhan and other cities in Hubei in an effort to quarantine the center of an outbreak of COVID-19.

b. The lock down lasted until the beginning of April (Davidson, 2020).

c. The transport time for containers from China to Singapore via the maritime route usually takes 5-14 days.

d. Singapore imposed a national lockdown from 7 April onwards (Beaumont, 2020).

e. There are no other plausible facts for the container throughput dip observed.

The impact has been noted from the beginning of April until August. The economic shock has a U-shape shock as the container throughput from July onwards seems to lag the predicted throughput from July onwards. The U-shape shows that the container throughput dropped and never rebounded to its pre-crisis path. The growth rate did recover (the slopes are the same), but the gap between the old and new path has remained and lost output over the time period.

The hypothesis is confirmed because there is a significant difference (> 5%) during the pandemic of the expected container throughput whereas this was not the case before the covid pandemic started.

4.4 Port of Rotterdam

As with the other 3 data sets, the “ndiffs” function was used to calculate stationarity, for Rotterdam this also resulted in a value of 1. The resulting optimal SARIMA model was a SARIMA (0,1,2) (1,1,0) model. This SARIMA model was used to forecast the throughput for 2019 and 2020 (annex 5, figure 12). In figure 12 the actual values and the forecasted data are compared in the same timeline, the blue line states the actual data and the orange line states the forecasted data. At the same time the MAPE value came out to an average of 5.6929 percent. This means that the discrepancy for this model is too high and not a good fit. This could be explained by the last 2 months of 2019 where there is significant dip in the container throughput. If the MAPE for the first 10 months is calculated, then the average is 4.275 percent, which gives a reasonable fit. Another reason why the model could be inconsistent is that on average the 2019 container throughput did not have the average increase it has been seen in the period 2012 till 2018.

The data of Rotterdam Harbour has a commercial classification and is not permitted to be released for public disclosure. Data is available for supervisors and will only be released to supervisors in a separate classified annex.

Figure 12. Rotterdam, comparison of the actual and fitted data.

Hypotheses 4: *During the Covid-19 pandemic there is less container throughput than was expected in the port of Rotterdam.*

Given the following facts:

a. The first outbreak started in Wuhan, Hubei, China in November 2019 and the Chinese government imposed a lockdown on 23 January 2020 in Wuhan and other cities in Hubei in an effort to quarantine the center of an outbreak of COVID-19.

b. The lock down lasted until the beginning of April (Davidson, 2020).

c. The transport time for containers from China to Europe takes - via the maritime route which runs through the South China Sea, the Malacca Strait, the waters of the Indian Ocean and the Suez Canal - usually 30-48 days.

d. The discrepancy for this model is too high and did not achieve an acceptable fit.

The hypothesis is not confirmed because the model is not accurate enough to draw solid conclusions. This is probably caused by of the inconsistency in the 2019 and 2020 data, which includes a drop in container throughput before the pandemic started (November 2019).

The initial observation for the port Rotterdam is that the type of shock seems to be a U-shape, keeping on overall an average decrease in container throughput of 15% from November 2019 till December 2020. However, as the model has no acceptable fit it is only a possible indication.

4.5 Concluding remarks

If in this research monthly data would be replaced with yearly figures, the data would be less revealing. For example, the impact the pandemic has from this research shows an average of 15 percent difference between the actual data and the forecasted data during the first COVID wave. In comparison the yearly decrease of the container throughput is “only” 1.2 percent [(total container throughput 2019 -/- total container throughput 2020) - 1].

There are a few statistical reasons why this difference is possible:

1. An annual percentage increase of about 3 percent in the model has been observed. To get a good comparison you need to add this 3 percent to the 1.2 percent reduction. resulting in a total difference of about 4.2 percent for 2020 than expected.
2. The Corona Pandemic is not aligned with a whole year, it only affected a part of a year (February – June),
3. Monthly data is highly volatile in comparison with yearly data, therefor monthly changes on average could be a lot higher than the yearly trend.

On average every port or combination of ports saw a decrease of 14 to 16 percent of the container throughput during the first part of the covid pandemic. The monthly maximum impact of the pandemic was 23 percent for the European ports and 25 percent for the port of Singapore in that period.

The impact the decrease of container throughput had on ports depends on what kind of recovery they have out of this economic shock. According to the theory discussed in 2.2, the long-term impact is related to whether the economic shock has a U or V shape. For the joint North-Range ports, the German ports and Singapore, the shock geometry has been a V shape. Therefor the long-term impact will not be significant. They will grow at the same pace and on the same path as they did before the pandemic, provided no other economic shock takes place. This is different for the port of Rotterdam since the economic shock seems to have a U-shape. This is likely to have a constant negative effect on the overall throughput figures in the long run. As a result, the long-term throughput figures will have to be recalculated to adjust the long-term view. The observation of the U-shape needs a proviso as the model did not show a good fit so this cannot be stated with certainty.

It is remarkable that the data of the port of Rotterdam shows a different pattern than the other data sets. The container throughput of Rotterdam started to decline already in November 2019 which cannot be linked to the Covid pandemic. According to the port authority, this dip in container throughput is due to declining industrial production in Germany (Port of Rotterdam, 2020), which led to cancellation of shipment from China in the period of November and December 2019. These industrial changes in the hinterland of Rotterdam can also explain why, for example the German ports didn't saw this decline. Rotterdam's hinterland contains the main German production center of North Rhine-Westphalia (NRW), while the German ports hinterland mainly consist of the rest of Germany

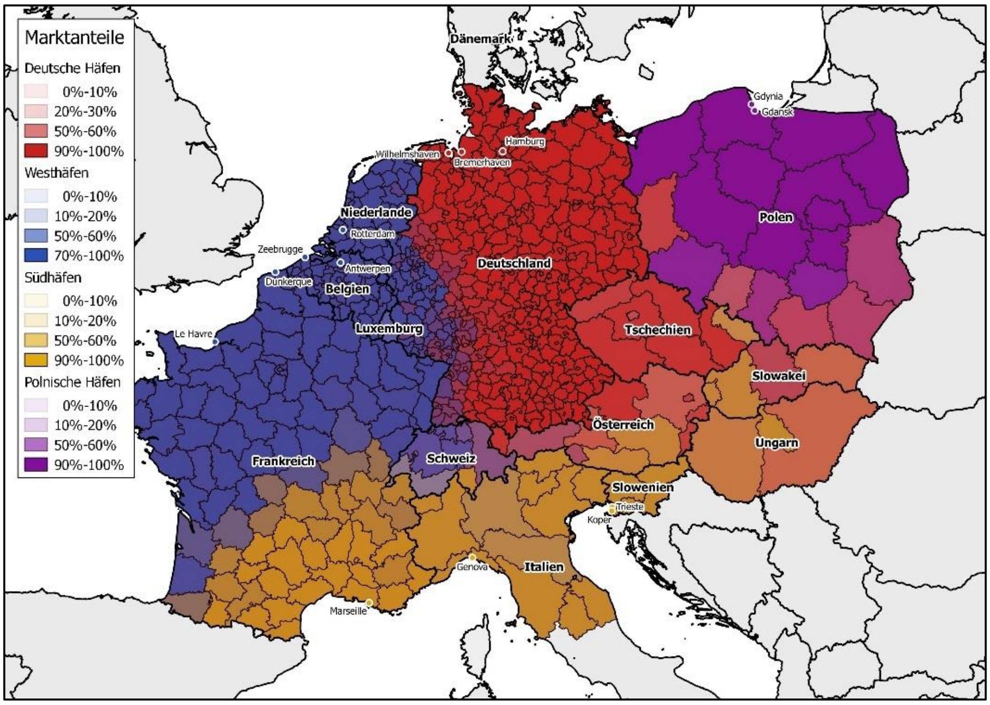

Figure 13. Hinterland shares of the different groups of ports (ISL, n.d.)

(ISL, n.d.) (figure 13).

NRW is home to the strongest industrial region in Europe and thus also of Germany (NRW.Global Business - Trade & Investment Agency, n.d.). Therefor it is possible that declining production in Germany may hit the container throughput in Rotterdam relatively harder in comparison with the German ports. The combination of declining industrial production in Germany and the COVID pandemic has resulted in a double economic shock. This makes it difficult to determine the precise impact of the pandemic on the port of Rotterdam.

5. Conclusion and Discussion

This research has been looking into the possibility of connecting data to an event and the impact of this event on the economy. The data of container throughput has been used to see if it is possible to detect the impact of the COVID pandemic. For this the following overarching research question has been formulated: "*What has been the impact of the COVID-19 pandemic on container throughput of ports in the Northern European region and specifically Rotterdam?*".

The economic theory has indicated that economic shocks can be caused by pandemics. Pandemics deliver a complex set of effects. Pandemics create a supply and demand shock, due to a decrease in supply and a differentiation of demand. Financially there could be a shock due to the failing of financial obligations by companies and an increase of pessimism by investors. Also, a policy shock could happen due to restrictions or lockdowns, but there could also be policies that lessen the shocks like relief aid.

To investigate the effects on container throughput in this study the SARIMA model has been used. The SARIMA model is the more suitable model for short-term forecasting, as it combines autoregressive models (AR) with moving average models (MA) and a seasonal component to forecast the container throughput data.

After the onset of the pandemic, the real data showed on average a 15% deviation (lower) of container throughput than predicted during the first COVID wave for every port or combination of ports (Rotterdam, Singapore, North-range and German ports). The maximum monthly deviation between the real data and the expected data in that period was 23% for the northern European ports and 25% for the port of Singapore. There was also a difference in when the pandemic started to have effect on the container throughput. In Northern Europe it started to have an impact from February 2020, this overlaps with when Covid lockdowns first started in Europe. Singapore deviation from the forecasting model started in April 2020 which coincides with the introduction of a Covid lockdown in Singapore.

Rotterdam has an inaccurate SARIMA model because 2 economic shocks have overlapped, the decline in industrial production in Germany and the COVID pandemic, so it is not possible to determine a precise impact of the pandemic. It seems that the economic shock is taking a U-shape, but this cannot be stated with certainty.

The data from Rotterdam is also included in the data from the North-Range ports. Because Rotterdam is for container throughput the largest of Europe and thus from the North-Range ports, it has a large effect on the data from the North-Range ports. Rotterdam seems to have a U-shape economic shock geometry while the North-Range ports as a whole seem to have a V-shape geometry. Therefore, it could be possible that the other North-Range ports have a much more positive impact than currently is visible. The relationship between the different ports requires additional research into the data from individual ports. Although the data from the port of Rotterdam was included in this dataset, it is not possible to make a good model with the data from the port of Rotterdam itself. The North-Range ports model is a good model despite the inclusion of the data from Rotterdam because the data from the port of Rotterdam is sufficiently diluted.

In all pre-pandemic datasets there was a yearly percentual increase in container throughput which was relatively constant. I expect that because of the U and V shaped shocks, the annual percentage increase in container throughput will resume to pre-pandemic levels of growth ceterus paribus.

This conclusion of the research has the following shortcomings:

a. Due to limited public availability of data, this research has only been focussed on North European harbours, Singapore, and Rotterdam.
b. Open-source data of container throughput is hardly available on a monthly interval. Mostly only data of yearly intervals are available of container throughput because the data is competitive-sensitive for harbours.
c. This research has not looked at structural effects and long-term impacts. Neither has it looked at indirect effects. The research focussed on detecting direct short-term effects on container throughput.

d. An interesting observation has been made with regards to the throughput of Rotterdam harbour. A decrease in container throughput has been detected from November 2019. The COVID pandemic did not start until February 2020 so this decrease was not caused by the covid pandemic. Herein lies a possibility for further investigation.
e. The yearly dip in February in container throughput seems to be a result of the Chinese New Year celebrations. It has no relation with COVID.

6. Epilogue

In August of 2020, I started with my Master and immediately started to search a subject for my thesis. Importantly was to find a subject which needed quantitative research to apply the theory read in the past 1.5 years.

The past two years the world is confronted with the COVID pandemic. Given my interest in port economics, I decided to have a deeper look into at the effects of the COVID pandemic on container throughput. My biggest challenge was to formulate a theoretical lens to investigate my research question. What I have learned is that a pandemic influences the economy in a particularly complex way. Establishing a clear link between cause and direct effects is not easy. You have to accept that you can only draw conclusions from a higher order level.

Without the help of others, I would not have been able to make this thesis. First of all, my thanks go to Martijn Streng, my mentor. In these special times, in which interaction was primarily done via email and ZOOM due to Covid-19, it was nice to know that I could rely on him to review my concepts and get his feedback in short time. I am grateful to him for his critical and constructive comments and the suggestions he has made for improvements. Martijn Streng, thank you very much, I couldn't have wished for a better supervisor.

I also want to thank the port of Rotterdam and especially Frank van der Laan for providing the container throughput data for the port of Rotterdam. Without this data my research was a lot less interesting. Not only as the effects of Rotterdam deviated from other Ports, but Rotterdam is also the port where my university is located. Hopefully the research may deliver some benefits for Rotterdam, a harbour to be proud of.

My parents, both with a busy job, have always shown an interest in my study, and they always made time to support me with my dilemma's and correcting my "Denglish" (Dutch English). Dear "mama" and "papa", thank you for your interest in everything I do and for your unconditional support and trust.

Finally, I would like to thank my girlfriend, Nienke, for giving me the time to write my thesis and my hobby of refereeing hockey matches in the top league of the KNHB. While you were having a “nice evening” or studying, I was completely withdrawn working on my thesis. You have always supported me, thank you for everything and especially for the fact that you are always there for me.

Haarlem
December 19th, 2020
Maurits Veen

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8. Annex

8.1 Annex 1; R code for SARIMA model

1. library("xlsx")
2. library("fpp2")
3. library("readxl")
4. library("ggfortify")
5. library("tseries")
6. Data1 <- read_excel("the data source", "Sheet1", col_types = c("date" , "numeric" , "numeric"))
7. myts <- ts(Data1[, c(2)], start=c(2011, 11), end=c(2018, 12), frequency=12) #setting the data to a time series, including which data is used in the arima model
8. ggseasonplot(myts) + ylab("Container volume") + xlab("month") #a yearly plot for container throughput
9. autoplot(myts) + ylab("Container throughput volume") + xlab("month") #a total plot of container throughput
10. ndiffs(myts) #see how many differentiations are needed for stationary data.
11. auto.arima(myts, d=1, seasonal="true") # automatic arima model created
12. fit1 <- Arima(myts, order=c(2,1,0), seasonal=c(2,1,0), include.drift = FALSE) #enter the values that come from the Auto.Arima line to complete the arima model
13. checkresiduals(fit1) #checking if the residuals are white noise
14. pred <- (forecast(fit1)) #forecasting the data from the arima model to the next 2 years.
15. print(pred) #data of the forecasting of the arima model.
16. autoplot(pred)

8.2 Annex 2; North-Range ports SARIMA model data comparison

Date	*Actual data*	*Forecasted Data*	*MAPE*
Jan/19	107,5	116,26	0,0817
Feb/19	107,9	113,42	0,050649
Mar/19	114,7	115,37	0,005971
Apr/19	116,3	111,55	0,041058
May/19	117,0	115,23	0,014964
Jun/19	110,9	117,69	0,061677
Jul/19	116,1	113,01	0,026988
Aug/19	115,1	117,83	0,023896
Sep/19	110,3	110,73	0,004215
Oct/19	118,8	110,15	0,073068
Nov/19	106,6	111,62	0,04711
Dec/19	103,0	110,41	0,07147
Jan/20	108,8	119,45	0,09758
Feb/20	101,9	116,49	0,143275
Mar/20	112,3	118,44	0,054302
Apr/20	105,0	114,62	0,091447
May/20	102,8	118,31	0,150544
Jun/20	98,0	120,76	0,232554
Jul/20	112,2	116,08	0,034734
Aug/20	110,0	120,90	0,099467
Sep/20	110,3	113,80	0,03152
Oct/20	120,3	113,22	0,058555
Nov/20	113,4	114,70	0,011861
Dec/20	110,2	113,49	0,02945

8.3 Annex 3; Germany SARIMA model data comparison

Date	*Actual data*	*Forecasted data*	*MAPE*
15/01/2019	116,5	115,7	0,00726
15/02/2019	100,5	105,8	0,052944
15/03/2019	115,5	116,3	0,007301
15/04/2019	115,7	117,0	0,010887
15/05/2019	118,4	121,2	0,023297
15/06/2019	117	119,4	0,020368
15/07/2019	121,4	121,6	0,001467
15/08/2019	119,9	121,9	0,016415
15/09/2019	117,5	119,3	0,015359
15/10/2019	118,5	121,5	0,02527
15/11/2019	114,4	119,8	0,047224
15/12/2019	112,5	121,0	0,075215
15/01/2020	114,8	121,2	0,055389
15/02/2020	94,6	110,1	0,164271
15/03/2020	110,4	122,7	0,111516
15/04/2020	106,5	122,8	0,152805
15/05/2020	108,3	127,2	0,174293
15/06/2020	110,6	125,2	0,131796
15/07/2020	118,8	127,7	0,074843
15/08/2020	119,8	128,1	0,068914
15/09/2020	121,3	126,1	0,039187
15/10/2020	125,9	127,4	0,011948
15/11/2020	121,7	125,6	0,032429
15/12/2020	118,8	126,5	0,064786

8.4 Annex 4; Singapore SARIMA model data comparison

Date	*Actual data*	*Forecasted Data*	*MAPE*
2019-01	2999,11	3124,48	0,041802
2019-02	2740,53	2991,208	0,09147
2019-03	3163,90	3166,714	0,000888
2019-04	2992,13	3102,822	0,036995
2019-05	3137,76	3303,974	0,052971
2019-06	2996,99	3209,555	0,070927
2019-07	3235,35	3233,243	0,000652
2019-08	3133,74	3299,974	0,053046
2019-09	3093,86	3174,058	0,025923
2019-10	3234,40	3221,961	0,003845
2019-11	3267,70	3171,187	0,029535
2019-12	3200,17	3329,403	0,040384
2020-01	3182,60	3252,598	0,021994
2020-02	2898,69	3021,75	0,042455
2020-03	3197,88	3307,856	0,034391
2020-04	2843,48	3294,802	0,15872
2020-05	2806,72	3527,86	0,256933
2020-06	2907,67	3396,293	0,168046
2020-07	3016,32	3434,622	0,13868
2020-08	3174,70	3504,167	0,103781
2020-09	3207,67	3368,206	0,050047
2020-10	3238,69	3469,333	0,071214
2020-11	3134,65	3456,53	0,102686
2020-12	3261,83	3525,251	0,080757

8.5 Annex 5; Port of Rotterdam SARIMA model data comparison (classified)

Will be transmitted separately, only accessible for supervisor and second readers.