Abstract
Port policy makers rely on demand traffic forecasts to support the decisions related to operation and future port infrastructure investments. It is a challenge to match capacity to demand. On the one hand, they face the risk of costly excess capacity, and on the other hand, under-capacity causes loss of market share.

In addition, the volatility and uncertainty of the global economy, and, consequently, of the maritime trade and port sector impose a challenge to modelling and forecasting container throughput. The main research question of this thesis is which model to use to forecast the container throughput at the port level?

The aim of the thesis is to provide an instrument to support stakeholders in making short-term operational decisions and long-term planning and investment decisions. This is achieved by developing quantitative models using a time series approach that analyses, identifies and quantifies the relationship between economic activity and container throughput at the port level.

Forecasting the number of TEUs at the port level in the short-term assists in the planning of the operational decisions such as the port capacity utilisation, loading and unloading planning, handling of containers and hinterland connections capacity. In comparison, the long-term forecasting is useful to assess the future infrastructure investment decisions. Application to other ports is feasible taking into account the specific characteristic of each port’s location and the country’s macroeconomic indicators.

Throughout the thesis, the analysis incorporates the 2008 financial crisis in the modelling process, which has the advantage of providing insight into the data generating process and the impact of the crisis. Moreover, the analysis identifies leading indicators with time lag that enable improving the monthly container throughput forecast. Combining different scenarios and the ARDL model provides reliable long term forecasts.

The findings show that for the short-term, the EU18 industrial confidence indicator and the index of industrial production are leading the container throughput at the Port of Antwerp. For the long-term, the elasticity of the container throughput in the Hamburg-Le Havre range to trade indices is about 1.4 on average.
Container Throughput Modelling and Forecasting: An Empirical Dynamic Econometric Time Series Approach

Thesis submitted in order to obtain the degree of Doctor in Applied Economics

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Yasmine Rashed
Abstract

Port policy makers rely on demand traffic forecasts to support the decisions related to operation and future port infrastructure investments. It is a challenge to match capacity to demand. On the one hand, they face the risk of costly excess capacity, and on the other hand, under-capacity causes loss of market share.

In addition, the volatility and uncertainty of the global economy, and, consequently, of the maritime trade and port sector impose a challenge to modelling and forecasting container throughput. The main research question of this thesis is **which model to use to forecast the container throughput at the port level?**

The aim of the thesis is to provide an instrument to support stakeholders in making short-term operational decisions and long-term planning and investment decisions. This is achieved by developing quantitative models using a time series approach that analyses, identifies and quantifies the relationship between economic activity and container throughput at the port level.

Forecasting the number of TEUs at the port level in the short-term assists in the planning of the operational decisions such as the port capacity utilisation, loading and unloading planning, handling of containers and hinterland connections capacity. In comparison, the long-term forecasting is useful to assess the future infrastructure investment decisions. The empirical analysis is carried out for the port of Antwerp. Nevertheless, application to other ports is feasible taking into account the specific characteristic of each port’s location and the country’s macroeconomic indicators.

Throughout the thesis, the analysis incorporates the 2008 financial crisis in the modelling process, which has the advantage of providing insight into the data generating process and the impact of the crisis. Moreover, the analysis identifies leading indicators with time lag that enable improving the monthly container throughput forecast. Combining different scenarios and the ARDL model provides reliable long term forecasts.

The findings show that for the short-term, the EU18 industrial confidence indicator and the index of industrial production are leading the container throughput at the port of Antwerp. For the long-term, the elasticity of the container throughput in the Hamburg-Le Havre range to trade indices is about 1.4 on average.
Abstract

Beleidsmakers in de havens hebben nood aan vraagvoorspellingen om hun beslissingen met betrekking tot operaties en toekomstige investeringen in de haveninfrastructuur te onderbouwen. Het is namelijk een uitdaging om de capaciteit te laten overeenstemmen met de vraag. Enerzijds lopen ze het risico op dure overcapaciteit, anderzijds veroorzaakt ondercapaciteit het verlies van marktaandeel.

Daarnaast vormen de volatiliteit en onzekerheid over de globale economie, en dus over de maritieme handel en de havenindustrie, een uitdaging om de containeroverslag te modelleren en te voorspellen. De belangrijkste onderzoeksvraag van deze thesis is welk model moet gebruikt worden om de containeroverslag op havenniveau te voorspellen?

Het doel van deze thesis is een instrument te verschaffen om de belanghebbenden te ondersteunen bij het nemen van operationele beslissingen op korte termijn en plannings- en investeringsbeslissingen op lange termijn om zo met de onzekerheid over de toekomstige vraag om te gaan. Dit wordt bereikt door kwantitatieve modellen te ontwikkelen vanuit een tijdreeksenadering, die de relatie tussen de economische activiteit en de containeroverslag op havenniveau analyseren, identificeren en kwantificeren.

Het aantal TEU op havenniveau op korte termijn voorspellen helpt bij de planning van de operationele beslissingen zoals het gebruik van de havencapaciteit, de laad- en losplanning, de behandeling van containers en de capaciteit van achterlandverbindingen. Daarnaast is voorspellen op lange termijn nuttig om de toekomstige investeringsbeslissingen over de infrastructuur te beoordelen. De empirische analyse werd toegepast op de haven van Antwerpen. Desalniettemin is toepassing op andere havens mogelijk omdat er rekening gehouden kan worden met de specifieke eigenschappen van de locatie van elke haven en de macro-economische indicatoren van het land.


De resultaten tonen aan dat de vertrouwensindicator van de industriële sector in de EU18 en de index van de industriële productie de containeroverslag in de haven van Antwerpen op korte termijn voorspellen. Voor de lange termijn is de elasticiteit van de containeroverslag met betrekking tot de handelsindices in de Hamburg - Le Havre range gemiddeld 1,4.
Executive Summary

The port sector is closely related to the changes in the global economic activity and international trade. The global financial crisis in 2008 had a significant impact on the ports’ activities. Moreover, the current changes in oil prices and the decline in the Chinese growth will affect the freight traffic to the port sector. Hence, following the evolutions of the economic activity allows forecasting the demand side. On the supply side, the port capacity plays a crucial role in the competitive position of the port in order to meet demand, avoid congestion, and hence, decrease the cost and time lost at the port and increase productivity. This is of importance to all the stakeholders: the shipping lines, port authority, shippers, terminal operators, and investors. However, the decision to provide new capacities and investments in the port should be supported by a growing potential demand. Therefore, port decision makers rely on demand traffic forecasts to support decisions related to operation and investment.

In the thesis, quantitative models using a time series approach are developed that analyse the data generating process (DGP) of the container throughput, identify leading indicators, and quantify the relationship between economic activity and container throughput at the port level. The main research question of this thesis is **which model to use to forecast the container throughput at the port level?**

The purpose of this thesis is to provide an instrument to support the decisions of policy makers and stakeholders, whether in public or private institutions, for the short and long-term planning and investment decisions in the port sector. Port planners should act ahead of any anticipated congestion problem. The short-term forecasts assist in the planning of the operational decisions, such as the port capacity utilisation, equipment and handling of container activities and hinterland connections capacity provision. In comparison, the long-term forecasting is useful to assess the future infrastructure investment decisions.

The methodology adopted in the thesis is a step-wise time series analysis applied to the port of Antwerp. In the first step, a univariate time series model is estimated – an autoregressive integrated moving average (ARIMA) intervention model – using monthly container throughput measured in TEUs. Moreover, the structural break of the financial crisis in 2008 is incorporated in the model. That provides the advantage of analysing the behaviour of the time series during and after different types of shocks and identifying the impact and magnitude of such shocks. The implications for the port of Antwerp are twofold. First, the short-term monthly forecasts in TEUs provide a reliable instrument for the port to plan operational decisions and to avoid congestion at the port and at the hinterland connections. Second, the shocks discussed are modelled differently according to the cause and impact of the shock. Hence, the port policy makers learn from these shocks. For example, the high peak in March 2002 that was caused by a change in the market
share had an effect of about 10.4% increase in the mean of the container throughput. The 2007 new developments in the port of Antwerp led to a 7.8% increase in container volume above the trend that implies that the port might have faced a congestion problem if the necessary actions were not taken. The financial crisis in 2008 caused a sharp decline in October of that year, which severely had an impact on changing the trend of the series. The rate of adjustment to the trend before the shock ($\delta$ - decay rate) is close to 1, which indicates that the impact of the shock is persistent and it will take about 3 years before it recovers to the trend before the crisis, assuming everything else remains constant.

In the second step, a multivariate approach is applied. Two dynamic time series modelling approaches are estimated: (a) an autoregressive integrated moving average with an exogenous variable (ARIMAX), and (b) a cointegration model using the Engle-Granger two-step procedure. The advantage of this approach is that these can capture the influence of external factors and identify the leading indicators. The variables are at aggregate level, encompassing the total throughput of containers at the port of Antwerp, and the economic indicators, including the index of industrial production, the composite index of leading indicators, and the industrial confidence indicator for Belgium, and one confidence indicator for the European Union. Based on the empirical analysis: (a) the EU18 industrial confidence indicator lagged two months and the index of industrial production lagged three months are leading the container throughput in the port of Antwerp, and (b) the relationship between container demand and economic activity is still coupled, although there is a significant change in the relationship due to the global financial crisis in 2008.

In the third step, a model combining the autoregressive distributed lag model (ARDL) with the economic scenarios is developed to capture the potential impact of specific risks and to provide long-term annual forecasts for the port of Antwerp until 2050. This step accounts for other regional and economic factors that are needed to develop demand projections, such as the GDP and trade growth scenarios and market share scenarios that reflects the competitive position of the port of Antwerp within the Hamburg - Le Havre range. The model estimates that the elasticity of the container throughput in the Hamburg - Le Havre range to trade indices is about 1.4 on average. The combined approach provides 4 different likely courses for the container throughput developments in the Hamburg-Le Havre range that addresses the capacity present in the range rather than focusing on capacity limits of a specific port. Moreover, 12 different likely courses are provided for the future development of the container throughput at the port of Antwerp based on 4 different economic scenarios for the EU and 3 scenarios for the port of Antwerp market share within the Hamburg - Le Havre range.

The application to other ports is feasible taking into account the specific characteristic of the location of each port, specific market segments, the hinterland connections and activity, and the country's specific trade relations and socio-economic indicators.
Managementsamenvatting

De havenindustrie is sterk afhankelijk van veranderingen in de globale economische activiteit en de internationale handel. De wereldwijde financiële crisis in 2008 had een significante impact op de activiteiten van de havens. Daarnaast zullen de huidige veranderingen in de olieprijzen en de afname van de Chinese groei het vrachtverkeer naar de havenindustrie beïnvloeden. Bijgevolg kan de vraagzijde voorspeld worden door de evoluties van de economische activiteit op te volgen. Aan de aanbodzijde speelt de capaciteit van de haven een cruciale rol in de concurrentiepositie van de haven om te voldoen aan de vraag, congestie te vermijden en dus kosten en verloren tijd in de haven te verminderen en de productiviteit te doen toenemen. Dit is belangrijk voor alle stakeholders: de rederijen, de havenautoriteit, de verladers, de terminaloperatoren en de investeerders. De beslissing om nieuwe capaciteit aan te bieden en te investeren in de haven zou echter gebaseerd moeten zijn op een groeiende potentiële vraag. Daarom zijn beslissingsnemers in de haven afhankelijk van vraagvoorspellingen om beslissingen gerelateerd aan de operaties en investeringen te onderbouwen.

In deze thesis worden tijdreeksmodellen ontwikkeld om het data-genererend proces (DGP) van de containeroverslag te analyseren, vooruitlopende indicatoren te identificeren en de relatie tussen de economische activiteit en de containeroverslag op havenniveau te kwantificeren. De belangrijkste onderzoeks vraag van deze thesis is welk model gebruikt moet worden om de containeroverslag op havenniveau te voorspellen?

Het doel van deze thesis is om een instrument aan te leveren om de beslissingen van beleidsmakers en belanghebbenden van zowel publieke als private instellingen te ondersteunen bij de korte en lange termijnplanning en investeringsbeslissingen in de havenindustrie. Havenplanners moeten anticiperen op elk mogelijk congestieprobleem. De korte termijnvoorspellingen helpen bij de planning van de operationele beslissingen, zoals het gebruik van de havencapaciteit, de uitrusting en de behandeling van containeractiviteiten en de voorziening van capaciteit op de hinterlandverbindingen. Daarnaast zijn lange termijnvoorspellingen nuttig om beslissingen over investeringen in de toekomstige infrastructuur te beoordelen.

De methodologie die gebruikt wordt om voorspellingen te maken voor de containeroverslag in de haven van Antwerpen verloopt in een aantal stappen. In de eerste stap wordt een univariaat tijdreeksmodel geschat - een autoregressive moving average (ARIMA) model met interventie - dat gebruik maakt van de maandelijkse containeroverslag, uitgedrukt in TEU. Verder wordt de structuurbreuk van de financiële crisis in 2008 meegenomen in het model. Dit biedt het voordeel dat het gedrag van de tijdreeks geanalyseerd wordt tijdens en na verschillende soorten structuurbreuken en dat de impact en grootte van zulke breuken geïdentificeerd kan worden. De implicaties voor de haven van Antwerpen zijn tweevoellig.
Ten eerste bieden de korte termijn maandelijkse voorspellingen in TEU een betrouwbaar instrument voor de haven om de operationele beslissingen te plannen en congestie in de haven en op de achterlandverbindingen te vermijden. Ten tweede worden de structuurbreuken verschillend gemodelleerd volgens de oorzaak en de impact van de breuk. De beleidsmakers in de haven kunnen bijgevolg leren van deze breuken. De hoge piek in maart 2002, veroorzaakt door een verandering in marktaandeel, leidde bijvoorbeeld tot een stijging van 10,4% in de gemiddelde containeroverslag. De nieuwe ontwikkelingen in 2007 in de haven van Antwerpen leidden tot een stijging van 7,8% bovenop de trend in het containervolume, wat betekent dat de haven een congestieprobleem had ervaren als de nodige acties niet ondernomen waren. De financiële crisis in 2008 veroorzaakte een sterke daling in oktober dat jaar, wat een duidelijke impact had op de het trendmatig verloop van de containeroverslag. De groeivertraging had tot gevolg dat het ongeveer drie jaar zal duren voor de trend van voor de crisis, ceteris paribus, weer bereikt is.

In de tweede stap wordt een multivariate aanpak toegepast. Twee dynamische tijdreeksmodellen worden geschat: (a) een autoregressive moving average model met een exogene variabele (ARIMAX) en (b) een cointegratie-model dat de twee stappen-procedure van Engle-Granger gebruikt. Het voordeel hiervan is dat deze modellen de invloed van externe factoren kunnen vatten en de vooruitlopende indicatoren kunnen identificeren. De variabelen die gebruikt worden zijn geaggregeerd en omvatten de totale containeroverslag in de haven van Antwerpen, de economische indicatoren, inclusief de index van de industriële productie, de samengestelde index van vooruitlopende indicatoren, de indicator voor het vertrouwen in de Belgische industriële sector en één vertrouwensindicator voor de Europese Unie. Gebaseerd op de empirische analyse kunnen de vertrouwensindicator voor de industriële sector in de EU18 en de index van de industriële productie gebruikt worden om de containeroverslag in de haven van Antwerpen twee tot drie maanden vooruit te voorspellen. Het verband tussen de containeroverslag en de economische activiteit is duidelijk aanwezig, maar er is een significante verandering merkbaar in deze door de globale financiële crisis in 2008.

In de derde stap wordt een model ontwikkeld dat een autoregressive distributed lag model (ARDL) combineert met de economische scenario’s om de potentiële impact van specifieke risico’s te vatten lange termijnvoorspellingen op jaarbasis voor de haven van Antwerpen te verschaffen tot 2050. Deze stap geeft vooruitzichten van de containeroverslag op basis van scenario’s voor de evolutie van regionale en economische factoren zoals het BBP, de internationale handel en voor veranderingen in het marktaandeel die de concurrentiepositie van de haven van Antwerpen binnen de Hamburg - Le Havre range reflecteren. Het model schat dat de elasticiteit van de containeroverslag in de Hamburg - Le Havre range met betrekking tot de handelsindices gemiddeld 1,4 is. De gecombineerde benadering geeft vier alternatieve evoluties voor de containeroverslag in de Hamburg - Le Havre range en confronteert die met de totale aanwezige capaciteit in de range. Voor
de containeroverslag in de haven van Antwerpen worden twaalf verschillende mogelijke evoluties weergegeven, gebaseerd op een combinatie van vier verschillende economische scenario’s voor de economische activiteit in de EU met drie scenario’s voor het marktaandeel van de haven van Antwerpen in de Hamburg - Le Havre range.

Toepassing op en veralgemening naar andere havens is mogelijk wanneer rekening gehouden wordt met de specifieke eigenschappen van de locatie van elke haven, de specifieke marktsegmenten, de hinterlandverbindingen en -activiteiten, de specifieke handelsrelaties van het land en de socio-economische indicatoren.
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<th>Description</th>
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<tr>
<td>ACF</td>
<td>Autocorrelation function</td>
</tr>
<tr>
<td>ADF</td>
<td>Augmented Dickey-Fuller</td>
</tr>
<tr>
<td>AIC</td>
<td>Akaike information criterion</td>
</tr>
<tr>
<td>ARDL</td>
<td>Autoregressive distributed lag model</td>
</tr>
<tr>
<td>ARIMA</td>
<td>Autoregressive integrated moving average</td>
</tr>
<tr>
<td>ARIMAX</td>
<td>Autoregressive integrated moving average with an exogenous variable</td>
</tr>
<tr>
<td>DGP</td>
<td>Data generating process</td>
</tr>
<tr>
<td>GDP</td>
<td>Gross domestic product</td>
</tr>
<tr>
<td>H-LH</td>
<td>Hamburg - Le Havre</td>
</tr>
<tr>
<td>KPSS</td>
<td>Kwiatkowski-Phillips-Schmidt-Shin</td>
</tr>
<tr>
<td>L</td>
<td>Natural logarithm</td>
</tr>
<tr>
<td>MAE</td>
<td>Mean absolute error</td>
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<tr>
<td>MAPE</td>
<td>Mean absolute percentage error</td>
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<tr>
<td>MSE</td>
<td>Mean square error</td>
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<tr>
<td>PACF</td>
<td>Partial autocorrelation function</td>
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<tr>
<td>PoA</td>
<td>Port of Antwerp</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error</td>
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<tr>
<td>sa</td>
<td>Seasonally adjusted</td>
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<tr>
<td>SIC</td>
<td>Schwartz information criterion</td>
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<td>SSE</td>
<td>Sum of squared errors</td>
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<tr>
<td>TEUs</td>
<td>Twenty-foot equivalent units</td>
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CHAPTER 1

SETTING THE RESEARCH FRAMEWORK

1.1 Rationale of the thesis and research objectives

The port’s capacity plays a crucial role in the port’s competitive position in order to meet demand, avoid congestion, and hence, decrease the cost and time lost at the port and increase productivity that is of importance to all the stakeholders: the shipping lines, port authority, shippers, terminal operators, and investors. Meersman et al. (2003) emphasised that the relative port competitiveness advantage is one of the important factors that determine the potential demand and is significantly considered by policy makers when dealing with investment decisions concerning increasing port capacity. However, the decision to provide new capacities and investments in the port should be supported by a growing potential demand. Meersman and Van de Voorde (2014) emphasised the importance of studying the trade-off between the costs and benefits of excess capacity and related funding. Therefore, demand traffic forecasts are needed as a tool to rationalise the investment decisions since infrastructure projects have an impact for the next 25 years, on average.

Modelling and forecasting maritime freight transport demand is a complex and a challenging process for the following reasons:

• The fact that transport service is a derived demand from the need of various goods in different locations of infinite economic activities. In that context, the demand is determined by socio-economic factors, among others. Moreover, these factors are volatile and dynamic and are changing over time and across regions.
• The ports’ handling of different types of cargo which have different determinants and market forces.
• The numerous decision-makers and stakeholders involved in the port sector, such as port authorities, shipping lines, terminal operators, shipowners, shippers and investors add another dimension to the complexity of modelling since their relationships are intertwined and correlated.
• The changes in the liner shipping market: the technological changes as the introduction of mega container ships and the changes in fuel prices.

The international trade is the main driver of maritime trade. The growth in the volume of the world merchandise and maritime trade was higher than that of the growth in GDP
UNCTAD (2014). In 2013, world merchandise exports grew by 2.5% while GDP grew by 2.0% (World Trade Organisation, 2014). Figure 1.1 shows the evolution of the world GDP and the maritime trade.

Consequently, the main driver of seaport activity is, and has always been, maritime trade which is driven by evolutions in economic activity and international trade (Meersman, 2009). As shown in Figure 1.2, the interactions among the different factors are dynamic. Equally, the correlation between the maritime sector and the social and macroeconomic trends is not stable over time as a result of, among others, shifts in global and regional maritime transport patterns along different trade routes.

The purpose of this thesis is to provide an instrument to support the decisions of policy makers and stakeholders, whether in public or private institutions, for the short and long-term planning and investment decisions in the port sector. This is achieved by developing quantitative models that analyse the data generating process (DGP) of the container throughput and identify causal models. As a result, it is possible to forecast the potential container throughput at the port level in the short and the long terms. Forecasting in that context is used as a planning tool to cope with the uncertainty and volatility of the future demand relying on data from the past and analysis of trends, on the one hand, and identifying causal relationships, on the other hand.

The main contribution of the thesis is that:

- The analysis throughout the thesis incorporates the structural break of the 2008 financial crisis in the modelling process, which has a number of advantages: (a) providing insight into the behaviour of the data generating process as a result of a structural break and quantifying the impact on the container throughput during and after the shock, and (b)
having a structural break, which enable to analyse and identify the potential leading variables of the container throughput that provide the port stakeholders with an insight into the coming few months.

- The container market is a volatile market that is closely related to the changes in the global macro-economic trends. In the short-term, monthly forecasts are provided based on identified leading indicators that assist the port operators for the planning of the activity at the terminal and the hinterland connections. While, in the long-run, the forecast provides the investors and the port authorities with an instrument to assess the need for future investments. The long-run forecast is based on socio-economic scenarios and the market share.

### 1.2 Research questions

The central research question (RQ) in the thesis is formulated as: *How to develop a quantified model to forecast the container throughput at the port level to support different stakeholders in the decision making process for the short-term and long-term planning and investment decisions?*. 
In order to provide an answer to the main question, the following three sub-questions are formulated to identify and understand the underlying process of forecasting container throughput according to different forecasting periods and objectives:

1. **RQ\textsubscript{1}:** What is the way of modelling the short-term fluctuations depending on the historical trend of the time series combined with the structural shifts?

2. **RQ\textsubscript{2}:** Which economic indicators might be identified as leading indicators for the container throughput?

3. **RQ\textsubscript{3}:** How will the container throughput in the port of Antwerp (PoA) evolve until 2050 under different scenarios?

### 1.3 Definitions and scope of the thesis

The focus in this thesis is on the container throughput at the port level measured in twenty-foot equivalent units (TEUs), that represents the demand side for the port. Levinson (2006) emphasised the vital role of containers transport in accelerating economic globalisation and international trade; *it made the world smaller and the world economy bigger.* The growing market of containerised cargo accounts for more than 50% by value and about 17% by volume of international maritime trade (UNCTAD, 2015). Bernhofen et al. (2013) concluded that containerisation had a stronger impact on driving globalisation than trade liberalisation, provided by an empirical study for 157 countries over the period 1962-1990.

The definition of *throughput* is adopted from the seminal work of Jansson and Shneerson (1982), and it is defined in terms of *output* as the volume in tonnes passing through the port per unit of time. The term is adopted in the context of the thesis as the number of TEUs handled in the port per unit of time and movement.

From a practical perspective, using the number of TEUs instead of tonnes to forecast the container throughput has many advantages and benefits to the terminal operators, carriers and port authority; since the operational decisions and services provided depend on the number of loading and unloading movements per unit. Nevertheless, using the counts of TEUs is not always comparable and representative of the country’s economic activity and raises a number of statistical concerns:

(i) The container’s content varies between semi-finished and final products, so the TEU as a unit is not an indication of the weight or the value of the economic activity.

(ii) The container throughput does not necessarily reflect the trade volume since it includes transhipment. However, transhipment is excluded by reporting the container throughput from the aggregation of the numbers in the through bill of lading.
(iii) The total container throughput includes counts for empty containers movements. According to UNCTAD (2015), the estimated global port throughput exceeds the observed number of full containers transported by 2.5 times, emphasising an increasing repositioning of empty containers.

(iv) The container throughput figures include inter-regional as well as intra-regional trade. Therefore, they are not always comparable and representative of the country’s economic activity.

The supply side at the port, Capacity as used in the context of this thesis, is not defined in terms of the ‘theoretical designed capacity’. Capacity is defined throughout the analysis in the thesis as ‘the terminal commercial capacity’ that is the maximum throughput that can be attained keeping the performance and quality at the desired level of the operator to avoid congestion and ensure high productivity. At this throughput, the average berth occupancy rate is around 65% (Drewry Maritime Research, 2010, p.41) and the utilisation rate\(^1\) is above 70% (Ilmer, 2006).

The port of Antwerp is used as the unit of analysis throughout the thesis. It is centrally located within the Hamburg - Le Havre (HLH) range of ports, in the Scheldt-Maas-Rhine delta, that share about the same hinterland, as shown in Figure 1.3. The port of Antwerp’s strategic location enables it to play a vital role in the global supply networks; the port serves the hinterland of France, Germany, and The Netherlands.

The port of Antwerp is one of the main European hub ports: it captured approximately 22% of the container market share of the main container ports in the Hamburg-Le Havre range and has the capacity to handle 15 million TEUs in 2014. The port of Antwerp is Europe’s second largest port by total throughput volume in tonnes and third in total container throughput measured in TEUs in 2014. The port handled approximately 199 million tonnes of total maritime freight volume\(^2\), of which 108 million tonnes in containers correspond with 8.9 million TEUs. In 2014, the port of Antwerp was ranked the 16th container port internationally (Antwerp Port Authority, 2015a).

The port activities have a significant importance and value added to the national economy. In 2013, the port of Antwerp’s share of direct and total value added in the Belgian GDP was 2.5% and 4.8% respectively, and its employment represented 1.5% (direct) and 3.7% (total) of Belgian employment (Van Nieuwenhove, 2015).

\(^1\)It is calculated as the ratio of the actual total port throughput divided by the designed capacity of a container terminal.

\(^2\)The total maritime freight volume handled in the other major ports in 2014 is approximately 445 million tonnes in the port of Rotterdam and 146 million tonnes in the port of Hamburg.
Chapter 1. Setting the Research Framework

Figure 1.3: The main container ports in the Hamburg-Le Havre range.
Source: The map is provided by Jeroen Cant, researcher at the University of Antwerp (2015).

1.4 Setting the modelling framework

In Section 1.4.1, the literature review relevant to the maritime freight modelling is presented emphasising the container demand modelling and forecasting. This is followed by the modelling approach presented in the different chapters of the thesis in Section 1.4.2.

1.4.1 Literature review

Many studies investigated the relationship between economic activity and the maritime freight to forecast the port traffic. However, the diversity across the studies is large, making it difficult to classify the literature review. From the methodology perspective, some studies are quantitative, some are qualitative and some are a combination of both. Form the level of analysis, studies may aim at forecasting the total port traffic, a specific cargo
category (liquid, dry bulk) or even at a disaggregate level looking into the commodity level. From the application perspective, some studies forecast at the port level, while others are conducted at a regional level or a range of ports. From the objective and forecast horizon, some studies are short-term using monthly or quarterly data, others are aimed at long-term forecasts for investment decisions. In this section, a non-exhaustive overview of the literature is provided focusing on the empirical studies to forecast port traffic by modelling the relationship between economic activity and maritime freight. The classification adopted is according to the unit of level – whether at the port level, country, or region. A more detailed literature review will be provided in each chapter.

In general, the study of Trujillo et al. (2002) has shown that four factors should be considered when forecasting freight traffic at the port:

1. Macro-economic trends and reforms, such as trade liberalisation, trade agreements, openness of the economy and evolution of industrial production.
2. The specific characteristic of each port's location in relation to the transport network that affects the competitive position of each port, which may be measured by the market share.
3. The specific advantage or competence of each port, e.g. large and well connected hinterland, dwell time and incurred costs at the port.
4. Innovation in ports and logistics services.

The studies of forecasting port cargo are important for many stakeholders. For example, port authorities need such studies to decide about infrastructure investment projects, terminal operators use the information to determine the ports with high potential growth for investment opportunities, international organisations such as the World Bank rely on such studies to allocate funds for developing countries. The studies may be conducted directly by the port authorities, regional or national organisations, consultancy companies or academics. Meersman et al. (2002, pg. 35-41) and Markianidou (2012, pg. 16-23) provided a detailed literature review on forecasting port throughput.

A number of studies quantify the port throughput at the port level, one of the earliest studies was conducted in the late 1960s for the port of Antwerp by the Department of Transport and Regional Economics (TPR) of the University of Antwerp and the study Centre for the Expansion of Antwerp (SEA) - a special unit of the port (see Coeck et al., 1996). The forecast is for general and bulk cargo that is based on expert insights and optimistic and pessimistic scenarios to forecast the macroeconomic conditions. Nonneman’s (1979) forecast was based on the assumptions that the growth rate of port traffic figures and the underlying determining factors will remain constant; then the import, export and transit maritime cargo flows for the port of Antwerp were extrapolated. SEA developed the methodology further to forecast at a disaggregate level (up to 1985) containerised traffic and non-containerised traffic based on econometric modelling of the historical traffic using

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3The abbreviation stands for the Dutch name: Studiecentrum voor Expansie van Antwerpen
explanatory variables such as the share of imports and exports in Belgian GDP, evolution of industrial production and the GDP index of EU, Japan and USA. Meersman et al. (2003) used a multiple regression model to investigate the long and short-run relations between exports and imports and a port’s loading and unloading activities, respectively. Meersman et al. (2003) estimated an error-correction model to forecast the number of tonnes loaded and unloaded at the port of Antwerp, such that the functions used are: \( \text{unload} = f(\text{import}, \text{quay length}, \text{real wage}) \) and \( \text{load} = f(\text{export}, \text{quay length}, \text{real wage}) \).

More studies at the port level have followed. At the port of New York, Sun and Bunamo (1973) conducted a linear regression using three exogenous factors: the commodity effect, the trading partner effect and a hinterland factor to forecast the share of New York’s port in total U.S. import and export volumes. Since 1976, the Municipal Port of Rotterdam has introduced seven Goods Flows Models (GSM\textsuperscript{4}) to forecast the container traffic in the long-term. The commodity groups included in the models and the methodology are changed from one version of the model to another. The GSM-2 incorporates a general goods classification ranging of 2 commodity categories, GSM-4 includes 9 commodity groups while GSM-7 has 26 commodity categories. From GSM-5, a new dimension of combining quantitative and qualitative analysis is added to the model. This comes in addition to another level of classification according to nature and orientation of the flow (transit, import and export), and the transport modes.

Hui et al. (2004) forecast the port cargo throughput in Hong Kong by estimating a cointegrated error correction model. While, Lam et al. (2004) developed a neural network model on the basis of historical data from 1983 to 2000. The model’s aim is to forecast 37 types of freight movements each explained by one or two explanatory factors. The explanatory factors include trade value of imports/exports/re-exports at 1990 prices, population, electricity demand, and Hong Kong GDP.

At the country level, a number of studies have been conducted for the main Spanish ports. Coto-Millán et al. (2005, 2010, 2011) used time series quarterly data from 1975.I to 1998.IV to forecast the general cargo. The scope was extended further to include containers, dry bulk, and liquid bulk. The objective of the studies was to identify and estimate the variables that determine the maritime imports and exports. A number of causal methods were used; Johansen and Juselius (1990) applied multivariate techniques of cointegration to examine long-run relationship, a vector autoregressive (VAR) model to estimate a short-run dynamic model, and the seemingly unrelated regression equations (SURE) model. The determinants of Spanish maritime imports are national income and prices of imports and maritime transport services. And the determinants of the exports are world income, prices of exports and maritime transport services and the utilisation degree of the productive capacity of Spanish business. Additional variables are the relative price of intermediate goods in dry bulk, and the price of energy in liquid bulk. Two dummy variables were in-

\textsuperscript{4}GSM is an abbreviation of the Dutch word GoederenStromenModel.
corporated in the model to estimate the effect of Spain’s accession to the EU (structural change); the learning adjustment of an innovation \( w_t = 1 + \exp[(\alpha - \beta(t - t_0 + 1))]^{-1} \) as in (Hendry and Ericsson, 1991, see p.12) to account for substitution of transport means, and a progressive adjustment (Winters, 1984, see p.110) that changes the slope rather than the intercept to account for the deregulation procedure.

Syafii et al. (2005) and Syafii (2009) used the cointegration test of Johansen and Juselius’s (1990) approach to estimate a vector error correction (VEC) model to forecast the container throughput in Indonesia based on an annual time series from 1982 to 2002. The exogenous variables used are the population, GDP, exports, and imports (in millions of US $) of Indonesia. He concluded that the GDP and export react more positively than population and imports by examining the impulse response function (IRF).

Meersman and Van de Voorde (2008, 2013) quantified the relation between freight transport and economic activity, based on panel data for total freight and GDP for a number of European countries, USA and Japan. The studies show that in some of the cases, the GDP was not the best indicator for modelling this relation in the long-run. For example, in the case of France, the production in the manufacturing sector is used as a relevant indicator for economic activity. They emphasise that the long assumed unit elastic relationship between GDP and the demand for freight transport is neither proven nor generalisable to all transport modes and regions; moreover, it has changed over time and across countries.

At the regional level, few studies have been conducted to forecast the traffic flows in the Hamburg-Le Havre (H-LH) range of ports. Blauwens and Van Steelandt (1992) used linear casual models to forecast the general cargo and container traffic in tonnes, using the industrial output of the EU. Verbeke et al. (1996) used the GDP for the industrialised world to estimate a simple linear regression model. Long-term projections for the H-LH range are found in the work of De Langen et al. (2012), van Dorsser et al. (2012). A 100 years forecast by estimating a causal model based on GDP is conducted in the work of van Dorsser et al. (2012). A combined forecasting model with expert opinions’ and major commodity specific factors is conducted and applied on a commodity level in De Langen et al. (2012).

The estimation of an error correction model for the terminals at Hong Kong and the Singapore Ports is found in Fung (2001, 2002). He studied the interactive relationship between the terminal operators in the ports of Hong Kong and Singapore accounting for the trade-interdependency and oligopolistic relationship in the East and Southeast Asian market. The VEC model and the IRF are used to estimate and analyse the results on the basis of China’s foreign trade and Southeast Asia’s foreign trade variables assuming different growth paths for the variables. The study has several purposes: studying the competitive interaction between terminal operators, emphasising the dependence of the forecasts on the interaction among ports, and providing a systematic approach to forecast the demand for container handling services.
Forecasting in a multi-port region of the Pearl River Delta (PRD) in China, Jiaweia et al. (USA) applied a systematic model that comprises two modules: a container throughput module and a trade module in addition to a dummy variable to account for the crisis effect.

To sum up, modelling the relationship between economic activity and maritime freight and forecasting the maritime freight has been often used in models for forecasting port throughput as seen from the previous literature overview. However, using this relationship in modelling is not problem free. First, there is the question of the stability of this relationship over a longer time period. The long assumed time lag among trade, production and shipment time is changing. Vanoutrive (2010) conducted an explanatory spatial analysis to explore the relationship between port throughput and GDP for the port of Antwerp. The study revealed that the time-lags between economic growth and transport growth are different across countries and commodity categories. Moreover, Tappeiner (2007) and Meersman and Van de Voorde (2013) concluded that the long-term assumed relationship between GDP and freight transport has changed over time, attributing this change to the role of government, international logistics developments, trade liberalisation, decreasing transport costs and capacity utilisation. Even if the relation is not stable in the long run, it still can be used for short to medium term forecasts, but this confronts us with the second problem which is the need for projections for the independent variables.

In conclusion, there is no unique or optimal method to forecast; each port and type of cargo has its specificity. Nonneman (1979), in his seminal work, defines traffic forecasting as an instrument to rationalize decision with an impact on the future. He emphasised that it is not necessary that the most sophisticated techniques provide more accurate results than the simple techniques. The methodology adopted in the thesis accounts for two important gaps in the literature. The first gap, in almost all of these studies, is that the forecasts were estimated in tonnes and either a naive simple method is used to convert from tonnes to number of TEUs or no method is explained. Therefore, the empirical models in the next three chapters use the container throughput measured in TEUs. The second gap is that most of the studies conducted are for the period before the 2008 USA financial crisis. Therefore, the intervention analysis is specifically considered in Chapter 2 to measure the effect of the crisis.

1.4.2 Modelling approach

In order to deal with the complexity and dynamic relationships in modelling the container throughput and to ensure a rigorous support instrument for the decision-making process, a step-wise approach is used for the econometric modelling in the context of the thesis. The steps and the outcome of each step are illustrated in Figure 1.4. The first step is to examine – through the literature review – the economic theory underlying the relationships
to formulate the model and the methodology. In the second step, data is collected to identify and analyse the measurable related available variables. This is followed by estimating the different empirical models and making inferences about the parameters estimated in the third step. Finally, in the fourth step, the appropriate model is chosen based on the validation process using different diagnostic tests and the economically sensible model to be used in forecasting. The estimated model in that framework is specified based on the process giving rise to the observed data, i.e. the DGP (see Spanos, 1986, pg.16-21).

![Figure 1.4: The methodological framework to econometric modelling.](image)

A brief overview about the research questions and the corresponding methodologies is provided in Table 1.1, with reference to the chapter that illustrates the methodology and the empirical analysis in details.

### 1.5 Implications of the thesis

Developing a tool to support the policy makers by forecasting the container throughput at the port level is the core of this thesis. The port’s stakeholders need to plan ahead and assess the likely alternative course of the future; hence, forecasting is one input in the planning process. In general, (Armstrong, 1985, chap. 1) attributed the need to forecast for two reasons: (1) we cannot control the future, and (2) we cannot respond rapidly. Making the correspondence of these two factors to the maritime sector, firstly, the general conditions of the social and macroeconomic factors which determine the volume and direction of maritime trade are changing over time and across countries. Nevertheless, the decoupling of the long-term assumed relationship between trade and containerised cargo is not possible. Secondly, the port’s infrastructure takes a long time to be built and is usually inflexible to change or adapt to unexpected events.
### Table 1.1: Research methodology overview.

<table>
<thead>
<tr>
<th>Chapter</th>
<th>Methodology</th>
<th>Research question</th>
</tr>
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<tbody>
<tr>
<td>Chapter 2</td>
<td>A univariate model, the autoregressive integrated moving average (ARIMA), is applied using the historical dynamics of the time series itself and incorporating the structural shift.</td>
<td>$RQ_1$</td>
</tr>
<tr>
<td>Chapter 3</td>
<td>Two causal models are tested, the ARIMAX (ARIMA with an exogenous variable) and the Engle-Granger two step procedure.</td>
<td>$RQ_2$</td>
</tr>
<tr>
<td>Chapter 4</td>
<td>The autoregressive distributed lag (ARDL) model combined with scenario analysis.</td>
<td>$RQ_3$</td>
</tr>
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</table>

Port authorities, terminal operators, investors and other stakeholders rely on demand traffic forecasts to support the decisions related to operation and future port infrastructure investments. It is a challenge to match capacity to demand. On the one hand, they face the risk of costly excess capacity, and on the other hand, under capacity causes loss of market share and logistics bottlenecks at the port and in the hinterland. Therefore, the short-term forecasts assist in the planning of the operational decisions such as the port capacity utilisation, loading and unloading planning, handling of container activities and hinterland connections capacity provision. In comparison, the long-term forecasting is useful to assess the future infrastructure investment decisions. Application to other ports is feasible taking into account the specific characteristic of each port’s location and hinterland activity and the country’s macroeconomic indicators.

### 1.6 Structure of the thesis

The structure of the thesis is as follows: In Chapter 2, the Box-Jenkins univariate procedure is applied to the monthly container throughput of the port of Antwerp to develop a model that incorporates the structural shocks. The model in this chapter provides monthly container forecast based only on the historical time series. Moreover, the empirical analysis in that chapter provide insight into the data generating process of the time series, which paves the way to understand the behaviour of the container throughput time series and carry on the analysis to the causal model. In Chapter 3, two multivariable methodologies are used: an ARIMAX model and the Engle-Granger two step cointegration procedure to identify and test for the leading indicators with respect to container throughput. In this
chapter, exogenous variables allowing for time lag are tested and included in the model to decrease the error and uncertainty of the monthly container throughput forecast. In Chapter 4, two approaches are combined: the ARDL model and the use of scenarios to account for the socio-economic changes and the port’s competitive position. That chapter presents the long-term annual container throughput forecast. Finally, Chapter 5 closes the thesis with the major findings, conclusions, policy implications and suggestions for further research. In the Appendix section, the software used to generate graphs and estimate the models are presented in Appendix A. In Appendix B, the mathematical notations and the concepts of the time series analysis used in the thesis are defined. The conventional and the structural break unit root tests are presented in Appendix C. Finally, the different definitions and formulas of evaluating the forecasting error are shown in Appendix D.
2.1 Introduction

The short-term decisions by terminal operators, port authorities and other stakeholders concerning the planning of the operations and resource allocation decisions are crucial for avoiding congestion and handle the volume of containers in an efficient way not only at the terminals but also on the connections with the hinterland. In this chapter, a univariate time series approach is applied to build a model that can be used as an instrument by the stakeholders for the short-term operational decisions at the port level. It provides a new application by combining the autoregressive integrated moving average (ARIMA) model with the intervention function to account for the shocks’ impact. Moreover, that model has the advantage of being independent on finding and forecasting explanatory variable. Given the uncertainty and volatility of the port traffic due to other factors rather than the historical trend, the short-term forecasts provided by this model is for a maximum of 12-months. Based on the demand forecasts, adjustments and improvements to the port productivity plans may be adapted. For example, increasing the utilisation of the existing facilities by making relatively small investments in advanced technology, container yard handling equipments and/or altering the working shifts at the port.

The univariate time series approach assumes that the historical behaviour; i.e. the stochastic process of the time series is expected to continue into the future. In addition to the trend and seasonality effect, the stochastic process that generates the series may show structural breaks caused by external shocks that change the behaviour of the time series. The advantage of the univariate approach is that it offers a systematic approach for building, analysing, and forecasting time series models, independent from other variables that are needed in multiple regression analysis; nevertheless, high frequency and long time series data are required for such a model. The resulting model addresses three objectives: (1) analysing the historical behaviour of the time series and having insight into the future
Chapter 2. A univariate-intervention model: Short-term forecast of container throughput

developments of the container throughput demand at the port level; (2) assessing the pattern and the impact of the shocks on the generating process of the container throughput; and (3) generating short-term forecasts for the demand of the container throughput.

In this chapter, the research question examined is how to model the short-term fluctuations depending on the historical trend of the time series combined with the structural shifts? To answer this question, the following sub-questions are tackled:

(i) Is a univariate forecasting model a reliable tool for the short-term forecasting of the container throughput at port level?
(ii) Did the intervention analysis improve the forecasting accuracy?
(iii) How to improve the accuracy of the forecasting process?

The remaining structure of the chapter is as follows. Section 2.2 reviews the literature that is relevant to the applied approach that serves the purpose of this chapter. The methodology of the univariate model and the intervention analysis is illustrated in Section 2.3, where the framework of the autoregressive integrated moving average (ARIMA) model is presented followed by defining the different types of the intervention analysis. Next, the dataset is defined and visualised. The empirical analysis for the port of Antwerp is conducted in Section 2.5, followed by the discussion of the results and main findings in Section 2.6. Finally in Section 2.7, the conclusion and further research are presented.

2.2 Literature review

Applying a univariate approach to maritime trade forecasting is found in the work of Klein (1996). He showed that using transformations and intervention models at a disaggregate commodity level provides useful insights into the behaviour of the time series and accounts for outliers in the time series. In order to forecast the cargo flow at the port of Antwerp, he studied the volumes of twenty-two commodity flows in during the period 1971-1982. The range of the commodities varies widely between general and bulk cargo (loading and unloading) expressed in tonnes. The intervention approach used depends on piecewise linear functions Melard (1981) rather than the output response Box and Tiao (1975) applied in this thesis.

A comparison of six univariate models was conducted and applied to three major ports in Taiwan for monthly time series in Peng and Chu (2009) to forecast the container throughput volume. They concluded that the classical decomposition method and the seasonal autoregressive integrated moving average (SARIMA) model give the best forecast based on the forecasting accuracy criterion used.

Other qualitative analyses are found in Pallis and De Langen (2010), which provides a qualitative analysis for the structural implications of the economic crisis on the ports, and the analysis of Slack (2010), which investigates the major impacts of the financial crisis on
maritime industries. Kou et al. (2011) estimated an ARIMA-intervention model to examine the impact of the 2008 global financial crisis on container throughputs for Hong Kong port. The results show that there is a lag between the impact on container throughput and its materialisation in the throughput time series.

Univariate models have been widely used in other sectors such as air transport; Lai and Lu (2005) conducted an intervention-ARIMA approach that incorporates the September 11, 2001 shock to measure the impact and forecast the air travel passenger demand in the USA. In the manufacturing sector, Chung et al. (2009) estimated an ARIMA-intervention model to investigate the impact of a sudden financial crisis on the manufacturing industry in China. Gröger et al. (2011) studied the intervention analysis in ecological applications distinguishing between a regime shift that causes a structural break in the data and a regime shift caused by the natural periodic cycles.

It is concluded from the previous literature review that the choice of the appropriate model used in forecasting depends on the forecasting period, exogenous factors affecting that period, the type of cargo and the structure of the time series. Moreover, most of the studies on port and shipping were conducted before the global financial crisis in 2008, and for the studies that examine the impact of the crisis, a qualitative analysis was applied (Pallis and De Langen, 2010, Slack, 2010). There is still a lack of quantitative work on the scale of impact from the financial crisis on the port and shipping industry.

2.3 Methodology

The univariate technique followed in the literature and adopted here is the methodology of Box-Jenkins. This method is justified by the fact that the observations measured over time are not independent; i.e., they often show strong correlation over time. Box et al. (1976) developed a systematic empirical approach for identifying and fitting a rigorous model. The methodology is illustrated in Section 2.3.1 followed by an introduction to the intervention analysis in Section 2.3.2.

2.3.1 The ARIMA model

Box et al. (1976) developed a systematic methodology for identifying and fitting a combination of an ARIMA\((p, d, q)\) model. Figure 2.2 illustrates the flow chart of the Box et al. approach (Makridakis et al., 1998). It involves a process of three phases: (1) model identification, (2) estimation and diagnostic testing, and (3) the application of forecasting. These steps are conducted in an iterative process that suggests a number of tentative models. For the suggested tentative models, the parameters are estimated followed by a number of diagnostic tests and visual inspections conducted to ensure: (a) the adequacy
of the model fit to the data, (b) the significance of the parameters and the satisfaction of
the invertibility condition, (c) the randomness of the residuals, and (d) cross-validation
to check the models’ ability to produce reliable forecasts. If the potential model passes
through all the diagnostic tests, then the selected model will be used to produce ex ante
forecasts comparing the forecasting error to ensure a profound dynamic instrument for
operational decision making.

Figure 2.1: The Box-Jenkins methodology for time series modelling.


The basic idea of a univariate time series model is that the value of variable $Y_t$ can be
considered a combination of its own history – Autoregressive (AR) $(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p})$ and
random effects – *Moving average (MA)*, which have taken place in the past \((a_{t-1}, a_{t-2}, \ldots, a_{t-q})\) \cite{Box1976,Gaynor1994}. The emphasis is on using the information in the historical values of a variable for forecasting its future behaviour, and the distribution of future values, conditional on the past \cite{Verbeek2008}. The specification of an \(ARMA(p, q)\) is shown in Equation 2.1, where \(p\) and \(q\) represent the number of terms of AR and MA, respectively. The error term \(a_t\) is assumed to be a white noise process such that \(a_t \sim N(0, \sigma^2)\).

\[
Y_t = \phi_0 + \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + a_t + \theta_1 a_{t-1} + \ldots + \theta_q a_{t-q}
\]  

(2.1)

Most of the economic series are *nonstationary*\(^1\), which implies that the distribution of the variable of interest depends upon time. If the process is nonstationary, linear detrending or a differencing filter is used as in Verbeek \cite{Verbeek2008}. Hence, the original series \(y_t\) must be stationary or made stationary around its mean and variance. In that case an AR and MA process can be combined into an \(ARIMA(p, d, q)\) model as shown in [2.2], where the integration order \((I)\) refers to the number of times that the series has to be differentiated until it is stationary – referred to as *integrated* and denoted by \(\Delta^d\). The importance of a stationary time series arises from the necessity of the validation and interpretation of the different test statistics to avoid spurious regression and to ensure the validity of using ordinary least squares (OLS) to estimate a model by ensuring not to violate the assumption of no serial autocorrelation.

\[
\Delta^d Y_t = \phi_0 + \Delta^d \phi_1 Y_{t-1} + \ldots + \Delta^d \phi_p Y_{t-p} + a_t + \theta_1 a_{t-1} + \ldots + \theta_q a_{t-q}
\]  

(2.2)

Another characteristic of some economic series is *seasonality*, which might be of two types: (i) an additive type that has a constant amplitude of the seasonal effect from one year to another, or (ii) a multiplicative type when the seasonal effect is proportional with time. In order to deal with seasonality in the time series, the ARIMA model is extended to \(SARIMA(p, d, q)(P, D, Q)_s\) model. In Equation 2.3, the SARIMA model is expressed in terms of the lag operator \cite{Box1976}. Where \((p)\) refers to the autocorrelation order, the \((d)\) refers to the order of differencing required to make the series stationary and \((q)\) denotes the order of the moving average. The capital letters \((P, D, Q)\) refer to the seasonal components respectively and the \((s)\) denotes the seasonal period\(^2\).

\[
\phi_p(B)\Phi_p(B^s)\Delta^d D^s Y_t = \theta_q(B)\Theta_q(B^s)a_t
\]  

(2.3)

\(^1\)A stationary process used in the context of the thesis is defined as *weak stationary*; i.e. if its statistical properties (mean, variance and covariance between equal lag length) are invariant with respect to displacement in time \cite[pg. 493-94]{Pindyck1997}.

\(^2\)It depends on the frequency of the time series. For example, if data is quarterly then \(s = 4\), for monthly data \(s = 12\).
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Where,
\[ Y_t = \text{the time series at level } t, \]
\[ B = \text{the lag operator}, \]
\[ \Delta_s^D = \text{the seasonal differencing operator and equal to } (1 - B^s)^D, \]
\[ \Delta^d = \text{the nonseasonal operator defined as } (1 - B)^d, \]
\[ \phi_p(B) = \text{the nonseasonal autoregressive operator of order } p \]
\[ \text{defined as } (1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p), \]
\[ \theta_q(B) = \text{the nonseasonal moving average operator of order } q \]
\[ \text{defined as } (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q), \]
\[ \Phi_p(B^s) = \text{the seasonal AR operators of finite orders } P, \]
\[ \Theta_Q(B^s) = \text{the seasonal MA operators of finite orders } Q, \text{ and } \]
\[ a_t = \text{the white noise which is assumed to be independently} \]
\[ \text{identically distributed (iid) with zero mean and variance } \sigma^2. \]

To practically apply the ARIMA model and use it for forecasting purposes, four steps are required:

1. Determining the order of \( d \) through the (Augmented Dickey-Fuller) unit root tests.
2. Appropriate specification of the lag or order of \( p \) and \( q \) through the use of correlation coefficients.
3. Estimating the value of the parameters in the model \( \phi_1, \ldots, \phi_p \) and/or \( \theta_1, \ldots, \theta_q \)
4. The seasonality in the series must be envisioned and the appropriate way of modelling such an effect must be specified. Usually the series is seasonally adjusted before modelling or by multiplicative seasonal models coupled with long-term differencing, if necessary, to achieve stationarity in the mean.

In what follows is an illustration of each phase’s procedure of the Box et al. (1976) identified in Figure 2.2.

2.3.1.1 Phase I: The Identification

This phase is two fold: first, to study the time series patterns and identify the degree of integration for the time series by determining the order of \( d \) through the Augmented Dickey-Fuller unit root test (ADF) (see Appendix C for the test details). Second, to identify the lag order of AR and/or MA terms – \( p \) and \( q \) respectively – which are needed through
the use of correlation coefficients. The Box and Jenkins model-building methodology depends on the pattern of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) to identify the order of the \((p, d, q)\). The steps followed are:

1. Plotting the time series; the time series at level, the transformations (like logarithms and first difference) and the decomposed time series into the different components (trend, random and seasonal).
2. Identifying the difference order of the model; i.e., finding the stationary time series or the order of \(d\).
3. Checking the series for a seasonal regular pattern, if necessary, taking appropriate measures. Usually the series is seasonally adjusted before modelling or by multiplicative seasonal models coupled with long-term differencing, if necessary, to achieve stationarity in the mean, as suggested by Box and Jenkins.
4. Determining a few tentative models by analysing ACF and PACF to choose the lag structure.

In addition to the trend and seasonality effect, the stochastic process that generates the series may show structural breaks that have to be considered in the model; this will be presented in section 2.3.2. At the end of this phase, different tentative models are suggested.

Moreover, if the series shows a seasonal pattern that can be identified based on the pattern of ACF and PACF, then the SARIMA model is used. For example, for a monthly time series the \(\Delta \Delta_{12} Y_t\) can be used to account for the seasonality, as indicated in Equation 2.4.

\[
\Delta \Delta_{12} Y_t = (1 - B)(1 - B^{12})Y_t = \Delta Y_t - \Delta Y_{t-12} = Y_t - Y_{t-12} - Y_{t-1} + Y_{t-13}
\]

The importance of a stationary time series arises from the necessity of the validation and interpretation of the different test statistics and to avoid spurious regression. A time series is called weak stationary if its statistical properties (mean, variance and covariance between equal lag length) remain constant over time. As elaborated by Heij et al. (2004) in a univariate time series model, it is the correlation with lagged values (autocorrelations

---

3The ACF(k) measures the correlation coefficient estimated between the time series at lag-zero and its \(k\)-th-lag. While the PACF(k) measures the coefficients of partial correlation of the time series observations at \(k\)-lags apart, after the correlation at intermediate lags has been controlled McCleary and Hay (1980).
of the stationary process) that describe the short-run dynamic relations within the time series. This is in contrast with the trend which corresponds to the long-run behaviour of the time series.

2.3.1.2 Phase II: The estimation and testing

For the selected orders of \((p, d, q)\), the model parameters are estimated for the different tentative models. Once the parameters are estimated, a diagnostic check is required for each of the models, the estimated residuals and the accuracy of holdout sample forecasting. If any of the tests are statistically insignificant, an iterative process starts over another set of tentative models. A number of tests are conducted to ensure the appropriateness of the selected model:

(i) test the adequacy and closeness of the model fit to the data,
(ii) test the randomness and the normality of the residuals; for example, by using the Box-Pierce Statistic or the Jarque-Bera test,
(iii) test the significance and relationships of the parameters, and
(iv) test the model ability; which is called cross-validation, to produce reliable forecasts.

There are several measures such as the mean square error (MSE), the root mean square error (RMSE) and the mean absolute percentage error (MAPE), see equations in Appendix B.

2.3.1.3 Phase III: The application

If the potential model passes through all the diagnostic tests: the normality of residual, the residual have constant variance, and the residuals are stationary. The model is then selected based on the selection criteria, Akaike information criterion (AIC) or Schwartz information criterion (SIC), to forecast out-of-sample time series.

2.3.2 The intervention analysis

Box et al. (1976), Box and Tiao (1975) introduced the intervention analysis to measure the influence of an event or a shock on the time path of the dependent variable. Intervention in that context refers to any event such as a change in the trade patterns, a change in the market share or the introduction of new regulations. Hence, the time series intervention analysis is a useful instrument for measuring the impact of such intervention on the trend of the dependent variable. This, however, requires an understanding of the nature and cause of the intervention variable.

The presence of an intervention in the observed series can cause serious problems in the identification and the estimation of the appropriate model. First, there is the forecasting
bias caused by the biased estimates of the autoregressive coefficients; hence, forecasting bias and larger corresponding forecasting intervals. *Second*, the biased estimates will affect the unit root test results\(^4\), which cause larger corresponding forecasting intervals may occur, since the estimated variance is larger than the true variance. The problems get worse especially in the case when the outliers are close to the forecasting origin (Franses, 1998, Serrano and Robles Fernandez, 2001).

Therefore, if these data points are neglected, the analysis of the future behaviour of the economic variable can be biased in the way that the in-sample fit of a model gives poor estimates to ex-ante forecast performance. Forecasting accuracy and unbiased estimation of the model parameters requires incorporating these outliers in the model to avoid the problems that might arise from the biased estimates of the autoregressive coefficients. Such observations are analysed and should be considered in the model not only for the forecasting accuracy and the correction of the unbiasedness in the estimation of the model’s parameters, but also because they might convey important information for policy makers about the data generating process.

An important distinction has been made in the work of Box and Tiao (1975), Tsay (1986), and Franses (1998) between outliers and intervention variables. On the one hand, *an outlier or an additive outlier* is defined as an anomaly observation in the time series, which is inconsistent with a model which is thought to be appropriate for the overwhelming majority of the observations (Harvey, 1991). An additive outlier occurs with no prior information on the date of its occurrence, and it only affects the mean function of the time series at the time of occurrence without changing the generating process.

On the other hand, *an intervention or an innovation outlier* is defined as any event with prior information that occurs between two time periods that are expected to cause abnormal observations or a change in the generating process of the time series that might affect the mean function or the trend of the process. This type is caused by an exogenous intervention such as a policy change, a strike, a crisis in the economy, or any external shock that hits the economy where it affects the driving noise process that might have a temporary effect that lasts for a few periods or a permanent effect, (Tsay, 1986) and (Franses, 1998). To sum up, outliers have no effect on the generating process of the time series and have a short-lived impact while an intervention changes the generating process of the time series.

\(^4\)See Appendix B: Mathematical notation for full details of the unit root test with outliers
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2.3.2.1 Types of interventions

In practice, the analysis depends on the interaction of three criteria: (1) the duration; whether it is a temporary or a permanent effect, (2) the impact effect; if the change is in the level or the slope or both and (3) the onset; whether it is abrupt or gradually (McCleary and Hay, 1980).

The general form of the dynamic intervention analysis model for a time series with \( k \) outliers occurring at time \( T_i \) where \( (i = 1, 2, \ldots, k) \) is represented in Equation 2.5 as suggested by Box et al. (1976), Chang et al. (1988), where \( Z_t \) is the response or output and \( m_t \) is the input function:

\[
Z_t = m_t + y_t \tag{2.5}
\]

Where \( Z_t \) is the observed contaminated series (output), \( y_t \) is the unperturbed process and \( m_t \) is the transfer (input) function. The transfer function models the impact of outliers such that:

\[
m_t = \sum_{i=1}^{k} V_i(B) \omega_i I_{T_i}^T \tag{2.6}
\]

where,

\( V_i(B) \): represents the dynamic impact of the outlier \( i \) at time \( T \),

\( \omega_i \): is the magnitude (coefficient) of the impact,

\( T_i \): occurrence time of the intervention or outlier, and

\( I_{T_i}^T \): is an indicator/intervention variable with choices as:

\[
P^T_t = \begin{cases} 
1, & \text{if } t = T \\
0, & \text{otherwise}
\end{cases} \quad \text{"pulse intervention"} \tag{2.7a}
\]

\[
S^T_t = \begin{cases} 
1, & \text{if } t \geq T \\
0, & \text{otherwise}
\end{cases} \quad \text{"step intervention"} \tag{2.7b}
\]

\[
R^T_t = \begin{cases} 
t - T + 1, & \text{if } t \geq T \\
0, & \text{otherwise}
\end{cases} \quad \text{"ramp intervention"}. \tag{2.7c}
\]

The unperturbed process \( y_t \) is modelled such that:
\[ \pi(B)y_t = a_t, \]
\[ \pi(B) = \frac{\phi(B)\alpha(B)}{\theta_q(B)}, \]
\[ \alpha(B) = (1 - B)^d(1 - B^s)^D \] and hence
\[ Z_t = \begin{cases} 
  y_t, & \text{if } t \neq T \\
  y_t + \sum_{i=1}^{k} V_i(B)\omega_iI_t^T_i & \text{if } t = T
\end{cases} \]

Based on the dynamic impact of the outlier, the $V_i(B)$ can take different forms:

Additive outlier: $V_i(B) = 1$

Innovation outlier: $V_i(B) = \frac{1}{\pi(B)}$

Permanent level shift: $V_i(B) = \frac{1}{1 - B}$

Transient level shift: $V_i(B) = \frac{1}{1 - \delta B}$

where $0 \leq \delta \leq 1$, $\delta$ is the rate at which the impact of the shock decays.

The closer $\delta$ is to 1, the longer the impact will last and vice versa.

Figure 2.3 illustrates some of the common different possible cases of the transfer function. For example, the step response intervention as in Equation 2.7b represents the impact that affects the mean function. While the short-lived intervention effects are specified using a pulse response intervention as in Equation 2.7a, these effects might die out gradually.

According to Fox (1972), Box et al. (1976), Tsay (1986, 1988), Franses (1998), Kaiser and Maravall (1999), Peña (2001) and Heij et al. (2004), the different impacts are modelled as follows:

1. **An additive outlier (AO)** is an incidental outlier that happen for a reason outside the economic environment, and hence it is unpredictable. It is called "a gross error model" since it only affects the measured value of the observed time series at one specific point in time; i.e. the point of shock ($T_i$). But there are no other effects on the observations afterwards which implies that the mean of the time series is not affected. In that case, $V_i(B) = 1$; and hence, it can be represented as:

\[ Z_t = y_t + \omega_t P_t^{T_i} \]

\[ Z_t = \frac{\theta(B)}{\phi(B)\alpha(B)} a_t + \omega_t P_t^{T_i} \quad (2.8) \]
Figure 2.3: The response to different types of input.

The Figures are illustrated as follows:

(a) represents an abrupt permanent change of the mean process by $\omega_i$ determined by the zero-order transfer function,

(b) is a gradual permanent increase to a new mean determined by the first-order transfer function,

(c) is a special case. Where $\delta = 1$, it is a ramp effect that implies that the intervention changes the mean function linearly in the post-intervention period,

(d) is an abrupt temporary pattern of impact determined by the first-order transfer function using an impulse indicator,

(e) is the post-intervention mean increase by $(\omega_1 + \omega_2)$ as a result of the pulse, and then it decays exponentially by a factor of $(\delta)$, and

(f) is an initial increase by $(\omega_0)$ above the mean level followed by decrease of $(\omega_1 + \omega_2)$ below the past mean level, and then a gradual increase starts again.
2. An innovation outlier (IO) occurs in the driving noise process. It affects the residual at the point of the initial shock and propagates in the subsequent observations $y_T, y_{T+1}, \ldots$, with the weights of the ARIMA model, such that $V_i(B) = \frac{1}{\pi(B)}$. Consequently, it shows as a pulse effect to the innovation sequence of the original process:

$$Z_t = y_t + \frac{1}{\pi(B)} \omega_i I_t^{T_i}$$

it shows as an impulse effect to the innovation sequence of the original process:

$$Z_t = \frac{\theta(B)}{\phi(B) \alpha(B)} [a_t + \omega_i I_t^{T_i}]$$
(2.9)

3. Level shift (LS) is a level shift of the deterministic trend of the time series; the shock effect might cause: (a) a permanent level shift (PLS), where $V_i(B) = \frac{1}{1-B}$, and the model form as in Equation 2.10, (Franses, 1998).

$$Z_t = \frac{\theta(B)}{\phi(B) \alpha(B)} a_t + \frac{1}{1-B} \omega_i I_t^{T_i}$$
(2.10)

where, $\frac{1}{1-B} \omega_i I_t^{T_i} = \sum_{i=0}^{k} \omega_i I_t^{T_i}$,
(2.11)

or (b) a transient level shift (TLS) as in Equation 2.12, where $V_i(B) = \frac{1}{1-\delta B}$. The effect of the shock ($\omega_i$) diminishes by the factor ($\delta$) exponentially over the subsequent observations, and eventually the series returns to its normal level, (Box and Tiao, 1975, Leone, 1987).

$$Z_t = \frac{\theta(B)}{\phi(B) \alpha(B)} a_t + \frac{1}{1-\delta B} \omega_i I_t^{T_i}$$
(2.12)

where $\frac{1}{1-\delta B} \omega_i I_t^{T_i} = \sum_{i=0}^{k} \delta \omega_i I_t^{T_i}$,

such that $|\delta| < 1$ and $\sum \delta$ is a geometrically declining weight of future values of outliers. Where, $\delta$ is the rate at which the impact of the shock decays, the closer the $\delta$ to 1, the longer the impact will last.

4. Changing trend (CT) is a divergence of the deterministic trend towards a different trend after $T_i$, which might be described as a structural break in the time series. The model is given by Equation 2.13. The model is extended in Equation 2.14 to include an intercept term as well as a dummy variable which takes value of 1 from $T_i$ onwards to account for
a different starting point for the trend rather than $y_t$. Additionally, the trend changes are incremental. Hence, dummy variables around $T_i$ and thereafter are included depending on the number of lags of $y_t$ needed to account for the dynamic patterns. The trend before $T_i$ is $\nu$ and $(\nu + \omega)$ from $T_i$ onwards.

$$Z_t = \nu t + \omega I_{T_i}^T t + a_t$$ (2.13)

$$Z_t = \mu + \nu t + \omega I_{T_i}^T t + \lambda_1 I_{T_i} + \lambda_2 I_{T_i}^T + a_t$$ (2.14)

Kaiser and Maravall (1999) stated that the effect of an outlier on the components of the time series depends on the outlier type such that the AOs are affecting the irregular component, LS and CT outliers are associated with the trend-cycle component, and IOs simultaneously affects the trend-cycle and the seasonal components. The effect of an AO or LS type are independent from the ARIMA model for the series; for the AO and TLS types, the effect is transitory, while for the PLS type it is permanent. The effect of an IO, a LS and a CT type depends on the particular model for the series.

### 2.4 Data exploration

In this section, the sample is analysed. The analysis is based on the time series of total monthly container throughput (loaded and unloaded) measured in units of TEUs for the port of Antwerp, from January 1995 to March 2015, denoted by $CTHRP_t$. During that period, the average proportion of the loading (unloading) to the total throughput is approximately 0.50. The highest average month is March, which is attributed to the effect of the Chinese new year (it varies between the months of January and February) where almost all the economic activities as production and export are on hold. Consequently, the Asia-Europe trade decreased significantly during the closure period and all the delayed exports are shipped in March\(^5\).

Figure 2.4 depicts the different decomposed components of the time series. It shows an increasing time trend, seasonality, and the random shocks to the container throughput.

\(^5\)The actual monthly numbers are only used to estimate the models but are not shown in the figures; a chained index is shown instead. This is in accordance with an agreement with the port of Antwerp to keep the monthly numbers confidential.
2.4.1 Data transformation and graphical representation

Transformation of the original series at level is necessary since the $CTHRP_t$ time series shows changes in levels due to trends (stochastic and/or deterministic) and seasonal effects.

Figure 2.5 depicts the different transformations of the monthly series of container throughput measured in TEUs in the following panels:

(i) Figure 2.5a plots $CTHRP_t$: it is the original monthly total container throughput in TEUs at level. The series shows a stable exponential growth until February 2007, starting from March 2007, it is difficult to depict a stable trend.

(ii) Figure 2.5b displays the natural logarithm of container throughput denoted by $LCTHRP_t$. The logarithmic form is used to stabilise the variance, but the series still shows a lin-
ear growth path with some fluctuations that may be caused by seasonal effects or shocks to the economy. This might have caused a level shift in trend after January 2009 as a result of the abrupt financial crisis that started in the United States of America in 2008 and spread globally.

(iii) Figure 2.5c shows the monthly growth rates for the container throughput measured in TEUs and denoted by: $\Delta CTHRP_t = CTHRP_t - CTHRP_{t-1}$ that shows unstable behaviour along the mean.

(iv) The problem in modelling the container throughput arises because the dynamic process of the time series is significantly interrupted. This is shown in Figure 2.5d that analyses the year-over-year monthly growth rate. During the period Jan. 1995 - Oct. 2008, the year-over-year monthly growth rate was stable around 11%. That declined sharply to -15% during the period Oct. 2008 - Nov. 2009. The analysis shows a stagnant growth rate that fluctuates around a mean of -0.12% over the period Aug. 2011 - Apr. 2014. Most of these fluctuations are attributed to the economic activity and trade; other factors include the competitive position of the port. It is denoted by: $\Delta_{12} CTHRP_t = CTHRP_t - CTHRP_{t-12}$.

Figure 2.5: Data Transformation for monthly container throughput in the port of Antwerp in TEUs.
2.4.2 The sample

In order to validate the model, the sample for the empirical model is split into two subsamples. The first is the experimental set or the training set (about 80% of the observations), which starts from January 1995 until March 2011, that accounts for 195 observations and is used to estimate the models. The second is the validation set or the holdout sample, which covers the period from April 2011 until March 2015, which accounts for 48 observations and is used to evaluate the accuracy of the out-of-sample forecasting performance of the proposed models. This cross-validation technique is a conventional approach used in statics to ensure the forecasting accuracy of the model. The sample is visualised in Figure 2.6.

Figure 2.6: Port of Antwerp monthly container throughput in TEU.

Figure 2.6 shows a linear behaviour of the series with stable exponential growth until Oct. 2008 (time of break ‘TB’) when the global financial crisis erupted, which led to a structural break that caused a change in the rate of growth that was significant in Jan.
Chapter 2. A univariate-intervention model: Short-term forecast of container throughput

2009. The lag is attributed to the time delay between the start of the crisis in the USA and the global impact on international trade and on the container throughput series. This is shown by the two different growth paths. The trend line is estimated from the regression on a constant and a trend (t), and the break in trend line is estimated in addition to a dummy variable taking zero prior, at TB and the value of (t-TB) afterwards. It is shown that the break is close to end points of the experimental set which imposes limitations on the model estimation and the ability to forecast. Moreover, for the period Mar. 2007 - Mar. 2010, it is difficult to depict a stable behaviour since many interruptions occurred. Analysing the significant changes, the following factors are identified as follows:

- The high peak in March 2002 was due to a substantial shift of container flows by the Mediterranean Shipping Company (MSC) in the first quarter of 2002 from the port of Felixstowe to the port of Antwerp (see Coppens et al., 2007, p.1).
- The significant increase in the time series that started in March 2007 could be linked to the developments in the port of Antwerp that are related to the new port capacity and operational developments in the port during the period 2005-2007 (Flemish Port Commission annual reports). The major developments are: firstly, the container terminal 'Antwerp Gateway' was opened in March 2005 in the eastern part of the Deurganck dock, followed by, secondly, the joint venture between the Port of Singapore Authority (PSA) and MSC in June 2005, which officially operates the MSC Home Terminal at the Delwaide dock on the right bank of the Scheldt. Thirdly, the completion and full operation of the new Deurganck container dock on the left bank of the Scheldt in 2006, and its ability to receive and handle the super-post-panamax ships with a maximum handling capacity of 7.5 million TEUs annually. The dock handled a volume of 810,000 TEUs in 2006 and more than 1.5 million TEUs in 2007 (reported in the annual reports of the Antwerp Port Authority).
- That booming period came to an end in the last quarter of 2008 as a result of the global financial crisis that erupted in the USA in 2007. The crisis resulted in a declining world trade and, consequently, dropping container volumes on all routes with a particularly sharp decline on the Far East route. By examining the year-over-year (y-o-y) growth rate of the container throughput for the port of Antwerp in Figure 2.5d, the financial crisis has a clear negative impact from August 2008 to December 2009 as the growth rate during this period exhibits a continuous negative percentage. This is the result of the decline in world trade and, hence, the decline of container volumes on all routes, particularly a sharp decline on the Far East route. The crisis effect lasts until March 2010, where the number of TEUs shows a trend-recovery. Notably, there is a time delay between the start of the crisis and the materialisation of its effect on the container throughput. This time lag is reasonable since some shipping companies and trade contracts still hold.
2.5 The empirical analysis

The empirical analysis is carried out on the monthly container throughput for the port of Antwerp. In this section, the Box and Jenkins methodology procedure is applied based on the data analysis in Section 2.4. The ARIMA model is identified and estimated in Section 2.5.1 followed by incorporating the intervention analysis in Section 2.5.2.

2.5.1 The ARIMA model

The objective of this section is to determine the order of integration and the lag order of the model as illustrated in Section 2.3.1.

Different transformations of $C_{THR}$ are tested for stationarity. The two most common unit root tests used in the literature are the Augmented Dickey-Fuller test (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Pindyck and Rubinfeld, 1997, Verbeek, 2008). The $LCTHR$ is found to be stationary of order one, i.e. $I(1)$ at 5% significance. Similarly, the same tests are conducted for $\Delta_{12}LCTHR$ and $\Delta\Delta_{12}LCTHR$ to account for the seasonality effect, all the test results are reported in Table 2.1.

To identify the possible tentative models, the graphical inspection of the ACF and PACF patterns depicted in Figure 2.8 provide information about the stationarity of the time series and the identification of the model. In Figure 2.7a the ACF plot shows a slow linear decay pattern which is a typical nonstationary time series, while in Figure 2.7b, the ACF indicates the presence of significant seasonal effects at lags 12, 24 and 36 since it lies outside the 95% boundaries. Similarly, the same figures are plotted for $\Delta_{12}LCTHR$ and $\Delta\Delta_{12}LCTHR$ in Figures 2.7c and 2.7d, respectively. Figure 2.7d shows a dampening of the seasonal effect where, only now, the $12^{th}$ lag is significant.
### Table 2.1: Unit root tests for the different transformations of $CTHRP_t$.

<table>
<thead>
<tr>
<th>Transformation</th>
<th>ADF Test Statistic</th>
<th>KPSS Test Statistic</th>
<th>P-value</th>
<th>LM-Statistic</th>
<th>ADF Test Statistic</th>
<th>KPSS Test Statistic</th>
<th>P-value</th>
<th>LM-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CTHRP_t$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>3.39</td>
<td>0.76</td>
<td>0.49</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend</td>
<td>-2.39</td>
<td>0.12</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta CTHR P_t$</td>
<td>-2.85</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.87</td>
<td>0.21</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend</td>
<td>-2.87</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Remarks:

(i) The sample is from January 1995 to March 2015.
(ii) The KPSS null hypothesis in case of a constant only is $H_0: Stationarity$ of the time series, while if a trend is included then the null hypothesis is $H_0: The time series is trend stationary$ (see Verbeek, 2008, p. 28).
(iii) The constant is significant and the trend is insignificant for $CTHRP_t$ and $\Delta CTHR P_t$.
(iv) The constant and the trend are both significant for $\Delta_{12} CTHR P_t$.
(v) The constant and trend are both insignificant for $\Delta_{12} CTHR P_t$.
(vi) Both the ADF and KPSS tests fail to reject that $CTHRP_t$ is stationary, while the tests do not reject that the time series has a unit root for $\Delta_{12} CTHR P_t$ and $\Delta_{12}^{d} CTHR P_t$.
(vii) The KPSS test shows that $\Delta_{12} CTHR P_t$ is trend-stationary only.

---

<table>
<thead>
<tr>
<th>1% Test Critical Values</th>
<th>5% Test Critical Values</th>
<th>10% Test Critical Values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t$-statistic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.64</td>
<td>2.56</td>
<td>2.86</td>
</tr>
<tr>
<td>1.95</td>
<td>2.88</td>
<td>3.13</td>
</tr>
<tr>
<td>2.58</td>
<td>3.46</td>
<td>3.99</td>
</tr>
</tbody>
</table>

---

<table>
<thead>
<tr>
<th>Test Critical Values</th>
<th>Asymptotic Values</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.64</td>
<td>2.56</td>
<td>2.86</td>
</tr>
<tr>
<td>1.95</td>
<td>2.88</td>
<td>3.13</td>
</tr>
<tr>
<td>2.58</td>
<td>3.46</td>
<td>3.99</td>
</tr>
</tbody>
</table>
(a) S(P)ACF of \( LCTHRP_t \).

(b) S(P)ACF of first difference of logarithmic of container throughput \( \Delta LCTHRP_t \).

(c) S(P)ACF of \( \Delta_{12} LCTHRP_t \).

(d) S(P)ACF of \( \Delta_{12} LCTHRP_t \).

Note: The dashed line represents the 95% confidence interval calculated as \((\pm 1.96/\sqrt{n})\).

Figure 2.8: The correlograms of the monthly container throughput transformations.

The ACF in Figure 2.7b for the series $\triangle LCTHRP_t$ shows spikes at lags 1, 12, …, etc. (which emphasise the seasonal effect), while the PACF shows spikes at lags 1, 12 and dampening effects for the other lags. That pattern does not give rise to a definite model. Therefore, many models have been considered with reference to the significance of the parameters and the invertibility condition to avoid over-differencing as a selection criterion in addition to AIC and SIC.

Many alternative tentative models were estimated; however, only the diagnostic checking for three models; $ARIMA(2, 1, 1)$, $SARIMA(1, 1, 0)(1, 1, 0)_{12}$ and $SARIMA(1, 1, 2)(1, 1, 1)_{12}$ are reported in Table 2.2. The other models that were estimated but not reported either do not satisfy one or all of the residual diagnostic tests (variance constancy and heteroscedasticity, and stationarity) and/or the invertibility condition, and for those who satisfy the tests the final selection criteria was based on the minimum AIC and the significance of the parameters. For example, the $SARIMA(1, 1, 2)(1, 1, 1)_{12}$ violates the invertibility condition. Although the residual of the other two models is not normally distributed, this is expected from the sample analysis in Section 2.4.2 due to the outliers. The model estimates are shown in Tables 2.5 and 2.6.

Among the proposed tentative models and according to the selection criterion of AIC and BIC, the $SARIMA(1, 1, 0)(1, 1, 0)_{12}$ model gives the best fit. In the following section, the intervention analysis is incorporated to the model.

2.5.2 The intervention analysis

Based on the methodology, the data analysis and the selected intervention parameters, the SARIMA$(1, 1, 0)(1, 1, 0)_{12}$ is estimated for the experimental set applying the maximum likelihood method to Equation 2.15. The estimates for the model are reported in Table 2.3.

$$Z_t = y_t + \omega_0 Mar02 + \frac{1}{\pi(B)}[\omega_1 Mar07] + \frac{\omega_2}{1 - \delta B} Jan09 \quad (2.15)$$
Table 2.2: Overview of diagnostic tests for the different tentative models.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Diagnostic test</th>
<th>$\Delta LCTHRP_t$</th>
<th>$\Delta_{12} LCTHRP_t$ - SARIMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criterion</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model fit</td>
<td>R-squared</td>
<td>0.1741</td>
<td>0.3533</td>
</tr>
<tr>
<td></td>
<td>Adj R-squared</td>
<td>0.1611</td>
<td>0.3424</td>
</tr>
<tr>
<td></td>
<td>Sum Squared Residual (SSR)</td>
<td>0.0569</td>
<td>0.0537</td>
</tr>
<tr>
<td></td>
<td>Std. Dev. of Residuals</td>
<td>0.6125</td>
<td>0.5124</td>
</tr>
<tr>
<td></td>
<td>Inverted $</td>
<td>\text{AR and MA roots}</td>
<td>&lt;1</td>
</tr>
<tr>
<td>Selection Criterion</td>
<td>AIC</td>
<td>-2.8663</td>
<td>-2.9737</td>
</tr>
<tr>
<td></td>
<td>SIC</td>
<td>-2.7821</td>
<td>-2.9033</td>
</tr>
<tr>
<td>Normality of Residual</td>
<td>Skewness</td>
<td>0.4034</td>
<td>0.0709</td>
</tr>
<tr>
<td></td>
<td>Kurtosis</td>
<td>4.4950</td>
<td>4.1158</td>
</tr>
<tr>
<td></td>
<td>Probability of J-B test</td>
<td>0.0000</td>
<td>0.0083</td>
</tr>
<tr>
<td>Variance of Residual</td>
<td>ARCH Test Prob. of $x^2(1)$</td>
<td>0.6283</td>
<td>0.8017</td>
</tr>
<tr>
<td>Serial Correlation of Residual (Probability)</td>
<td>Ljung-Box (36 lags)</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>Breusch-Godfrey (12 lags)</td>
<td>0.0000</td>
<td>0.0158</td>
</tr>
<tr>
<td>Ex-post Forecast (2011.04-2015.03)</td>
<td>RMSE of Static Forecast</td>
<td>31802.3</td>
<td>26775.1</td>
</tr>
<tr>
<td></td>
<td>RMSE of Dynamic Forecast</td>
<td>182887.7</td>
<td>171133.2</td>
</tr>
<tr>
<td></td>
<td>MAPE of Static Forecast</td>
<td>3.6071</td>
<td>3.1170</td>
</tr>
<tr>
<td></td>
<td>MAPE of Dynamic Forecast</td>
<td>22.5768</td>
<td>20.8674</td>
</tr>
</tbody>
</table>

(a) Jarque-Bera test null hypothesis is that the residuals are normally distributed.
(b) Autoregressive conditional heteroscedasticity test (ARCH) null hypothesis is that the residuals are homoscedastic; i.e. have constant variance.
(c) The Ljung-Box test is also known as Q-statistic or a portmanteau test that considers the significance of autocorrelation collectively at a set of lags.
(d) The Breusch-Godfrey test null hypothesis is that there is no serial correlation in the residuals; i.e. the series is a white noise.

The estimates in Table 2.3 show that the additive outlier in March 2002 has an effect of approximately 10.4% (calculated as: \((e^{0.0991} - 1) \times 100\)) increase in the mean of the series. The intervention in March 2007 is interpreted as an increase of 7.8% in container volume above the general trend associated with the introduction of the new developments. Moreover, the financial crisis led to an abrupt temporary change with a slow decay rate to the original level by \(\delta = 0.90\), which reduced the container throughput by an asymptotic change of approximately 16% (calculated as: \((e^{-0.172} - 1) \times 100\)). The hypothetical inference of the expected filter of the financial crisis is that after 3 years the impact of the crisis is still approximately 0.4% (calculated as: \((1 - e^{-0.1782 \times 0.8998^{36}}) \times 100\)). That confirms with the empirical evidence that shows that the recovery starts in March 2010.

Table 2.3: Estimation of SARIMA\((1, 1, 0)(1, 1, 0)_{12}\) Intervention model.

<table>
<thead>
<tr>
<th>(\hat{\phi}_1)</th>
<th>(\hat{\phi}_{12})</th>
<th>(\hat{\omega}_0)</th>
<th>(\hat{\omega}_1)</th>
<th>(\hat{\omega}_2)</th>
<th>(\hat{\delta})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>-0.4559</td>
<td>0.0991</td>
<td>0.0784</td>
<td>-0.1782</td>
<td>0.8998</td>
</tr>
<tr>
<td>Pr(&gt;</td>
<td>t</td>
<td>)</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>SE</td>
<td>(0.0603)</td>
<td>(0.0623)</td>
<td>(0.0301)</td>
<td>(0.0239)</td>
<td>(0.0332)</td>
</tr>
</tbody>
</table>

The model estimated is for the period 1995.01-2015.03. \(\sigma^2=0.002064\), AIC = -757.58.

The comparison of the models in Table 2.4 shows that the MAPE for the validation sample Apr. 2011 - Mar. 2015 is 19.96% in the ARIMA model with no intervention, while the ARIMA-intervention is 7.93%. Not only is the advantage of the ARIMA intervention model in forecasting, but also the interpretation of the intervention parameters is important in giving an estimation of the extent of the impact of different changes.

Table 2.4: Comparison of the forecast accuracy for the model estimation using the training and full sample.

<table>
<thead>
<tr>
<th>Sample used to estimate the model</th>
<th>Model</th>
<th>MAPE (2011.04-2015.03)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training (1995.01-2011.03)</td>
<td>No intervention</td>
<td>19.96%</td>
</tr>
<tr>
<td></td>
<td>Intervention</td>
<td>7.93%</td>
</tr>
<tr>
<td>Ex-post (2015.04-2015.09)</td>
<td>No intervention</td>
<td>1.14%</td>
</tr>
<tr>
<td></td>
<td>Intervention</td>
<td>1.25%</td>
</tr>
</tbody>
</table>

The estimated model is used to predict the container throughput in TEUs for the time period April 2015-December 2016, as shown in Figure 2.9 with the 95% confidence interval. During the analysis, more data were provided by the Antwerp Port Authority and; hence, the ex-post MAPE was calculated as shown in Table 2.4.
Figure 2.9: The actual, fitted and forecast of container throughput using ARIMA-intervention model.

2.6 Discussion and policy implications

In this chapter, the model developed provides an instrument for policy makers that serves three purposes: the first is to generate short-term forecasts, the second is to assess the impact of the shocks on the generating process of container throughput and the third is to provide insight into the behaviour of the container throughput of the port of Antwerp. A general purpose of this contribution is to provide a model that can be continuously updated and applied to any port.

The univariate methodology is conducted in this chapter applying the Box-Jenkins approach. One of the main advantages of this approach is the independence of other variables. Nevertheless, looking back at long historical data requires understanding the factors that drive the underlying behaviour of the time series and incorporating this in the model. It is very important not only to examine the DGP statistically but also to identify the economic factors that provide insight about the time series process and the significant factors like policy changes, extra capacity added, or terminal operators decisions. Moreover, the
intervention parameters allow for a rich dynamic structure and are proved helpful to analyse structural breaks in numerous fields (Box and Tiao (1975), Chung et al. (2009)). The use of the intervention analysis is helpful in explaining the dynamics and in assessing the impact of the interruptions.

The ARIMA intervention has the advantage of understanding two important phases in the DGP. The first is the changes during the shock, which is related to the immediate impact and the scale and scope of the shock. The second is what comes after, the consequences and the adjustments; for example, if it recovers to the previous trend or it is a permanent change. Results could be used to provide terminal operators and port authorities with the monthly forecast that is helpful in the planning of the terminal operations and the hinterland activities.

Based on the empirical analysis discussed in Section 2.5, the univariate analysis is considered a reliable instrument to forecast the container throughput at the port level, which is in accordance with the literature. However, any structural break will have an impact on the stochastic process. Therefore, the analysis was carried out for two models: (1) an ARIMA model without intervention parameters and (2) an ARIMA intervention model. The intervention terms incorporated in the model significantly improved the forecasting performance and provided insight into the behaviour of the time series. The empirical results showed that the ARIMA intervention model decreased the MAPE by about 12% (see Table 2.4).

From an empirical perspective when applying the univariate methodology, two aspects should be critically examined. First, this approach requires long time series to capture the trend and examine the changes and factors underlying the DGP; moreover, the frequency of the time series depends on the purpose and the horizon of the forecast. Second, the model is generic, can be applied to other ports, and can be updated frequently when more data points are available, and that improves the model’s fit. Nevertheless, updating the model may change the identification process of the model and the lag structure that should be examined.

The implications for the port of Antwerp are two fold. First, the short-term forecasts provide an instrument for the port planning operational decisions and avoid congestion at the port and at the hinterland connections. Second, the shocks discussed in Section 2.4.2 are modelled differently according to the cause and impact of the shock. Hence, the port policy makers learn from these shocks. For example, the high peak in March 2002 that was caused by a change in the market share had an effect of about 10.4% increase in the mean of the container throughput. The 2007 new developments in the port of Antwerp led to a 7.8% increase in container volume above the trend that implies that the port might have faced a congestion problem if the necessary actions were not taken (that will be discussed further in Chapter 4. The financial crisis in 2008 caused a sharp decline in October 2008,
which was caused by the significant decrease in world trade volumes, had a severe impact on changing the trend of the series. The slow decay rate of $\delta$ close to 1 indicates that the impact of the shock is persistence and it will take long to recover.

2.7 Conclusion

The analysis described and carried out in this chapter starts by an introduction and a relevant literature review related to the methodology in Sections 2.1 and 2.2, respectively. The analysis was carried out through a univariate methodology applying the Box-Jenkins methodology to systematically build an ARIMA model. Furthermore, the intervention analysis is incorporated in the model to evaluate the pattern and duration of shocks to the container throughput. The methodology is illustrated in Section 2.3. The empirical analysis investigate, in details, the monthly container throughput, measured in TEUs, of the port of Antwerp for the period January 1995 to March 2015, in Section 2.4, where the sample is divided into two sub-samples for cross-validation. The empirical analysis based on the methodology is estimated and validated in Section 2.5.

The analysis has led to important conclusions. First, adding the intervention parameters to the model improves the forecasting accuracy. Second, the model proposed is useful to assess the impact of disturbances in the time series that provides a tool for the decision making to have insight into the dynamic and stochastic processes, and the effect of the intervention. Third, forecasting the container throughput is of importance for terminal operators and port authorities as it affects the economic planning and allocation of resources for port operations at the terminal and at the hinterland connections. Forecasting the number of TEUs at the port level in the short-term assists in the planning of the operational decisions such as the port capacity utilisation, loading and unloading planning, handling of container activities and hinterland connections capacity provision.

It is very important to understand the cause of any intervention in the time series, to correctly assess and model the impact of such a shock. There are many factors that may influence the container throughput time series. Some of these factors are related to changes in the maritime sector such as changes in the port’s competitive position, and; hence, the market share, the changes in the ports of call or ship routing by the shipping lines, the terminal operators decisions, or an additional capacity investments by port authority. In addition to other macroeconomic factors, like changing oil prices or the volatility of trade volumes. Moreover, in order to recover from such breaks, the port authorities and terminal operators need to take the appropriate actions; for example, if the impact of the shock is temporary due to a congestion problem at the terminal that will require operational adjustments such as increasing the working shifts. On the contrary, if the impact is permanent and leads to a change in the level, an advanced technology or a new crane is needed.
Can the past predict the future? An assessment of the forecasting performance suggests that this approach is appropriate for forecasting the short-term demand variations for the container throughput. The advantage of this approach is that it offers a systematic approach to building, analysing, and forecasting time series models. However, such an approach depends on the assumption that the historical pattern will not change during the forecast period. Therefore, the intervention analysis was incorporated in the model to measure the impact of the different shocks on the trend. The conclusion is that the univariate analysis provides insight into the generating process of the time series and provides reliable forecasts for a short-period (3 to 12 months) assuming that the trend remains the same. The key to understand the results and the dynamics of the time series lies in the economic factors that anticipate the series’ behaviour. Therefore, in the next Chapter, the model is developed further to examine causal dynamic models by testing for cointegration relationships based on economic activity leading indicators and past performance.

2.8 Appendix

Table 2.5: ARIMA(2,1,1) Model Estimation using $\Delta LCHRP_t$.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.007121</td>
<td>0.001134</td>
<td>6.279273</td>
<td>0.0000</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.480749</td>
<td>0.097010</td>
<td>4.955663</td>
<td>0.0000</td>
</tr>
<tr>
<td>AR(2)</td>
<td>0.232633</td>
<td>0.084641</td>
<td>2.748458</td>
<td>0.0066</td>
</tr>
<tr>
<td>MA(1)</td>
<td>-0.924954</td>
<td>0.059404</td>
<td>-15.57045</td>
<td>0.0000</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.174136</td>
<td></td>
<td></td>
<td>0.00729</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.16200</td>
<td></td>
<td></td>
<td>0.06199</td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.05678</td>
<td></td>
<td></td>
<td>-2.87654</td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>0.61246</td>
<td></td>
<td></td>
<td>-2.80916</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>283.0240</td>
<td></td>
<td></td>
<td>-2.84925</td>
</tr>
<tr>
<td>F-statistic</td>
<td>13.35400</td>
<td></td>
<td></td>
<td>1.974854</td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Inverted AR Roots: .78  -.30
Inverted MA Roots: .92
Table 2.6: Model estimation of SARIMA(0, 1, 2)(0, 1, 1)\textsubscript{12}.

Dependent Variable: $\Delta\Delta_{12} \log(CTHRP)$
Method: ARMA Generalized Least Squares
Sample (adjusted): 1996M02 2011M03
Included observations: 182
Convergence achieved after 10 iterations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.000108</td>
<td>0.001855</td>
<td>0.058268</td>
<td>0.9536</td>
</tr>
<tr>
<td>AR(1)</td>
<td>-0.462555</td>
<td>0.066557</td>
<td>-6.949742</td>
<td>0.0000</td>
</tr>
<tr>
<td>SAR(12)</td>
<td>-0.497025</td>
<td>0.066661</td>
<td>-7.456010</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared       | 0.354170    | Mean dependent var | 0.000587    |
Adjusted R-squared | 0.346954  | S.D. dependent var | 0.066162    |
S.E. of regression | 0.053466  | Akaike info criterion | -2.983155  |
Sum squared resid | 0.511697  | Schwarz criterion | -2.930341   |
Log likelihood   | 274.4671   | Hannan-Quinn criter. | -2.961745  |
F-statistic      | 49.08130   | Durbin-Watson stat  | 2.025654    |
Prob(F-statistic)| 0.000000   |                        |            |

Inverted MA Roots

\[.91+.24i\]
\[.91+.24i\]
\[-.46\]
\[-.91-.24i\]
\[.91-.24i\]
\[.91-.24i\]
\[.67+.67i\]
\[.67+.67i\]
\[.67+.67i\]
\[.67+.67i\]
\[.67+.67i\]
\[.91+.24i\]
\[.67-.67i\]
\[.67-.67i\]
\[.67-.67i\]
\[.67-.67i\]
\[.91+.24i\]
CHAPTER 3

A MULTIVARIATE MODEL: TESTING FOR LEADING INDICATORS

3.1 Introduction

The long-term relationship between economic activity and container freight flow guides the efficient allocation and economic sustainability of resource allocation and investment decisions whether the infrastructure needed is financed by the public or the private sector. The objective of this chapter is to provide an instrument for the different stakeholders in the port sector by developing a forecasting model for the container demand at the port level based on the leading indicators of the economic activity.

The methodology conducted is based on the hypothesis that economic activity indicators can be used in leading the container throughput. In this chapter, the relationship between economic activity and the container throughput is tested to develop a model to forecast the container throughput at the port level allowing for a time lag between the variables. The variables are at aggregate level, encompassing the total throughput of containers at the port of Antwerp and the economic indicators, including the index of industrial production, the composite index of leading indicators, the industrial confidence indicator for Belgium and one confidence indicator for the European Union. The dataset is based on a monthly time series from January 1995 to March 2015.

Two dynamic time series modelling approaches are adopted in this chapter. First, an autoregressive integrated moving average with an exogenous variable (ARIMAX) model is estimated based on the Box and Jenkins methodology (illustrated in details in Chapter 2). The advantage of this model over the ARIMA intervention model applied in Chapter 2 is that it can capture the influence of external factors and identify the lead-lag relationship. Second, an error correction model is estimated using the Engle-Granger two-step procedure (Engle and Granger, 1987). This approach relies on testing for common patterns and trends in the historical dataset between the container throughput and economic activity indicators using a cointegration test. The advantage of this approach is that it evaluates the short-term and long-term effect of the explanatory variable on the dependent variable.
A successful decision-making process depends on taking the right action at the right time to be prepared for the future. However, there is no crystal ball where stakeholders can see accurately into the future. Therefore, rational forecasting based on economic theory and the analysis of the relevant data is needed to reduce uncertainty. This chapter is of interest in financial and organisational planning for port authorities, terminal operators, and stakeholders not only for providing short-term forecasts based on the economic indicators, but also for identifying the long-term relationship development. Consequently, the empirical analysis contributes to provide insight into the data generating mechanism that allows answering the research question that is examined in this chapter: Which economic indicators might be identified as leading indicators for the container throughput? and why? and whether this relationship is stable over the long-run or not.

Figure 3.1 shows a time plot of the actual total container throughput for the port of Antwerp during the period January 1995 - March 2015. The series shows a developing upward trend with a large shift upward in March 2007 that was attributed to the capacity developments in the port of Antwerp (more details is in Section 2.4.2). The increasing trend came to an end in October 2008 where the global financial market crisis that started in the US had a significant impact on the global economy. Since the arising of the crisis, it has been difficult to depict a stable trend based on analysing the relationship between the container demand at the port level and the leading indicators of the economic activity.

![Figure 3.1: Trend-break of the total container throughput at the port of Antwerp.](image)

In Section 3.1, an introduction about the problem setting and the rationale of the chapter is explained. This is followed by a brief literature review in Section 3.2 that is related to modelling the relationship between maritime freight and economic activities.
The dataset definition, visualisation and analysis are described in Section 3.3. As a result of the data analysis and the specific characteristic of the time series behaviour, the modelling approaches are selected. The methodology and empirical findings are presented in Section 3.4. Finally the conclusion is in Section 3.5.

3.2 Literature review

The long-term forecast depends on the interrelated relationship between maritime transport and economic activities. Although this relation is often used in models for forecasting port throughput, it is not without problems. First, there is the question of the stability of this relationship over a longer time period. Second, there is the need for projections for the independent variables.

However, if the long-run relationship is not stable or the shocks are not accounted for, it would be of rather limited use for policy analysis. As Keynes put it: 'But this long run is a misleading guide to current affairs. In the long run we are all dead. Economists set themselves too easy, too useless a task if in tempestuous seasons they can only tell us that when the storm is long past the ocean is flat again.' (see Keynes, 1923, chap. 3, pg. 80). In the context of the thesis, the long run is defined in terms of the equilibrium concept adopted from Hendry, 1995, pg. 213. The concept of equilibrium is the state where no inherent tendency to change, and any deviation from the long-run path is a disequilibrium which induces a change in the dependent variable in the next period. Therefore, the speed of adjustment is estimated in the cointegration analysis.

For the long run, causal approaches that depend on the assumption that there is a positive causation that goes from the economic activity to the container throughput were applied. The correlation between the dependent variable to be forecast and the independent variable(s) is tested. A multivariate autoregressive model is used in Veenstra and Haralambides (2001) to forecast the long-term trade flow at a commodity level. Fung (2002) estimated an error correction model for the terminals at the ports of Hong Kong and Singapore to study the competitive interaction between terminal operators. He emphasised the dependence of the forecasts on the interaction between ports and provided a systematic approach for forecasting the demand for container handling services. A multiple regression model was used to investigate the long-run and short-run relations between exports and imports and a port’s loading and unloading activities, respectively in Meersman et al. (2003) and Meersman and Van de Voorde (2013). The work of De Langen (2003) identified seven determinants of maritime container transport demand, where four factors were related to the volume and flow of trade and three were related to the containerised share of transport flows. Hui et al. (2004) forecast the port cargo throughput in Hong Kong by estimating a cointegrated error correction model. A combined forecasting model with expert opinions is developed and applied at a commodity level to the Hamburg-Le
Havre range by De Langen et al. (2012). Pallis and De Langen (2010) concluded that the recent decline of throughput is strongly related to industrial output rather than to GDP development.

### 3.3 The dataset description and visualisation

The dataset is sampled at a monthly frequency from January 1995 to March 2015—except for trade indices data, which is only available until December 2013. The description of the data series and sources is given in Table 3.1. The sample is split into two parts: the estimation sample from 1995m01 to 2011m03 and the validation (or hold-out) sample from 2011m04 to 2015m03. With the exception of the trade indices where data is available only until 2013m12. The estimation sample is used to fit the model, and a prediction over the validation sample is made, where the forecast data is compared with the actual data using the MAPE.

Choosing the variables that represent the economic activity related to the container throughput is a challenge. The choice is based on the literature review and availability of data. Other variables might have been of interest to be studied and incorporated in the model such as the ‘Liner shipping connectivity index’ that measures how well countries are connected to global shipping networks. Nevertheless, it is not possible to use that variable since it is only available from 2004 and is only reported annually (UNCTAD, 2004).

The aggregate macro-economic data impose limitations on the analysis arising from the non-availability of monthly frequency data, the different units of measurement (volumes/values) and the different base year for long time series. Therefore, in practice, the empirical analysis is restricted to a limited number of relationships.

The total, loading and unloading of container throughput at the port of Antwerp is depicted in Figure 3.2. The visual inspection of the time series at levels suggests an upward trend, seasonality, a structural break and no significant trend difference between the growth of loading and unloading of containers throughput. In-depth analysis for the total container throughput series is given in Figure 3.3.
Table 3.1: Definitions and sources of the variables.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Variable</th>
<th>Definition</th>
<th>Sample</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOT_CTHRP</td>
<td>Total</td>
<td>Container throughput at the port of Antwerp measured in TEUs.</td>
<td>1995m01-2015m03</td>
<td>Provided by the Antwerp Port Authority</td>
</tr>
<tr>
<td>UNLOD_CTHRP</td>
<td>Unloaded</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOD_CTHRP</td>
<td>Loaded</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLI-BE</td>
<td>Composite Index of Leading Indicators. Trend restored, sa.</td>
<td>According to OECD Statistics Directorate (2007), OECD (2009), Gyomai and Guidetti (2012) and OECD (2013), the CLI is made up of a bundle of six economic time series (referred to as component series) that have similar cyclical fluctuations to those of the business cycles, and have a tendency to turn earlier than business cycles. It is used to indicate early signs of turning points in the growth cycle in the short term: the turning points of the CLI precede those of business cycles by about 6-9 months.</td>
<td>1995m01-2015m03</td>
<td>OECD.StatExtracts (data extracted on Nov 2015)</td>
</tr>
<tr>
<td>ESI-BE</td>
<td>Economic Sentiment Indicator (2010=100)</td>
<td>The scale and scope of European surveys were developed within the framework of the Joint Harmonised EU Programme of Business and Consumer Surveys (BCS) in November 2000 (Commission of the European Communities, 2000) to encompass five sectors namely: (1) manufacturing industry, (2) services, (3) consumers, (4) construction and (5) retail trade.</td>
<td>1995m01-2015m03</td>
<td><a href="http://ec.europa.eu/economy_finance/db_indicators/surveys/time_series/index_en.html#data_extraced_on_Nov_2015">http://ec.europa.eu/economy_finance/db_indicators/surveys/time_series/index_en.html#data_extraced_on_Nov_2015</a></td>
</tr>
<tr>
<td>ICI-BE and ICI-EU18</td>
<td>Industrial Confidence Indicator</td>
<td>It is calculated as the arithmetic average of the balances of responses on production and employment expectations, the assessment of order-book levels, stocks of finished products and selling price. It is used for Belgium and Euro area.</td>
<td>1995m01-2015m03</td>
<td><a href="http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&amp;plugin=0&amp;language=en&amp;pcode=teibs020">http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&amp;plugin=0&amp;language=en&amp;pcode=teibs020</a></td>
</tr>
<tr>
<td>IIP-BE</td>
<td>Index of industrial production (2010m06=100)</td>
<td>Industrial production refers to the volume of output generated by production units classified under the industrial sector; mining and quarrying, manufacturing industries, electricity, gas and water supply and construction.</td>
<td>1995m01-2015m03</td>
<td>OECD.StatExtracts (data extracted on Nov 2015), edition October 2015.</td>
</tr>
<tr>
<td>T-IM-VOL-BE</td>
<td>Total Import Volume Index</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The graphical inspection of Figure 3.3a shows the trend component of the natural logarithm of the total container throughput\(^1\). After removing short-term fluctuations, a fitted non-linear trend is depicted\(^2\) that shows a constant trend starting 2011. A linear trend is plotted: the estimated line is from the regression of the time series on a constant and a trend.

Panels 3.3b to 3.3d show the trend of the logarithm of the total container throughput with the different structural break types to show the different trend paths of the development of the time series and the effect of a structural shock. The date of the structural break (TB) in October 2008 \((TB = 2008\text{m10})\) is caused by the global financial crisis in 2008. Perron (1989) pointed out that there are three types of changes that might occur as a result of the potential structural break points that are defined as follows:

---

\(^1\) Using the Census X-13 in EViews 9, assuming a linear trend based on the argument of Nelson and Plosser (see 1982, p. 141).

\(^2\) Applying the Hodrick-Prescott filter, a data smoothing technique used to remove short-term fluctuations to extract a long-term trend component from the series.

---
(i) A change in the level (panel 3.3b) where the trend line is estimated from the regression on a constant, a trend and a dummy variable taking value zero before and at TB and the value of 1 afterwards. As implied from the figure, the change is temporary only at the time of the TB and has no effect on the exponential trend.

(ii) A change in the slope (panel 3.3c) where the trend line is estimated from the regression on a constant, a trend and a dummy variable taking value zero prior and at TB and the value of (t-TB) afterwards. As the figure shows, the trend or the growth rate is changed permanently after the TB.

(iii) A change in both level and mean (panel 3.3d) where a sudden change in the level of the series and a slower growth rate. It is estimated from the regression on a constant, an intercept dummy (0 prior and at TB, 1 after) and a slope dummy (0 prior and at TB and t after TB).

Figure 3.3: Trends and breaks of the total container throughput measured in TEUs for the port of Antwerp.
The economic indicators are visualised in Figure 3.4 with the appropriate trend break type. For the total container throughput $\text{Tot} - CTHRP$, a change in the rate of growth (slope) is fitting the data. A break in both level and slope is adequate for $CLI - BE$, $IIP - BE$, $ESI - BE$, $ICI - BE$ and $ICI - EU18$, while a change in level is depicted for the export and import volume indices; $T_{EX\_VOL}$, and $T_{IM\_VOL}$.

(a) LCLI

(b) LESI

(c) ICI

(d) ICI_EU18

(e) LIIP
3.4 Methodology and empirical findings

Patterson (2000) emphasised that the aim of quantitative economics is to test the development of the economic theory to investigate how the dynamics in the economy functions rather than numerically parametrising function and estimating models. Selecting an adequate and simple computational technique with an accepted degree of precision is challenging. This is attributed to the complex and dynamic nature of macroeconomic variables (Granger, 1997, p.169), the intertwined actors and factors in the maritime sector and the limitations of data availability.

Since the seminal work of Nelson and Plosser (1982), the unit root tests have received significant attention in modelling time series data. Therefore, to ensure the robustness and the validity of the model, it is a necessary condition to test for the stationarity of the time series.

3.4.1 Unit root tests

In this chapter, two tests are applied. First, the conventional tests without structural break: the Augmented Dickey-Fuller unit root test (ADF) (Engle and Granger, 1991), and the second is the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) Kwiatkowski et al. (1992),
All unit root test regressions are run with a constant and trend term using the critical values tabulated by Dickey-Fuller, hence, the null hypothesis of unit root is only rejected. In spite of splitting the sample, assuming a break in October 2008, it was not powerful to reject the null hypothesis of unit root, even though the coefficient of the lag dependent variable decreased slightly; the results are reported in Table 3.2.

However, Phillips (1987) and Perron (1989) argued that in the presence of a structural break, the time series might be trend-stationary and the conventional unit root test – the ADF and the KPSS – are biased towards non-rejection of the unit root in the presence of a structural break. Consequently, as a relevant alternative, Perron (1989, p.1364-65) proposed a modified DF unit root test procedure that incorporates a dummy variable of a known single structural break in the trend function. This approach allows three scenarios to test for the unit root on the full sample that permits different types of structural break effects; (A) a change in the level of the series, (B) a change in the rate of growth, and (C) changes in both level and growth rate (see details for the methodology in Section 5.4).

The exogenous break is assumed to be in 2008m11 due to the U.S. financial crisis. Based on Figures 3.4 and 3.3c, a trend function is estimated with a change in the level in October 2008 for the trade indices (see Equation 5.3), a change in level and slope for the confidence indicators and industrial production (see Equation 5.5) and only a change in slope for the container throughput time series (see Equation 5.4). The test estimates are shown in Table 3.3 showing that the hypothesis of trend-stationary is rejected. But that result should be taken with consideration due to the limited sample post-break period.

### 3.4.2 The ARIMAX

The ARIMAX model depends on finding an exogenous variable that leads the container throughput. Based on the theory that there exists a relationship between the economic activity and container throughput, the cross-correlation function (CCF) is used to test this relationship for different economic variables to include as an exogenous variable in the framework of an ARIMAX model. To identify the lead-lag relationship, the CCF is used on a stationarity time series. The sample CCF is defined in terms of the cross-covariance function (CCVF) as follows (see Chatfield, 2004, pag. 155-159):

---

3 The detailed test methodology is illustrated in Section 5.4.
4 Unless stated otherwise, all hypothesis tests are conducted at the 5% significance level.
5 A breakpoint in that context means the point at which a maximum proportion of observations can be changed without changing the estimator.
Table 3.2: ADF and KPSS unit root tests (1995.01-2015.03).

<table>
<thead>
<tr>
<th>Time Series</th>
<th>ADF test statistic</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$H_0$: The time series has a unit root</td>
<td>$H_0$: The time series has no unit root</td>
</tr>
<tr>
<td></td>
<td>None</td>
<td>Constant</td>
</tr>
<tr>
<td>$\Delta TOT_CTHRP_t$</td>
<td>P-value</td>
<td>0.9708</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>1.5577</td>
</tr>
<tr>
<td>$\Delta TOT_CTHRP_t$</td>
<td>P-value</td>
<td>0.0042</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>-2.8713</td>
</tr>
<tr>
<td>$CLI - BE_t$</td>
<td>P-value</td>
<td>1.0000</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>3.8637</td>
</tr>
<tr>
<td>$\Delta CLI - BE_t$</td>
<td>P-value</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>-4.9189</td>
</tr>
<tr>
<td>$ESI - BE_t$</td>
<td>P-value</td>
<td>0.5559</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>-0.3557</td>
</tr>
<tr>
<td>$IPI - BE_t$</td>
<td>P-value</td>
<td>0.0116</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>-2.5227</td>
</tr>
<tr>
<td>$IPI - EU18_t$</td>
<td>P-value</td>
<td>0.0051</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>-2.8042</td>
</tr>
<tr>
<td>$\Delta IPI - BE_t$</td>
<td>P-value</td>
<td>0.9799</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>1.7304</td>
</tr>
<tr>
<td>$T - EX - VOL - BE_t$</td>
<td>P-value</td>
<td>0.8327</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>0.5434</td>
</tr>
<tr>
<td>$\Delta T - EX - VOL - BE_t$</td>
<td>P-value</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>-5.3037</td>
</tr>
<tr>
<td>$T - IM - VOL - BE_t$</td>
<td>P-value</td>
<td>0.8378</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>0.5661</td>
</tr>
<tr>
<td>$\Delta T - IM - VOL - BE_t$</td>
<td>P-value</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>t-statistic</td>
<td>-5.1352</td>
</tr>
</tbody>
</table>

Note: (a) The p-values of ADF is the MacKinnon (1996) one-sided p-values. (b)*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1). If the trend in included in the test statistic, then $H_0$: Time series is stationary around a deterministic trend.
Table 3.3: Perron tests for unit root with structural break.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$T\neq\lambda$</td>
<td>$T\neq\lambda$</td>
<td>$T\neq\lambda$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\beta}$</td>
<td>$\hat{\gamma}$</td>
<td>$\hat{\alpha}$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\phi}$</td>
<td>$\hat{\theta}$</td>
<td>$\hat{\phi}$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\mu}$</td>
<td>$\hat{\mu}$</td>
<td>$\hat{\mu}$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\sigma}^2(e)$</td>
<td>$\hat{\sigma}^2(e)$</td>
<td>$\hat{\sigma}^2(e)$</td>
</tr>
</tbody>
</table>

Remarks:

(i) The natural logarithm is used for all the variables except for the industrial confidence indicators since they are measured in net balance.

(ii) Since the data set is monthly, $k=12$ in all the models.

(iii) The breakpoint is determined exogenously using global maximizers of Schwarz information criterion.

(iv) $\lambda$ is the ratio of pre-break sample size to the total sample size.

(v) The year of the break ($T_B$) is 2008 with different months selected.

(vi) To evaluate the significance of the $t$-statistic on $\hat{\alpha}$, we use the critical values from Table IV.B for Model (A), Table V.B for Model (B) and Table VI.B for Model (C); (see Perron, 1989, pg. 1376-7). Where $\hat{\alpha}$ refers to the standard error of the $t$-statistic on $\hat{\alpha}$.

Remarks:

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\hat{\beta}$</td>
<td>$\hat{\gamma}$</td>
<td>$\hat{\alpha}$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\phi}$</td>
<td>$\hat{\theta}$</td>
<td>$\hat{\phi}$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\mu}$</td>
<td>$\hat{\mu}$</td>
<td>$\hat{\mu}$</td>
</tr>
<tr>
<td></td>
<td>$\hat{\sigma}^2(e)$</td>
<td>$\hat{\sigma}^2(e)$</td>
<td>$\hat{\sigma}^2(e)$</td>
</tr>
</tbody>
</table>
The sample CCVF is:

\[
c_{xy}(k) = \begin{cases} 
\frac{\sum_{t=1}^{n-k} (x_t - \mu_x)(y_{t+k} - \mu_y)}{n}, & k = 0, \ldots, n - 1 \\
\frac{\sum_{t=1-k}^{n} (x_t - \mu_x)(y_{t+k} - \mu_y)}{n}, & k = -1, -2, \ldots, -(n - 1)
\end{cases}
\]

(3.1)

Note that in Equation (3.1), if \( k > 0 \) it implies that \( x \) leads \( y \), i.e. \( y \) lags \( x \) and \( k < 0 \), it refers to the converse.

The sample CCF is:

\[
\rho_{xy}(k) = \frac{c_{xy}}{(\sigma_x^2 \sigma_y^2)^{1/2}}
\]

(3.2)

where,
- \( n \): the sample size,
- \( k \): the lag number,
- \( \mu_x \): the mean of \( x_t \),
- \( \mu_y \): the mean of \( y_t \),
- \( \sigma_x^2 \): the variance of \( x_t \), and
- \( \sigma_y^2 \): the variance of \( y_t \)

Testing for the different economic variables to include as an exogenous variable in the framework of an ARIMA model, the industrial confidence indicator for the EU 18(ICI_EU18) with two lag shows the best fit as a leading indicator; estimates of the CCF are reported in Figure 3.5. That can be explained by the fact that the port of Antwerp provides a widespread hinterland access by means of road, inland navigation, and rail mainly to The Netherlands, Germany and France.

As concluded from Chapter 2, the \( ARIMA(1,1,0)(1,1,0)_{12} \) is the appropriate model for the container throughput time series. Since the \( ICI\_EU18 \) is measured in net balance, therefore the time series of the de-trended container throughput is used and the ARIMA model is modified to \((1,0,0)(1,0,0)_{12}\); estimates of the model are shown in Table 3.5.
3.4.3 Cointegration and error correction model

In time series when the observations are not independent, using ordinary least squares (OLS) estimation will lead to spurious regression. However, a long-run relationship between the variables might exist indicating a cointegration process. Hamilton (1994) defined cointegration as a long-run equilibrium tying the relation between the individual series represented. In that context, cointegrated time series imply that even if two time series are individually nonstationary, there might exist a stationary linear combination of those variables, referred to as co-movements (Charemza and Deadman, 1997).

Engle and Granger (1987) defined cointegration for two time series, \( x_t \) and \( y_t \), of order \( d, b \) where \( d \geq b \geq 0 \), denoted as \( x_t, y_t \sim CI(d, b) \) if:

1. \( x_t \) and \( y_t \) are integrated of order \( d \), and
2. There exists (\( \exists \)) a linear combination \( \alpha_1 x_t + \alpha_2 y_t \) which is integrated of order \( d - b \), and the cointegrating vector is \([\alpha_1, \alpha_2] \)

The Engle-Granger (EG) two-step procedure (Engle and Granger, 1987) is used to test the hypothesis of no cointegration against the alternative hypothesis of cointegration.
The EG two-step procedure is a residual-based cointegration test that is based on a single equation. The basic idea of the EG test is that if $y_t$ and $x_t$ are cointegrated, then the error term $u_t$ must be stationary, i.e. $I(0)$. The two steps are as follows:

1. **Step 1**: Check if the condition of cointegration holds by testing the order integration of $y_t$ and $x_t$. Then, estimate the long-run relationship as in Equation 3.3 by OLS and test for the stationarity of $u_t$. Proceed to the next step if the unit root hypothesis of $u_t$ is rejected.6

2. **Step 2**: estimate the error correction mechanism as in Equation 3.4 replacing $\beta$ by $\hat{\beta}$ from Equation 3.3.

\[
y_t = \beta x_t + u_t \tag{3.3}
\]

\[
\Delta y_t = \alpha_1 \Delta x_t + \alpha_2 (y_{t-1} - \beta x_{t-1}) + \epsilon_t \tag{3.4}
\]

Where $\alpha_1$ is the short-term coefficient, $\alpha_2$ is the speed of adjustment factor, and $\beta$ is the long-term coefficient.

In the empirical analysis, two estimation issues arise. The first issue is the question of how to define the correct dummy variables to account for the different events in the differenced equation. Juselius (2006) showed that a shift in the level of the variables corresponds to a blip in the differences, and an impulse effect in the levels corresponds to a transitory blip in the differences. Accordingly, the dummy variables tested in the models were modified to be used in the differenced equations. The second issue is that the serial correlation in the regressors prevents using OLS; and hence, the fully modified ordinary least squares method (FMOLS) is used to estimate the first step in the EG approach to account for that problem and the critical values from Davidson and MacKinnon (1993, Table 20.2) are used.

The different economic variables are tested for the cointegration relationship. The industrial production index gives the best fit. Figure 3.6 shows that the three months lagged index of the industrial production and the container throughput are closely related. That is confirmed by the CCF, estimates are shown in Figure 3.7.

---

6The asymptotic distributions of residual-based cointegration test statistic are not the same as those of the ordinary unit root tests. The critical values used are in Davidson and MacKinnon (1993, Table 20.2 pg. 722).
Figure 3.6: The relationship between the container throughput and the industrial production 3 months lagged.

Sample: 1995M01 2015M03
Included observations: 242
Correlations are asymptotically consistent approximations

<table>
<thead>
<tr>
<th>D_IIP, D_TOT_CTHRP(-i)</th>
<th>D_IIP, D_TOT_CTHRP(+i)</th>
<th>i</th>
<th>lag</th>
<th>lead</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0</td>
<td>0.1015</td>
<td>0.1015</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.0162</td>
<td>-0.0202</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.1748</td>
<td>-0.1090</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>-0.0524</td>
<td>0.1201</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>-0.0469</td>
<td>-0.0514</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5</td>
<td>0.1343</td>
<td>0.0695</td>
</tr>
<tr>
<td></td>
<td></td>
<td>6</td>
<td>-0.0245</td>
<td>0.0009</td>
</tr>
</tbody>
</table>

Figure 3.7: The cross-correlation function for the IIP and the container throughput.

Three models are estimated, each for a different sample to test the model's stability and the impact of the global financial crisis in 2008. The models are estimated using the Engle-Granger approach, and the models' robustness is ensured by the stationarity of the residual. ‘Model (1)’ is estimated for the training sample, the results are reported in Tables 3.6, 3.7 and 3.8 (in the Appendix of this chapter). For model (1), equation 3.5 estimates
the long-run equilibrium, and Equation 3.6 is the error correction model\(^7\). The long-run impact is about a 2.64% increase in the current container throughput as a result of a 1% increase in the three months lagged industrial production. The speed of adjustment (-0.12) on \(ecm_{t-1}\) suggests a current monthly adjustment of 12% of any disequilibrium in the container throughput relative to 1% change in three months lagged industrial production.

\[
L_{Tot\_CTHRP_t} = 1.41 + 2.64 L_{IIP_{t-3}}
\]

\[
(0.481) \quad (0.110) \\
[2.94] \quad [23.99]
\]

\[
\Delta L_{Tot\_CTHRP_t} = 0.007 + 0.54 \Delta L_{IIP_{t-3}} - 0.12 ecm_{t-1}
\]

\[
(0.004) \quad (0.207) \quad (0.037) \\
[1.62] \quad [2.60] \quad [-3.21]
\]

\[(3.5) \quad (3.6)\]

Hence, the residual of the long-term equation is:

\[
ecm_{t-1} = L_{Tot\_CTHRP_{t-1}} - 1.41 - 2.64 L_{IIP_{t-4}}
\]

Furthermore, the behaviour of the co-movement changed after 2008m11 as shown from Figure 3.6; such that they are weakly moving together or diverging. Therefore, the short-run and long-run coefficients are estimated splitting the sample before the break point ‘Model (2)’ (1995m01-2008m10) and post-crisis ‘Model (3)’ (2008m11-2015m03). Tables 3.9 to 3.14 show the estimated short-run and long-run models for the two samples before and after the structural break of the financial crisis. Table 3.4 shows a summary of the results. It is clear that the crisis had an effect on changing the relationship: the speed of adjustment increased from 14% to 32%, which indicates that the container throughput rate of adjustment monthly increase by 18% to get back to the long-run equilibrium.

Table 3.4: Summary of the estimated coefficients for the crisis impact on the cointegration relationships.

<table>
<thead>
<tr>
<th>Models</th>
<th>Long-run</th>
<th>Rate of adj.</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model (1) Tables 3.8 &amp; 3.6</td>
<td>2.64</td>
<td>0.12</td>
<td>1995m01-2011m03 (195 obs.)</td>
</tr>
<tr>
<td>Model (2) Tables 3.9 &amp; 3.11</td>
<td>2.79</td>
<td>0.14</td>
<td>1995m01-2008m10 (166 obs.)</td>
</tr>
<tr>
<td>Model (3) Tables 3.12 &amp; 3.14</td>
<td>1.12</td>
<td>0.32</td>
<td>2008m11-2015m03 (77 obs.)</td>
</tr>
</tbody>
</table>

Note: The estimated results are in the Appendix of this chapter.

\(^7\)The standard errors are in parentheses and the t-Statistics are in square brackets.
3.4.4 Forecasting evaluation

In general, the MAPE is used to compare the different forecasting accuracy of the two models estimated in this Chapter; the ARIMAX and the error-correction model. Moreover, the Theil’s inequality coefficient\textsuperscript{8} is used to evaluate the forecast in terms of change. The bias proportion in the dynamic forecast is high (0.9)\textsuperscript{9} and that is reflected in the large difference between the dynamic and static forecast in Figure 3.11.

Figures 3.8 and 3.9 show the forecast for the validation sample using the ARIMAX model estimated in 3.5. The dynamic forecast depends on the previous forecast values while the static forecast (one-step ahead) uses actual rather than forecast values. The MAPE is 1.87% and 2.03% of the static and dynamic forecasts, respectively.

The forecast generated by the error-correction model for the validation set is shown in Figures 3.10 and 3.11 where the MAPE for the static forecast is 3.82% and 19.25% for the dynamic forecast. It is clear that dynamic forecast provides a low accuracy since it depends on the previous forecast values. The instability of the model is due to the structural break as shown in Table 3.4. The estimation sample after the breakpoint is relatively small with 39 observations (2008m11-2011m03) that do not allow to analyse the full effect of the structural break.

\textsuperscript{8}The formula calculated by EViews software is defined as $U_1 = \frac{\sqrt{\sum_{t=1}^{n} \hat{e}_t^2}}{\sqrt{\sum_{t=1}^{n} e_t^2}}$. It is decomposed into three components. (1) The bias proportion indicates the systematic error that measures the mean discrepancy of the forecast from the actual paths’ of the variable. (2) The variance proportion measures the variability of the forecast from the actual series. (3) The covariance proportion measures the unsystematic error in the forecasts (see Pindyck and Rubinfeld, 1997, p. 210-1).

\textsuperscript{9}Pindyck and Rubinfeld (1997) argued that a value above 0.2 is troubling
Figure 3.8: The 95% confidence interval for the dynamic and static within sample forecast for the container throughput using ARIMAX model.
Figure 3.9: The ARIMAX model forecast of the validation sample for the container throughput.

Figure 3.10: The 95% confidence interval for the dynamic and static within sample forecast for the container throughput using the ECM for Model (1).
3.5 Conclusion

The growth of the economic activity is the main driver for maritime trade. Therefore, following the developments of the economic activity such as trade, production and consumption allows to foresee what will happen to the development of the container throughput. As a result, a multivariate approach is applied in this chapter, where other exogenous variables are tested to incorporate in the model. However, in the previous chapter, the forecast of the container throughput was based only on the historical pattern of the time series, which do not allow to incorporate the other factors that might impact the container flows. The main focus in Chapter 2 is in analysing the changes in the trend, quantifying the impact of the shocks and generating 3-12 months forecast assuming that everything else is constant.

Although the relationship between demand of maritime transport and economic activity is often used in models for forecasting port throughput, it is not without problems. The first problem is the question of the stability of this relationship over a longer time period; the long assumed time lag between trade, production and shipment time is chang-
This might be attributed to the developments and advanced techniques used in logistics and supply chain activities and customisation of the production processes. Meersman and Van de Voorde (2013) showed that the relation between GDP and freight transport has changed over time, attributing this change to the role of government, international logistics developments, and capacity utilisation. Therefore, two dynamic time series modelling approaches were estimated: (a) an autoregressive integrated moving average with an exogenous variable (ARIMAX), and (b) a cointegration model using the Engle-Granger error-correction two-step approach.

Beside testing for the stability, another problem was confronted: Which economic indicators might be identified as leading indicators for the container throughput? and why? To answer this question, a number of economic indicators were tested. The choice of these indicators was guided by the literature review and the availability of data. The variables were at aggregate level encompassing the total throughput of containers at the port of Antwerp and the economic indicators; including the index of industrial production, the composite index of leading indicators and the industrial confidence indicator for Belgium and one confidence indicator for the European Union. Based on the empirical analysis: (a) the ARIMAX model shows that the EU18 industrial confidence indicator lagged two months was leading the container throughput in the port of Antwerp, (b) the three months lagged index of industrial production is leading the container throughput in the port of Antwerp, and (c) the relationship between container demand and economic activity was still coupled, although there is a significant change in the relationship due to the global financial crisis in 2008. In addition, as evaluated by the forecasting accuracy, the ARIMAX model with the EU18 industrial confidence indicator lagged two months has lower MAPE than the error correction model using the index of industrial production lagged three months. This implies that the ARIMAX model is more accurate for forecasting. However, the advantage of the error correction model over the ARIMAX is in explaining the dynamics of the long-run relationship and how that is affected by the breakpoints in the time series. Moreover, the findings provide two different leading indicators that might be attributed to the nature of statistical model used in each approach. The ARIMAX model estimation depends on the historical pattern and the independent variable while the cointegration approach depends on finding common patterns and trends in the historical dataset between the two variables.

According to the analysis in this chapter, there was a significant change in the relationship between container demand and economic activity in the long-run: the speed of adjustment of the container throughput as a result of changes in the industrial production has changed before and after the global financial crisis in 2008. Despite the fact that the relationship between container throughput and economic activity is changing, it is still coupled. Even if the relation is not stable in the long run, it still can be used for short- to medium-term forecasts, but this confronts us with the second problem which is the need
for projections for the independent variables. For some of the economic indicators, one can rely upon forecasts made available by different national and international institutions; while for some others, leading indicators are utilised. However, there is a need to account for other qualitative factors such as the port’s competitive position and capacity to the analysis to increase the explanatory power of the models. In Chapter 4, the scenario analysis is conducted to account for other factors depending on annual aggregated data for the long-term forecasting.

3.6 Appendix

Table 3.5: ARIMAX(1, 0, 0)(1, 0, 0)_{12} with exogenous variable ICI_{EA_{t-2}}.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>590.6343</td>
<td>3323.035</td>
<td>0.177739</td>
<td>0.8591</td>
</tr>
<tr>
<td>ICI_EU18(-2)</td>
<td>143.9843</td>
<td>101.6859</td>
<td>1.415971</td>
<td>0.1581</td>
</tr>
<tr>
<td>AR(1)</td>
<td>-0.055952</td>
<td>0.065777</td>
<td>-0.850631</td>
<td>0.3958</td>
</tr>
<tr>
<td>SAR(12)</td>
<td>0.714319</td>
<td>0.049129</td>
<td>14.53958</td>
<td>0.0000</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.465590</td>
<td>Mean dependent var</td>
<td>308.2429</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.458826</td>
<td>S.D. dependent var</td>
<td>23289.56</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>17132.86</td>
<td>Akaike info criterion</td>
<td>22.38740</td>
<td></td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>6.96E+10</td>
<td>Schwarz criterion</td>
<td>22.44524</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2693.682</td>
<td>Hannan-Quinn criter</td>
<td>22.41070</td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>68.82664</td>
<td>Durbin-Watson stat</td>
<td>1.996006</td>
<td></td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Inverted MA Roots: .97, .84+.49i, .84-.49i, .49+.84i
Table 3.6: Long-run relationship between total container throughput and industrial production lagged for 3 months.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>1.412973</td>
<td>0.480823</td>
<td>2.938656</td>
<td>0.0037</td>
</tr>
<tr>
<td>LOG(IIP(-3))</td>
<td>2.640971</td>
<td>0.110071</td>
<td>23.99343</td>
<td>0.0000</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.916266</td>
<td>Mean dependent var</td>
<td>12.94642</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.915822</td>
<td>S.D. dependent var</td>
<td>0.416012</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.120699</td>
<td>Sum squared resid</td>
<td>2.753404</td>
<td></td>
</tr>
<tr>
<td>Long-run variance</td>
<td>0.053750</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.7: Engle-Granger cointegration Test for Equation 3.6.

**Equation:** 3.6

Specification: LOG(TOT_CTHRP) C LOG(IIP(-3))

Cointegrating equation deterministics: C

Null hypothesis: Series are not cointegrated

Automatic lag specification (lag=0 based on Schwarz Info Criterion, maxlag=14)

<table>
<thead>
<tr>
<th>Value</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engle-Granger tau-statistic</td>
<td>-4.738082</td>
</tr>
<tr>
<td>Engle-Granger z-statistic</td>
<td>-39.72600</td>
</tr>
</tbody>
</table>

Table 3.8: Error correction model between total container throughput and industrial production lagged for 3 months.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.007017</td>
<td>0.004321</td>
<td>1.624072</td>
<td>0.1060</td>
</tr>
<tr>
<td>D(LOG(IIP(-3)))</td>
<td>0.537149</td>
<td>0.206864</td>
<td>2.596625</td>
<td>0.0102</td>
</tr>
<tr>
<td>LOG(TOT_CTHRP(-1))-(2.64*LOG(IIP(-3)))-1.41</td>
<td>-0.117662</td>
<td>0.036708</td>
<td>-3.205331</td>
<td>0.0016</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.068203</td>
<td>Mean dependent var</td>
<td>0.007125</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.058291</td>
<td>S.D. dependent var</td>
<td>0.060989</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.059185</td>
<td>Akaike info criterion</td>
<td>-2.800718</td>
<td></td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>0.658536</td>
<td>Schwarz criterion</td>
<td>-2.749636</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>270.4686</td>
<td>Hannan-Quinn criter.</td>
<td>-2.780028</td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>6.880370</td>
<td>Durbin-Watson stat</td>
<td>2.463510</td>
<td></td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.001307</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.9: Pre-breakpoint long-run relationship between total container throughput and industrial production lagged for 3 months.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.800579</td>
<td>0.554117</td>
<td>1.444785</td>
<td>0.1505</td>
</tr>
<tr>
<td>LOG(IIP(-3))</td>
<td>2.785427</td>
<td>0.127866</td>
<td>21.78396</td>
<td>0.0000</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.915156</td>
<td>Mean dependent var</td>
<td>12.94642</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.915822</td>
<td>S.D. dependent var</td>
<td>0.398759</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.116150</td>
<td>Sum squared resid</td>
<td>2.158542</td>
<td></td>
</tr>
<tr>
<td>Long-run variance</td>
<td>0.050605</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3.10: Engle-Granger cointegration test for Equation 3.9.

<table>
<thead>
<tr>
<th>Equation: 3.9</th>
<th>Specification: LOG(TOT_CTHRP) C LOG(IIP(-3))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cointegrating equation deterministics: C</td>
<td></td>
</tr>
<tr>
<td>Null hypothesis: Series are not cointegrated</td>
<td></td>
</tr>
<tr>
<td>Automatic lag specification (lag=0 based on Schwarz Info Criterion, maxlag=14)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Value</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engle-Granger tau-statistic</td>
<td>-4.234488</td>
</tr>
<tr>
<td>Engle-Granger z-statistic</td>
<td>-33.11850</td>
</tr>
</tbody>
</table>


Table 3.11: Pre-breakpoint error correction model between total container throughput and industrial production lagged for 3 periods.

<table>
<thead>
<tr>
<th>Dependent Variable: D(LOG(TOT_CTHRP))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method: Least Squares</td>
</tr>
<tr>
<td>Sample (adjusted): 1995M05 2008M10</td>
</tr>
<tr>
<td>Included observations: 162 after adjustments</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.003172</td>
<td>0.004777</td>
<td>0.664124</td>
<td>0.5076</td>
</tr>
<tr>
<td>D(LOG(IIP(-3)))</td>
<td>0.719691</td>
<td>0.240869</td>
<td>2.987892</td>
<td>0.0033</td>
</tr>
<tr>
<td>LOG(TOT_CTHRP(-1))-(2.79*LOG(IIP(-3)))-0.8</td>
<td>-0.143755</td>
<td>0.040963</td>
<td>-3.509385</td>
<td>0.0006</td>
</tr>
</tbody>
</table>

R-squared 0.102371 Mean dependent var 0.008117
Adjusted R-squared 0.091080 S.D. dependent var 0.061848
S.E. of regression 0.058964 Akaike info criterion -2.805440
Sum squared resid 0.552801 Schwarz criterion -2.748262
Log likelihood 230.2406 Hannan-Quinn criter. -2.782225
F-statistic 9.066622 Durbin-Watson stat 2.499976
Prob(F-statistic) 0.000187
Table 3.12: Post-breakpoint long-run relationship between total container throughput and industrial production lagged for 3 periods.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>8.313326</td>
<td>0.825910</td>
<td>10.06566</td>
<td>0.0000</td>
</tr>
<tr>
<td>LOG(IIP(-3))</td>
<td>1.118291</td>
<td>0.179365</td>
<td>6.234732</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Cointegrating equation deterministics: C

Long-run covariance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

| R-squared        | 0.434516 | Mean dependent var | 13.46244 |
| Adjusted R-squared | 0.426976 | S.D. dependent var | 0.079417 |
| S.E. of regression | 0.060118 | Sum squared resid  | 0.271060 |
| Long-run variance | 0.006759 |                     |          |

Table 3.13: Engle-Granger cointegration test for Equation 3.12.

**Equation: 3.12**

Specification: LOG(TOT_CTHRP) C LOG(IIP(-3))
Cointegrating equation deterministics: C
Null hypothesis: Series are not cointegrated
Automatic lag specification (lag=0 based on Schwarz Info Criterion, maxlag=14)

<table>
<thead>
<tr>
<th>Engle-Granger tau-statistic</th>
<th>Value</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engle-Granger z-statistic</td>
<td>-4.369355</td>
<td>0.0039</td>
</tr>
</tbody>
</table>

Table 3.14: Post-breakpoint error correction model between total container throughput and industrial production lagged for 3 periods.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.000172</td>
<td>0.005468</td>
<td>-0.031517</td>
<td>0.9749</td>
</tr>
<tr>
<td>D(LOG(IIP(-3)))</td>
<td>0.282659</td>
<td>0.233018</td>
<td>1.213035</td>
<td>0.2290</td>
</tr>
<tr>
<td>LOG(TOT_CTHRPM(-1))-(1.12*LOG(IIP(-3)))-8.31</td>
<td>-0.315755</td>
<td>0.103016</td>
<td>-3.065096</td>
<td>0.0030</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.112668</td>
<td>Mean dependent var</td>
<td>0.001782</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.088686</td>
<td>S.D. dependent var</td>
<td>0.049924</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.047659</td>
<td>Akaike info criterion</td>
<td>-3.211327</td>
<td></td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>0.168079</td>
<td>Schwarz criterion</td>
<td>-3.12009</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>126.6361</td>
<td>Hannan-Quinn criter</td>
<td>-3.174801</td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>4.698025</td>
<td>Durbin-Watson stat</td>
<td>2.017954</td>
<td></td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.012000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
CHAPTER 4

FORECASTING CONTAINER THROUGHPUT IN THE HAMBURG - LE HAVRE RANGE: COMBINING ARDL MODEL AND SCENARIO ANALYSIS

4.1 Introduction

The capacity of the port plays an important role in the port’s competitive position and the potential growth of the market share. However, the decision to provide new investment and capacity in the port is challenging due to the interrelated interaction between the different players in the market and the dynamic factors of the socio-economic variables. Meersman et al. (2003) emphasised that the relative port competitiveness advantage is one of the important factors that determine the potential demand and is significantly considered by policy makers while dealing with investment decisions concerning increasing port capacity. The ports stakeholders’ main objectives, among other things, are to retain and expand their market share and to provide potential capacity for the expected growth in the future. The dynamic nature, volatility, and risks of the global economic activity should be taken into account while identifying the specific determinants affecting the port market share. Brooks et al. (2014) brought to the fore that the undercapacity of the port infrastructure can cause logistics bottlenecks and put a constraint on growth. Therefore, port policy makers rely on long-term demand forecasts to justify their decisions for port infrastructure projects and avoid unneeded costly over-investment.

The objective of this chapter is to develop a model which can assist stakeholders involved in the ports infrastructure investment-decision-making process. The model is considered a profound quantified tool to forecast the container throughput, with an application to the Hamburg - Le Havre range. This is based on the assumption that containerised trade consists mainly of finished or semi-finished products that are related to the economic activity and global trade. However, container throughput is not only related to the economic activity, but also to other dynamic factors such as the port competitive position, logistical services provided and hinterland connectivity.
Chapter 4. Forecasting Container Throughput in the Hamburg - Le Havre Range: Combining ARDL Model and Scenario Analysis

The third research question of the thesis that is examined in this chapter is: how will the container throughput in the port of Antwerp evolve until 2050 under different scenarios? That implicitly provides insight about the question how much capacity developments are needed in the future? To tackle these questions, a three-step approach is developed to overcome the complexity of modelling the container throughput.

The first step is applying an autoregressive distributed lag (ARDL) model. This causal model type is useful to test for a cointegration relationship and to quantify the short-run and the long-run dynamic interactions. The ARDL model depends on understanding the past developments and building a structural model that estimates the causal relationships among the variables.

The second step is developing different scenarios for the likely future evolution of the variables used in the models, where the goal of scenario planning is not predicting the future, but rather seeing the differences in future evolutions under certain conditions (Chermack et al., 2001).

The third step is combining the outcome of the estimated relationship in step one and the scenario analysis in step two to assess the impact of different economic courses of action on the container throughput for the Hamburg - Le Havre (H-LH) range of ports. Then, the port of Antwerp container throughput is calculated based on different growth rates of the Antwerp port market share. The market share of the port accounts for the qualitative factors such as the port competitive position, the connectivity of the port to the hinterland and the performance of the port terminals. Figure 4.1 shows the structure of the three-step approach applied in this chapter.

The dataset of the empirical analysis is based on an aggregate annual time series (1995-2014) for the loading, unloading and total container throughput measured in twenty-foot equivalent units (TEUs) for the main ports within the Hamburg-Le Havre range (Antwerp, Bremen, Hamburg, Le Havre, Rotterdam, and Zeebrugge), which share about the same hinterland. The main ports in Belgium, France, Germany and The Netherlands handled 38% of the EU28 total gross weight of goods in 2013\(^1\). The economic activity is measured based on a number of indices related to industrial production and trade.

\(^1\)According to Eurostat database, mar_mg_am_cwhc time series, extracted on 11th August, 2015.
The chapter is structured as follows. The relevant literature review is presented in Section 4.2. Step one of the approach is illustrated in Section 4.3, where the methodology of the ARDL model is presented, the dataset is described and the empirical model is estimated. Section 4.4 provides step two of the approach introducing the different scenarios and the likely growth rates for the variables used in the models. Step three, in Section 4.5, combines both steps to generate forecasts for the container throughput in the port of Antwerp followed by the interpretation and discussion of the results and the main findings. Finally, the conclusion and further research are addressed in Section 4.6.

### 4.2 Literature review

Many studies investigated the relationship between economic activity and the maritime freight to forecast the port traffic at a port in general, as presented in Chapter 1, Section 1.4.1. In general, the study of Trujillo et al. (2002) showed that four factors should be considered when forecasting freight traffic at the port:

(i) macroeconomic trends and reforms, such as trade liberalisation, trade agreements, openness of the economy and evolution of industrial production,
(ii) the specific characteristic of the location of each of the ports in relation to the transport network that affects their competitive positions, which may be measured by the market share,

(iii) the specific advantage or competence of each port, for example, large and well connected hinterland, dwell time and incurred costs at the port, and

(iv) innovations in ports and logistics services. The literature review presented in this section focuses on studies that used causal models.

Verbeke et al. (1996) forecast the container throughput for the period 2000-2015 for the port of Antwerp by estimating a number of models for the period 1985-1995. Verbeke et al. assumed a correlation between a sustained gross domestic product (GDP) growth rate in industrialised countries and the cargo volume at the Hamburg-Le Havre range, and the same degree of containerisation and market share. By comparing the forecast of the same study to the actual throughput, it is found that the container throughput is underestimated by approximately 50% in 2010. The difference may be related to the strong expansion and demand growth related to globalisation and the boom of the Chinese economy starting from 2000 until the global financial crisis in 2008.

The estimation of an error correction model for the terminals at Hong Kong and the Singapore Ports in Fung (2002) is used for several purposes: studying the competitive interaction between terminal operators, emphasising the dependence of the forecasts on the interaction between ports and providing a systematic approach to forecasting the demand for container handling services. In recent studies, Pruyn (2013) and Taneja (2013) integrated transport scenarios in their research.

There is a number of studies that developed long-term scenarios for the shipping sector. Lejour (2003) provided four quantified economic scenarios for Europe, and, based on that, projections of the port throughput in The Netherlands were provided for 2020 and 2040. DNV (2012) provided four scenarios to describe likely outcomes on technology uptake in the maritime industry with economic growth on one axis and regulatory and stakeholder pressure on the other axis. A recent study was conducted for Port Metro in Vancouver to evaluate its container terminal capacity expansion investments by forecasting the container throughput until 2050 based on the potential container demand outlook for North America (Ocean Shipping Consultants, 2014).

Artuso et al. (2015) develop future scenarios for the EU shipping based, among others, on the macroeconomic conditions and the EU-global maritime trends. The report analyses the geographical trade relationships of container shipping expressed in volumes of manufactured products, emphasising the dominant role of the China-Europe trade lane, followed by the North America-Europe trade lane, and the smaller scale trade lane between South Asia and Africa on the one hand, and Europe on the other hand. The relationship between economic growth and trade developments is of crucial importance to the maritime trade.
The report describes the dynamic and complex relationship between GDP and trade, reporting an elasticity of trade with respect to GDP, at a global level, at an average of 1.9 during the period 1998-2008.

In conclusion, most studies conducted were based on expert opinions and trend extrapolation using the GDP and trends in exports and imports; however, only few studies estimated the relationship. The advantages of the combined approach adopted in this chapter are that: (i) the relationship between trade and container throughput is estimated, and (ii) the port throughput is forecast in TEUs contrary to the previous studies that use tonnes.

4.3 Step 1: Estimating the ARDL model

In this step, the methodology of the ARDL model is illustrated in section 4.3.1, followed by defining the variables used in the model in section 4.3.2. Finally, in section 4.3.3, the estimation and interpretation of the empirical models are presented.

4.3.1 The ARDL model

The Engle-Granger two-step procedure was used in Chapter 3 to test and estimate the relationship between the container throughput and the economic activity using monthly data for the purpose of short-term forecasts. The ARDL model is applied in this chapter using annual data for the long-term forecasts (Engle and Granger, 1987). The advantages of the ARDL modelling over the other models are: (i) overcoming the small sample size, (ii) providing unbiased standard errors (Pesaran and Shin, 1998), (iii) avoiding problems resulting from different non-stationary integrated order, and (iv) allowing for a lagging relationship with the possibility of assigning different lag-lengths.

The ARDL model combines dynamics and interdependence in a single linear equation. Hendry (1995, pg. 211-12) defined the functional form of an ARDL(1,1) as a stationary stochastic process as in Equation 4.1. The model is explained by lagged values (autoregressive) of the dependent variable, $y$, and successive lags (distributed lag) of the explanatory variable, $x$, such that, $| \beta_2 | < 1$, $\epsilon_t \sim IN[0, \sigma^2_{\epsilon}]$ and allowing for one unit root. The model can be generalised to ARDL($p, q_1, \ldots, q_n$), where $n$ is the number of explanatory variables and with maximum lags of $p$ and $q$ on $y_t$ and $x_t$, respectively. The model interpretation and estimation depend on the assumption that $x_t$ is weakly exogenous for $\beta$.

\[ y_t = \beta_0 + \beta_1 x_t + \beta_2 y_{t-1} + \beta_3 x_{t-1} + \epsilon_t \]  

(4.1)

The long-run equilibrium solution is defined in terms of a ‘steady state’, which describes a situation in which there are no more changes. As such, all the first differences are zero.
and the expected values are constant due to the assumption of stationarity in the long run; therefore, $E[x_t] = x^*$ and $E[y_t] = y^*$ $\forall t$. Consequently, the long-run response of $y$ to $x$ is represented as in Equation 4.2, where $K_1$ is the long-run dynamic multiplier.

$$y^* = K_0 + K_1 x^*, \tag{4.2}$$

where,

$$K_0 = \frac{\beta_0}{(1-\beta_2)}, \text{ and } K_1 = \frac{\beta_1 + \beta_3}{(1-\beta_2)}.$$

Any deviation from the equilibrium; i.e. in the form $(y^* - K_0 - K_1 x^*) \neq 0$, will induce an adjustment of $y_t$ via an adjustment factor to equilibrium deviations in the previous period, $(y - K_0 - K_1 x)_{t-1}$, denoted by an error correction mechanism as long as there is no regime switch. The error-correction model in Equation 4.3 is derived from the reparametrisation and rearrangement of the ARDL model in Equation 4.1, subtracting $y_{t-1}$ from both sides and using $\Delta y_t = (y_t - y_{t-1})$:

$$\Delta y_t = \beta_1 \Delta x_t + (\beta_2 - 1)(y - K_0 - K_1 x)_{t-1} + \epsilon_t \tag{4.3}$$

Here, the short-run impact (the immediate impact) of a change in $x_t$ on $y_t$ is estimated by the coefficient $\beta_1$; the speed of the adjustment by which $\Delta y_t$ converges to the equilibrium output depends on the value of $(\beta_2 - 1)$ and the equilibrium correction term is $(y - K_0 - K_1 x)_{t-1}$.

**Hendry (1995)** applied a recursive Monte Carlo study to investigate the validation of the least-squares estimation on a finite sample from a dynamic process. The estimate of the study showed unbiased coefficients, minimum variance and parameter constancy. In the empirical model in Section 4.3.3, the following post-estimation diagnostic tests are conducted to ensure the validity of the parameters of the model:

1. Residual diagnostic. The errors of the model are checked for serial correlation using the Breush-Godfrey test.
2. Stability diagnostic. The stability of the model is assessed to ensure the constancy of the coefficients over time using the CUSUM (cumulative sum) recursive estimation.
3. Cointegration test. The Wald test and the Bounds test suggested by Pesaran et al. (2001) are used for testing whether there exists a long-run relationship between the dependent variable and the regressors or not.
### 4.3.2 The dataset

Table 4.1 provides an overview of the variables with their measurement unit, the level of aggregation, the definition, the available periodicity and the source of the data. The sample size for the empirical model is limited to 20 observations from 1995 to 2014. There are six main ports for container handling in four countries\(^2\) that serve the North-West European hinterlands namely Antwerp - Zeebrugge (Belgium), Le Havre (France), Hamburg-Bremen\(^3\) (Germany) and Rotterdam (The Netherlands), where Rotterdam, Hamburg and Antwerp are the top European transhipment hubs that handle in excess of two million TEU per quarter each.

#### Table 4.1: Description of the variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Level</th>
<th>Definition</th>
<th>Period</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exports (EX)</td>
<td>Chain linked volume index</td>
<td>EU19</td>
<td>Goods exported, imported and final consumption from GDP expenditure approach.</td>
<td>1995-2014</td>
<td>Eurostat database (nama_10_gdp) extracted on 06.07.15</td>
</tr>
<tr>
<td>Imports (IM)</td>
<td>Final Consumption (FC)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production in total manufacturing (MFY)</td>
<td>Index (2010=100)</td>
<td>EU19</td>
<td>The total manufacture output in the industrial sector measures the changes in the volume of output, sa.</td>
<td>1990-2014</td>
<td>OECD.Stat extracted on 06.07.15</td>
</tr>
<tr>
<td>Loading container throughput (OUT_HLH_TEU)</td>
<td>Million TEUs</td>
<td></td>
<td>The outgoing and incoming of the cargo throughputs of each individual port.</td>
<td>1990-2014</td>
<td>Individual Ports Authorities</td>
</tr>
<tr>
<td>Unloading container throughput (IN_HLH_TEU)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^2\)Other ports such as Ghent, Amsterdam and Dunkirk were not selected since the selection criteria were based on ports handling ≥ 0.2 million TEU annually during the analysis period (1990-2014).

\(^3\)Bremen port refers to the throughput for the ports of Bremen and Bremerhaven.
The variables are depicted in Figure 4.2. The graph indicates no difference between the loading and unloading; both have almost the same trend. The graphical inspection shows a cointegrated relationship between the exports and imports on the one hand, and container throughput on the other hand. The final consumption expenditure index shows a slow growth rate that reached about 0.86% in 2014.

![Graphical representation of the variables.](image)

**Figure 4.2:** Graphical representation of the variables.

### 4.3.3 The empirical models

The models estimates, standard errors, t-statistics and confidence intervals are reported in Table 4.2. The models that did not pass the verification tests are excluded; either the residuals are serially correlated, the model is not stable, or there is no cointegration relationship. The models are estimated using the natural logarithmic allowing interpreting the coefficients as elasticities.

The error correction coefficient (ECC) indicates the annual speed of adjustment towards equilibrium within the regimes; i.e. does not correct towards a changed equilibrium
(Hendry, 1995, pg. 213). The ECC estimated from the models using the manufacture index indicates a relatively slow adjustment of 7% and 12% in models no. 4 and 2, respectively. The speed of adjustment differs in the case of using the trade indices and final consumption components of GDP; it is relatively moderate – about 22% for the loading of TEU (see model no. 1) and 23-33% for the unloading of TEU (see models no. 3 & 5).

The short-run coefficient (SRC) represents the elasticity: the immediate impact of a change in the economic indices on the container throughput, about 1.03 on average. On the other hand, the long-run coefficient (LRC) represents the equilibrium elasticity, which is significantly high (above 4) (models no. 2, 3 & 4), in the case of manufacture index and final consumption. This might be attributed to the indirect multiplier effect of changes in manufacture sector and final consumption patterns. At the same time, the use of exports and imports indicators yields an elasticity of about 1.4 (models no. 1 & 5) with relatively lower standard errors.

As a result of the different models estimations in Table 4.2, the exports and imports provide the best fit in accordance with the literature review. Therefore, models number 1 & 5 (in Table 4.2) are chosen for the application of the scenarios. The model estimation indicates that changes in the loading and unloading of container throughput are explained by the exports and imports, respectively. The estimated models are represented by the following linear equations.

The ARDL estimated for the loading of container throughput of the total Hamburg - Le Havre range and the exports of the EU19 is represented in Equations 4.4 and 4.5.

\[ L(OUT\_HLH_t) = -0.83 + 1.00 L(EX_t) + 0.78 L(OUT\_HLH_{t-1}) - 0.69 L(EX_{t-1}) \]
\[ (0.617) \quad (0.148) \quad (0.143) \quad (0.232) \]
\[ [-1.34] \quad [6.77] \quad [5.41] \quad [-2.95] \]
\[ (4.4) \]

\[ \Delta L(OUT\_HLH_t) = 1.00 \Delta L(EX_t) - 0.22 \Delta L(OUT\_HLH) - 1.40 L(EX) - 3.68 \]
\[ (0.111) \quad (0.092) \quad (0.160) \quad (0.749) \]
\[ [8.98] \quad [-2.43] \quad [8.77] \quad [-4.91] \]
\[ (4.5) \]

The standard errors are in parentheses and the t-Statistics are in square brackets.
Table 4.2: Models estimation summary.

<table>
<thead>
<tr>
<th>Output M.#</th>
<th>Input ARDL (p, q)</th>
<th>ECC</th>
<th>SRC</th>
<th>LRC</th>
<th>LB-CI</th>
<th>UB-CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>L(OUT_HHLH_TEU)</td>
<td>(1)</td>
<td>1.07</td>
<td>1.00</td>
<td>0.16</td>
<td>8.77</td>
<td>1.13</td>
</tr>
<tr>
<td>L(EX)</td>
<td>(2)</td>
<td>1.01</td>
<td>0.09</td>
<td>-2.43</td>
<td>-0.22</td>
<td>0.09</td>
</tr>
<tr>
<td>L(FC)</td>
<td>(3)</td>
<td>1.40</td>
<td>0.11</td>
<td>8.98</td>
<td>0.16</td>
<td>8.77</td>
</tr>
<tr>
<td>L(MFY)</td>
<td>(4)</td>
<td>4.36</td>
<td>0.33</td>
<td>13.18</td>
<td>4.36</td>
<td>5.01</td>
</tr>
<tr>
<td>L(IM)</td>
<td>(5)</td>
<td>4.71</td>
<td>0.60</td>
<td>7.98</td>
<td>4.71</td>
<td>5.94</td>
</tr>
</tbody>
</table>

Notes:
(a) The data and other estimates will be reported upon request.
(b) The models estimation and diagnostic tests are conducted using EViews 9.
(c) The value of $|\hat{\beta}|$ is $> 1$ in all the models.
(d) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(e) The models are stable based on CUSUM test.
(f) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(g) The models' estimation and diagnostic tests are conducted using EViews 9.
(h) The models are not serially correlated using Breusch-Godfrey LM test.
(i) The models are not serially correlated using Breusch-Godfrey LM test.
(j) The Wald test (Hendry, 1995, pg. 223-7) and bounds test are used to validate that there exists a cointegration relationship. Since the sample is small (20 observations), the Narayan (2004) critical values are used. There is evidence at 10% that the model has a long run solution.
(k) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(l) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(m) |$\beta$| is $< 1$ in all the models.
(n) The models are not serially correlated using Breusch-Godfrey LM test.
(o) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(p) The models are not serially correlated using Breusch-Godfrey LM test.
(q) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(r) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(s) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(t) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(u) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(v) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(w) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(x) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(y) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
(z) The residuals of the model are not serially correlated using Breusch-Godfrey LM test.
The ARDL estimated for the unloading of container throughput of the total Hamburg - Le Havre range and the imports of the EU19 is represented in Equations 4.6 and 4.7.

\[ L(IN_{HLH}) = -1.00 + 1.07 L(IM_t) + 0.77 L(IN_{HLH} t_{-1}) - 0.71 L(IM_{t-1}) \]

\[ \text{(0.525) (0.142) (0.120) (0.208)} \]

\[ [-1.90] [7.53] [6.37] [-3.40] \]

\[ \Delta L(IN_{HLH}) = 1.07 \Delta L(IM_t) - 0.23 [L(IN_{HLH}) - 1.53 L(IM) - 4.27]_{t-1} \]

\[ (0.099) (0.080) (0.137) (0.624) \]

\[ [10.81] [-2.93] [11.22] [-6.84] \]

\[ \text{(4.6)} \]

\[ \text{(4.7)} \]

### 4.4 Step 2: The scenario analysis

In this step, the scenarios are developed to provide alternative likely courses for the future for the exports and imports indices based on the statistical and economic significance of the models estimated (see Section 4.3.3). Moreover, an analysis is provided for the port of Antwerp demand and supply side.

The focal question in developing the scenarios is: *how will the container throughput in the port of Antwerp evolve until 2050?* The choice of 2050 is guided by the long life span of the infrastructure port investment projects. The long time horizon is split into three periods: 2015-2020, 2021-2040 and 2041-2050. The splitting of the time horizon allows assigning various growth rates and updating changes to the model at different periods according to the changes in the economic growth. Each scenario is determined by the interaction of three aspects: economic growth, trade outlook and the market share of the Antwerp port within the H-LH range, where the scope of the scenarios is at the EU level.

The CPB Netherlands Bureau for Economic Policy Analysis (de Mooij and Tang, 2003) developed and quantified four future scenarios for Europe. On the one hand, the scenarios of *Strong Europe (SE)* and *Global Economy (GE)* are characterised by high and broad international cooperation and trade liberalisation and removing barriers to trade. While, in *Regional Communities (RC)* and *Transatlantic Market (TM)*, international cooperation is limited. On the other hand, the *SE* and *RC* are significantly characterised by the pres-
ence of the public institutions, expanding public sector, limiting international cooperation and focusing on income redistribution policies. In GE and TM the emphasis is on efficient market and private initiatives.

The estimates developed for the future growth of the EU trade indices, which are used in the models to forecast the container throughput of the H-LH range, are based on the scenarios for the EU annual average GDP growth rate, the EU GDP per capita index, the openness indicator, the destination of the EU-15 export flows indicator and the production growth of manufacture sectors, reported in Lejour (2003). The study reports figures until 2040; the figures for the period 2041-2050 are simple extrapolation from the previous periods.

Table 4.3: The EU GDP growth, annual averages.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td>2.2</td>
<td>1.3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strong Europe</td>
<td>1.8</td>
<td>1.3</td>
<td>0.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regional Communities</td>
<td>1.1</td>
<td>0.2</td>
<td>0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transatlantic Market</td>
<td>2.3</td>
<td>1.6</td>
<td>1.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global Economy</td>
<td>2.7</td>
<td>2.3</td>
<td>1.96</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Lejour (2003, pg.41-2).
(1): The scenarios of the CPB provides figures in 2040, the 2050 horizon is extrapolated from the 2000-2040 number.
(2): Real GDP growth rate - volume from Eurostat.

According to the GDP growth estimates (Lejour, 2003), the GE is considered the high case scenario with annual average world growth rate of 2.9% and 2.3% for the EU, while the regional communities is the low case scenario of 1.4% world growth rate and 0.2% in EU, in 2040 respectively. The EU annual average growth rates in 2040 are 1.3% and 1.6% in the scenarios of SE and TM, respectively. The various growth rates are based on estimating a general equilibrium model using, among other variables, the variation in the population growth, employment growth and labour-market participation rate (details are shown in Table 4.3). Although the GDP growth rates estimated by these scenarios were produced prior to the 2008 shock, the GDP growth rates are comparable to other reports such as the (PwC, 2015, pg. 21), where an average annual growth rate of around 2.5% for the EU is estimated.

The per capita GDP index is an indicator for the change in the consumption patterns; the relatively low figure (163) in Strong Europe is attributed to the high population growth. The indices for the GE, TM and RC are 235, 210 and 135, respectively. In general, the per capita GDP growth in non-OECD (mainly Asia) and Eastern Europe exceeds that in the EU and USA because of higher productivity growth.
The trade outlook (Lejour, 2003, Section 7) and (de Mooij and Tang, 2003, Section 16.2) describes the trade policies and changes in trade direction focusing on the regional and global cooperation. Trade policies affect the degree of openness, the composition of trade, trade pattern and trade direction. The trade openness indicator is measured by dividing the average value of trade by national income (it includes intra-regional trade). In GE and SE, a liberalised trade policy is successfully implemented by eliminating tariff and non-tariff procedures that are reflected in growth rates of 46% and 55% in trade openness in 2040 compared to 2000 in GE and SE, respectively. However, TM and RC will encounter a slow average growth of about 13% in trade openness in 2040 compared to 2000.

In 2000, regional EU intra-trade accounted for almost 54% of EU exports and 18% was shipped to non-OECD (mainly Asia). The remaining 28% is almost equally divided on US, Eastern Europe and the rest of OECD countries. In general, Asia will become an important trade partner to Europe with a maximum growth rate in GE of 85% and a minimum of 10% in TM. In the RC, there is almost no growth in exports due to the strict trade barriers (see Table 4.4 for more details).

Table 4.4: Destination of EU-15 export flows, in 2000 and 2040 (all aggregates include intraregional trade).

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Scenario</th>
<th>SE</th>
<th>RC</th>
<th>TM</th>
<th>GE</th>
</tr>
</thead>
<tbody>
<tr>
<td>EU15 exports index</td>
<td></td>
<td>100</td>
<td>428</td>
<td>208</td>
<td>411</td>
</tr>
<tr>
<td>EU15 (intra-trade)</td>
<td></td>
<td>53.5</td>
<td>47.3</td>
<td>52.8</td>
<td>49.3</td>
</tr>
<tr>
<td>US</td>
<td></td>
<td>10.1</td>
<td>6.70</td>
<td>9.4</td>
<td>13.9</td>
</tr>
<tr>
<td>non-OECD (mainly Asia)</td>
<td></td>
<td>18.3</td>
<td>29.4</td>
<td>22.9</td>
<td>20.1</td>
</tr>
<tr>
<td>Eastern Europe</td>
<td></td>
<td>8.2</td>
<td>9.6</td>
<td>8.3</td>
<td>9.9</td>
</tr>
<tr>
<td>rest of OECD</td>
<td></td>
<td>9.9</td>
<td>7.0</td>
<td>6.6</td>
<td>7.8</td>
</tr>
</tbody>
</table>


Based on the indicators of the four economic scenarios for the EU described above, the growth rates for the variables (see Table 4.1) Exports and Imports are calculated for the different periods based on the EU annual average GDP growth rate adjusted by the openness indicator and export-flow direction in the case of exports, and by the per capita GDP growth rate in the case of imports. The export factor and the imports and exports growth rates are shown in Table 4.5.
Chapter 4. Forecasting Container Throughput in the Hamburg-Le Havre Range: Combining ARDL Model and Scenario Analysis

Table 4.5: Model indicators growth rate

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Export factor (^d)</th>
<th>Export (^c)</th>
<th>Import (^c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-2020</td>
<td>SE</td>
<td>-0.43</td>
<td>1.14</td>
</tr>
<tr>
<td></td>
<td>RC</td>
<td>-0.49</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>-0.44</td>
<td>1.42</td>
</tr>
<tr>
<td></td>
<td>GE</td>
<td>-0.35</td>
<td>2.08</td>
</tr>
<tr>
<td>2020-2040</td>
<td>SE</td>
<td>1.00</td>
<td>3.30</td>
</tr>
<tr>
<td></td>
<td>RC</td>
<td>1.00</td>
<td>2.20</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>1.00</td>
<td>3.60</td>
</tr>
<tr>
<td></td>
<td>GE</td>
<td>1.00</td>
<td>4.30</td>
</tr>
<tr>
<td>2040-2050</td>
<td>SE</td>
<td>0.25</td>
<td>1.44</td>
</tr>
<tr>
<td></td>
<td>RC</td>
<td>0.25</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>TM</td>
<td>0.25</td>
<td>1.61</td>
</tr>
<tr>
<td></td>
<td>GE</td>
<td>0.25</td>
<td>2.46</td>
</tr>
</tbody>
</table>

Source: Own calculation based on de Mooij and Tang (2003).
(a) Calculated as the average change in the production growth of sectors in EU15.
(b) Calculated as the average GDP growth adjusted by the openness indicator and the ex. factor.
(c) Calculated as the average GDP growth adjusted by the per capita GDP growth rate.

4.4.1 The port of Antwerp within the Hamburg-Le Havre range

In 2014, the port of Antwerp was the second-largest port in Europe\(^5\). The port handled approximately 199 million tonnes of total maritime freight volume, of which 108 million tonnes were in containers corresponding with 8.9 million TEUs. It is centrally located within the H-LH range with ports that share about the same hinterland. The port of Antwerp’s strategic location enables it to play a vital role in the global supply networks; the port serves the hinterland of France, Germany, and The Netherlands.

Figures 4.3a and 4.3c show the development of the loading of containers in absolute numbers measured in millions of TEUs. There is no clear difference in the trend between the loading and unloading figures in the ports under study except that during the period after the crisis, the loadings of the port of Antwerp exceed those of the port of Hamburg. During the period 1985-2014, the ports of Le Havre and Zeebrugge had a slow growth rate of an average 6% and 9%, respectively, with no difference between the volumes of loadings and unloadings, as in Figure 4.3e.

Figures 4.3b and 4.3d show the market share of each selected port in the H-LH range. The port of Rotterdam market share dropped significantly in 1999 by about 5% for both

\(^5\)The total maritime freight volume handled in the major ports in 2014 is approximately: 445 million tonnes in the port of Rotterdam and 146 million tonnes in the port of Hamburg.
loading and unloading, which is attributed to congestion problems. That loss was gained by the ports of Antwerp and Hamburg, where Hamburg port captured more of the unloading and Antwerp port attracted more of the loading containers. This might be attributed to the position of the port in the calling sequence of the liner shipping loop. There were no drastic changes for the other ports: the port of Bremen remained on an average of 15%, while the ports of Le Havre and Zeebrugge achieved an average of 6% each. In total, the ports of Antwerp and Hamburg were competing closely; during the period 1999-2008, the port of Hamburg exceeded the port of Antwerp while after the global financial crisis, the two ports shared almost the same market share, as shown in Figure 4.3f.

Figure 4.3: Evolution of container throughput volumes and market share in the Hamburg-Le Havre range (in TEUs) covering the period 1985-2014.

Source: own compilation based on Port Authorities data.
The capacity available at the port terminals to meet the potential demand plays a crucial role in the port competitive position in order to avoid congestion; and hence, in decreasing the cost and time lost at the port for the shipping lines. The decision to make new investments is a complex issue. Meersman and Van de Voorde (2014) emphasised the importance of studying the trade-off between the costs and benefits of excess capacity and related funding.

Capacity in the context of this chapter is defined as ‘the terminal commercial capacity’ that is the maximum throughput that can be attained keeping the performance and quality at the desired level of the operator to avoid congestion and ensure high productivity. At this throughput, the average berth occupancy rate is around 65% (Drewry Maritime Research, 2010, p.41) and the utilisation rate is above 70% (Ilmer, 2006). Capacity is a function of terminal operating efficiency and productivity; as a result, the analysis benefits from comparing the actual container throughput with the commercial capacity, rather than the designed port capacity (Brooks et al., 2014). The capacity of the Hamburg - Le Havre range of ports is examined rather than the single port capacity, which allows to provide an overview of the market and the potential competitive position.

The ports actual container throughput, commercial capacity and the utilisation rate from 2000 to 2015 are shown in Figure 4.6. In what follows is a brief analysis of each port within the selected ports of the Hamburg - Le Havre range:

• The port of Antwerp faced congestion problems during 2003-2005. The utilisation rate had a stable average of 70% during 2010-2014, that slightly increased to 75% as shown in Figure 4.5a.
• The Port of Rotterdam faced congestion problems almost during the whole period of 2003-2012, with the exception of few years 2006 and 2009, as shown in Figure 4.5b. It is difficult to depict a stable pattern of the utilisation rate.
• The Port of Hamburg faced congestion problems during 2005-2008. The utilisation rate was unstable after the structural break in 2009 and had a steady increasing growth from 2012-2014 as shown in Figure 4.5c.
• Figures 4.5e, 4.5f and 4.5d for the ports of Zeebrugge, Le Havre and Bremen, respectively, show a decreasing utilisation rate with no congestion problems except during the period 2007-2009 in the port of Zeebrugge.

\[\text{It is calculated as the ratio of the actual total port throughput divided by the designed capacity of a terminal.}\]
The Port Authority of Antwerp has a master plan to invest for additional container handling capacity on the left bank 'Saettinghe Development Area' that provides more than 1000 hectares. The project is planned in phases to provide 11 million TEUs. The first phase is planned to be ready for operation as of 2021 with a capacity of 5.1 million TEUs.
The Hamburg Port Authority (HPA) has a development plan until 2025 to expand the capacities of Waltershof port area by 2 million TEUs, further expansion of both Altenwerder and Tollerort to create about 2 million TEUs handling capacity and a major development project, the ‘Central Terminal Steinwerder (CTS)’ to create additional berths for large ships. The Port of Rotterdam vision to 2030 is to further develop the space in the Maasvlakte 2 reaching the target of 12 million TEUs. For the other ports, no master plans are publicly available.

4.5 Step 3: The combination

In this step, the four future scenarios for the development of the H-LH range container throughput are estimated incorporating the future potential capacity developments. The forecasts are shown in Figure 4.7. Compared to 42 million TEUs handled in 2014, a maximum of 143 and a minimum of 6 million TEUs in 2050 in the High Antwerp-Global Economy and How Antwerp-Regional Communities scenarios are forecast, respectively. For the capacity, the forecast shows that the master plan for the ports capacity is to be revised in 2022 since congestion will be a problem for all the scenarios except the Regional Communities.

Figure 4.7: Demand and capacity of the Hamburg - Le Havre actual ports total container throughput actual (1996-2014) and forecast (2015-2050) in million of TEUs.
Three scenarios for Antwerp’s market share within the H-LH range are developed under each of the four scenarios of the H-LH range. That results in 12 different combinations for the future development of the port of Antwerp container throughput based on an annual growth rate for the market share of 1.1% for unloading and 1.4% for loading in the base scenario (B), and ±3% for the high (H) and low (L) scenarios, respectively.

Figure 4.8 shows the forecast for the port of Antwerp with the future potential capacity in the three different scenarios.

What if the port of Antwerp market share increased by 3% annually? As shown in Figure 4.8a, the port will face congestion in the four economic scenarios during the period 2025-2030. What if the port of Antwerp market share remains the same? Figure 4.8b shows that the port will face congestion problems in 2030 approximately for the three scenarios; Global Economy, Transatlantic Market and Strong Europe. While, in the Regional Communities scenario, the port of Antwerp will not face congestion problems until 2045. If the port of Antwerp faces a 3% decreasing market share as in the low case scenario, then the port of Antwerp will not face congestion problems until 2050 in all of the four economic scenarios as shown in Figure 4.8c.
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Combining ARDL Model and Scenario Analysis

Figure 4.8: The Antwerp port total container throughput forecast and capacity in million of TEU.
Despite the fact that the sample size is small (from 1995 to 2014, i.e. \( n = 20 \)), the resulting analysis can lead to valid and interpretable results. The fact that using one independent variable allows for a larger number of degrees of freedom. The advantage of the scenarios analysis is not only providing different likely courses for the independent variables and accounting for the qualitative factors, but is also in accounting for the uncertainty of using the model estimated from 20 years to forecast for the coming 35 years.

### 4.6 Conclusion

The importance of free commercial capacity is critical in the port competitive position. However, the decision to provide new capacities and investment in the ports should be supported by a growing potential demand. However, modelling the demand of container throughput is complex due to many factors such as the interrelated relationship between the different players in the market, the technological changes in the shipbuilding sector with the introduction of mega container ships and the dynamic factors of the socio-economic variables; i.e. production, consumption and fuel prices.

Therefore, a three-step approach was developed to capture the potential impact of specific risks and to provide long-term annual forecasts for the port of Antwerp until 2050. The approach combined a quantitative model, namely the autoregressive distributed lag model (ARDL) to estimate the relationship between the economic activity and the container throughput with the economic scenarios to provide future evolution of the economic activity. As compared to the previous chapters, the analysis was conducted using annual data to model and forecast the container throughput in TEUs.

This approach estimated the container throughput elasticities with respect to trade indices and accounted for other regional and economic factors that are needed to develop demand projections, such as the GDP and trade growth scenarios. Moreover, three scenarios that reflect the competitive position of the port of Antwerp within the Hamburg - Le Havre range were provided. The combined approach provide four different likely courses for the container throughput developments in the Hamburg-Le Havre range that addressed the commercial capacity present in the Hamburg - Le Havre range rather than focusing on limits of at a specific port. Moreover, 12 different likely courses were provided for the future development of the container throughput at the port of Antwerp based on the 4 different economic scenarios for the EU and the three scenarios for the port of Antwerp market share within the Hamburg - Le Havre range. The empirical results show that there exists a long-run relationship between the trade indices of EU19 and the total container throughput in the Hamburg - Le Havre range. The model estimates that the elasticity of the container throughput in the Hamburg - Le Havre range to trade indices is about 1.4 on average.
Chapter 4. Forecasting Container Throughput in the Hamburg - Le Havre Range: Combining ARDL Model and Scenario Analysis

The stakeholders of the port will benefit from producing different likely courses for the future development of the container demand at the port of Antwerp, over which they can identify when the capacity limits might be critical. One of the limitations is the sample size that raise the concern about the stability of the cointegration relationship in the future. Whether the cointegration relationship will hold in the future and whether the relationship estimated during 20 years is valid to forecast the next 35 years or not.
Chapter 5

Conclusions and Policy Implications

The port sector is closely related to the changes in the global economic activity and international trade. The global financial crisis in 2008 had a significant impact on the ports activities. Moreover, the current changes in oil prices and the decline in the Chinese growth will affect the freight traffic to the port sector. Hence, following the evolutions of the economic activity allows forecasting the demand side. On the supply side, the port capacity plays a crucial role in the competitive position of the port in order to meet demand, avoid congestion, and hence, decrease the cost and time lost at the port and increase productivity, which is of importance to all the stakeholders: the shipping lines, port authority, shippers, terminal operators, and investors. However, the decision to provide new capacities and investments in the port should be supported by a growing potential demand. Therefore, port decision makers rely on demand traffic forecasts to support decisions related to operation and investment. The port of Antwerp is used as a case study across the different chapters of the thesis.

The purpose of this thesis is to provide an instrument to support the decisions of policy makers and stakeholders, whether in public or private institutions, for the short-term and long-term planning and investment decisions in the port sector. Port planners should act ahead of any anticipated congestion problem. The short-term forecasts assist in the planning of the operational decisions such as the port capacity utilisation, equipment and handling of container activities and hinterland connections capacity provision. In comparison, the long-term forecasting is useful to assess the future infrastructure investment decisions. The literature review conducted showed that there is a gap in providing insight in the drivers of maritime freight transport, in particular when the maritime flow is analysed in the category unit of the cargo (number of containers) instead of cargo volume (weight). The methodology adopted in the thesis is a step-wise time series analysis. The advantage of this approach is that it provides different forecasting approaches depending on the availability of data and the horizon of the forecast.

In the following sections, I will provide answers to the research questions raised and studied in Chapter 1, then I will put forward what has been learned from my research and what the main implications and contributions are to the academic field and practical sector.
5.1 Discussion of research questions

RQ 1: What is the way of modelling the short-term fluctuations depending on the historical trend of the time series combined with the structural shifts?

In order to find an answer to this question a univariate time series model is estimated – an autoregressive integrated moving average (ARIMA) intervention model – using monthly container throughput measured in TEUs, applying the Box-Jenkins approach in Chapter 2. One of the main advantages of this approach that is independent from other variables and provides insight about the time series process. Moreover, the intervention parameters allow for a dynamic structure and provide help for analysing structural breaks. For example, the structural break of the financial crisis in 2008 is incorporated in the model.

The ARIMA intervention has the advantage of understanding two important phases in the DGP. The first deals with the changes during the shock, which are related to the immediate impact and the scale and scope of the shock. The second is what comes after, the consequences and the adjustments, for example, if it recovers to the previous trend or if it is a permanent change. Results could be used to provide terminal operators and port authorities with monthly forecasts, which is significant in the planning of terminal operations and hinterland activities.

The model developed in Chapter 2 provides a tool for policy makers that serves three purposes. The first is to generate short-term forecasts; the forecasting of the container throughput is of importance for terminal operators and port authorities, as it affects the economic planning and allocation of resources for port operations at terminal and the hinterland connections. The second is to assess the impact of the shocks on the generating process of container throughput. The third is to provide insight into the behaviour of the container throughput of the port of Antwerp and to form the basis for the second research question to identify leading indicators.

Based on the empirical analysis in Chapter 2, including the intervention terms in the model significantly improved the forecasting performance and provided insight about the behaviour of the time series. The implications for the port of Antwerp are twofold. First, the short-term monthly forecasts in TEUs provide a reliable instrument for the port to plan operational decisions and to avoid congestion at the port and at the hinterland connections. Second, the shocks discussed are modelled differently according to the cause and impact of the shock. Hence, the port policy makers learn from these shocks. For example, the high peak in March 2002 that was caused by a change in the market share had an effect of about 10.4% increase in the mean of the container throughput. The 2007 new developments in the port of Antwerp led to a 7.8% increase in container volume above the trend that implies that the port might have faced a congestion problem if the necessary actions hadn't been taken. The financial crisis in 2008 caused a sharp decline in October of the same year, which had a severe impact on changing the trend of the series. The rate
of adjustment to the trend before the shock ($\delta$ - decay rate) is close to 1, which indicates that the impact of the shock is persistent and it will take about 3 years before it recovers to the trend before the crisis, assuming everything else remains constant. The empirical estimates report an MAPE of 7.93% for the ARIMA intervention model.

**RQ 2: Which economic indicators might be identified as leading indicators for the container throughput?**

This question is dealt with using a multivariate approach in Chapter 3, where two dynamic time series modelling approaches are estimated. The first is an autoregressive integrated moving average with an exogenous variable (ARIMAX) model which is estimated based on the Box and Jenkins methodology. The second is an error correction model which is estimated – *a cointegration model* – using the Engle-Granger two-step procedure. This approach relies on testing for common patterns and trends in the historical dataset between the container throughput and economic activity indicators using cointegration test that allows, if following the evolutions of the economic activity, to foresee the container throughput. The advantages of these two approaches are: (a) they can capture the influence of external factors and identify the leading indicators and (b) they evaluate the short-term and long-term effect of the explanatory variable on the dependent variable.

The variables are at aggregate level which encompasses the total throughput of containers at the port of Antwerp, and the economic indicators which include the index of industrial production, the composite index of leading indicators, and the industrial confidence indicator for Belgium and one confidence indicator for the European Union.

Based on the empirical analysis: (a) the two-months lagged EU18 industrial confidence indicator and the three-months lagged index of industrial production are leading the container throughput in the port of Antwerp, and (b) the relationship between container demand and economic activity is still coupled although there is a significant change in the relationship due to the global financial crisis in 2008. Moreover, the empirical analysis showed that the ARIMAX model with the the two-months lagged EU18 industrial confidence indicator was the best fit, with an MAPE 2.03% for the dynamic forecasts. The forecast generated by the error-correction model using the the three-months lagged index of industrial production for the validation set reports a MAPE 19.25% for the dynamic forecast.

In addition, based on the analysis in Chapter 3, there is a significant change in the relationship between container demand and economic activity in the long-run: the speed of adjustment of the container throughput, as a result of changes in the industrial production, has changed before and after the global financial crisis in 2008. Although the relationship between container throughput and economic activity is changing, it is still coupled.
RQ 3: How will the container throughput in the port of Antwerp evolve until 2050 under different scenarios?

The question is discussed in Chapter 4, where a three-step approach is carried. A model is developed by combining the autoregressive distributed lag model (ARDL) with the economic scenarios to capture the potential impact of specific risks and to provide long-term annual forecasts for the port of Antwerp until 2050.

This approach accounts for other regional and economic factors that are needed to develop demand projections, such as the GDP and trade growth scenarios and market share scenarios that reflect the competitive position of the port of Antwerp within the Hamburg - Le Havre range. The model estimates that the elasticity of the container throughput in the Hamburg - Le Havre range to trade indices is about 1.4 on average. The combined approach provides 4 different likely courses for the container throughput developments in the Hamburg-Le Havre range that address the capacity present in the Hamburg - Le Havre range rather than focus on limits at a specific port. Moreover, 12 different likely courses are provided for the future development of the container throughput at the port of Antwerp based on 4 different economic scenarios for the EU and 3 scenarios for the port of Antwerp market share within the Hamburg - Le Havre range.

The aim of the scenarios analysis is not accurately predict the future, rather to provide different likely courses for the independent variables and accounting for the qualitative factors; hence, account for the uncertainty about the changes in the economic activity and be prepared with flexible and adjustable planning for possible futures, especially since the model is estimated from 20 year data to forecast the coming 35 years.

5.2 Implications and generalisation

Beside the academic methodological research, the research aims to provide the port practitioners and stakeholders with insight into the empirical application of forecasting approaches and trend analysis. Edward de Bono wrote in his book Serious Creativity; “if you cannot accurately predict the future then you must flexibly be prepared to deal with various possible futures.”

The application to other ports is feasible taking into account the specific characteristic of the location of each port, specific market segments, the hinterland connections and activity, and the country’s specific trade relations and socio-economic indicators. However, the availability of data for long time series is often a limitation. The models are generic; i.e. they may be applied to other ports, and frequently updated when more data points are available, and that improves the fit of the model. Nevertheless, updating the model may change its identification process of the model and the lag structure since the data
generating process might change. For example, the new-investments plans at the Saeftinghe Development Area in the port of Antwerp were based on a study that the port will face congestion in container handling capacity as of 2020-2021 (Antwerp Port Authority, 2015b). That is in accordance with the high case scenario of the market share developed in Chapter 4, Figure 4.8a. However, the other two scenarios should be considered by the port authorities in a way to develop flexible master plan for the new infrastructure planned.

Another application would be of interest in the case of the Egyptian ports, the ports of Alexandria and East Port Said which have great opportunities. However, when modelling the container throughput at the port of Alexandria, particular consideration is needed for its location within the range of the Mediterranean Seaports, where competition is very high. The Port of East Port Said location on the main shipping route (East-West trade lane) and close to the Suez Canal provides a potential for investment opportunities and for the development of the port into a hub port. From the trade outlook of the Egyptian economy, the focus should be on developing the export of fruits and vegetables that will require the development of the reefer container terminal. However, the problem arises from the instability of the political situation during the period from 2011-2013, the bureaucracy of the government procedures and the lack of understanding the market-specific requirements.

5.2.1 Conclusion regarding the different forecasting models

The main unit of analysis in the thesis is at the port level focusing on the demand forecasting of the container throughput in TEUs that enable to compare to the port capacity and assess the future decision for the port investment. The importance of the port capacity is that it plays a crucial role in the competitive position of the port in order to avoid congestion at the terminal and at the hinterland connections. However, the decision to provide new capacities and investments in the port should be supported by a growing potential demand. The consequences arising from an unnecessary investment decision or ineffective timing of the investment will be reflected in inefficient operation at the terminal and congestion that may result from under-capacity or extra unjustified cost of over-capacity, in case the potential demand is less than the planned supply.

Two different paths guide the methodology of the thesis. The first path is for the short-term forecast that focuses on the historical data in Chapter 2 and the leading indicators in Chapter 3. This approach is used on condition that a long time series is available and on monthly basis, which allows to closely follow the evolutions of the trends and analyse the economic evolutions. Moreover, such models are useful for identifying and understanding the drivers of growth of the container throughput, can be easily updated and can include other variables.

The second path is for the long-term forecast that relies on annual data (Chapter 4). Here, the approach goes top-down. The model starts with forecasting container through-
put at a port region (the Hamburg - Le Havre range of ports) then providing forecast at the port level (the port of Antwerp) by means of different scenarios for the port market share within the range. This approach is useful in the case where the dynamic interaction and competition between ports is present for the following reasons:

- It provides an overview of the aggregate demand and capacity limits in the region rather than focusing on a single port (Figure 4.7). In that way, it captures the dynamic interaction between ports, where the decrease in the market share at one port is captured by an increase in other port(s).
- Uncertainty cannot be eliminated in long-term forecast. Therefore, different scenarios were examined to analyse the impact of different economic and trade growth rates on the development of the container throughput until 2050. Moreover, each scenario is split into 10 years’ period, which is useful to provide the possibility of making changes or accounting for any potential risks.
- The low case scenario shows what happens in the worst case if demand did not materialise as in the case of the Amsterdam Container Terminals (previously known as Ceres-Paragon) where demand never materialised and the ‘White Elephant’ is shut down. Moreover, the global financial crisis in 2008 is a clear evidence that things might go very bad.

To sum up, which model to use? Few aspects should be considered and examined to answer this question:

- How the data generating process underlying the behaviour of the time series looks like?
- To what extent is the data available? Time series analysis requires large sample size to capture the trend and examine the changes and factors underlying the DGP.
- Which frequency is used (monthly or annually)? The frequency of the time series depends on the purpose and the horizon of the forecast in one’s objective.

5.2.2 The implications of incorporating the intervention analysis

One of the main advantages of this thesis is that it incorporates structural breaks in the model (Chapter 2) unlike most of the previous studies in the literature. The theoretical approach and the empirical analysis are provided in Sections 2.3.2 and 2.5.2, respectively. The aim of the intervention analysis is to measure the influence of an event or a shock on the time path of the dependent variable;

In addition, it is not to speculate on when the recovery will occur after a shock, but rather to consider the following conditions that are likely to help the port decision makers in managing their risks:

- The nature of the shock is crucial for determining the impact as introduced in Figure 2.3, which depends on the interaction of three criteria: (1) the duration; whether it is a
temporary or a permanent effect, (2) the impact effect; if the change is in the level or the slope or both the level and slope and (3) the onset; whether it is abrupt or gradual (McCleary and Hay, 1980).

• How the shock affects the evolutions and the recovery of the global economic growth and trade, and production patterns.

For example, if the shock is temporary and does not affect the mean growth of the time series, this will require only operational improvements. But if the shock is permanent and has an impact in the trend, other measures should be considered, as pricing or revise expansion projects and master plans.

5.3 Challenges and limitations

There are two main challenges that were faced throughout the analysis in the different chapters.

(1) The modelling of the maritime freight demand is a complex process for two reasons:

(a) The fact that transport service is a derived demand from the need of various goods in different locations of infinite economic activities, which is determined by socio-economic factors, among others. Moreover, these factors are dynamic and changing over time and across regions.

(b) The ports' structure and activity add another dimension to the complexity of modelling. On the one hand, the port deals with different types of cargo and each type has different determinants and market forces. On the other hand, there is the intertwined relationship between the various decision-makers and stakeholders, which are involved in the market, for example, port authorities, shipping lines, terminal operators, shipowners, shippers and investors.

(2) The significant structural break in 2008 due to the global financial crisis is close to the end of sample period. This raised a two-fold impact:

(a) On the one hand, it imposes restrictions to divide the sample into estimation and validation sets. The time series in the estimation was not fully adjusted to evaluate the impact of the structural effects.

(b) On the other hand, it provides an advantage to the analysis to show the effect of the shock on the time series and to understand what the impact would be if another shock of similar characteristics happened in the future.

The limitations of the thesis are presented as follows.

• The availability of detailed and long-time series data on monthly basis limits the use of the variables included in the models throughout the thesis. Disaggregated data is required to differentiate between local, regional and global drivers of container throughput.
• The estimation of the univariate model in Chapter 2 assumes that the historical trend continues in the same pattern. The multivariate models in Chapter 3 provide a useful approach to study the relationship between the container throughput and the economic activity; however, to use this model for more than 3 months, projections are needed for the economic activity. To overcome the challenge of modelling the container throughput, the combination of the ARDL model and the scenario analysis is developed in Chapter 4. In spite of that, it is difficult to distinguish the impact of the changes attributed to global shipping market trends from the regional and local economic factors.

• The analysis was applied on the port of Antwerp that has some special characteristics due to the location within the Hamburg - Le Havre range and the hinterland connections. Nonetheless, the models, as an instrument for port policy makers, are flexible and suitable for other ports. The application to other ports should be considered within the framework of the port specific location, characteristics, type of cargo and the competitive position of the port.

5.4 Further research

From the methodological perspective, the analysis conducted depends on a time series methodology; however, this technique does not allow measuring the dynamics between different ports and actors. Therefore, for further research, the extension of the methodology to use panel data models will be of value added to model. Moreover, using the time varying coefficients models is important to explore the dynamic patterns, such as the shipping loops, the choice of the ports and the measurement of the dynamic relationship between the ports in the Hamburg - Le Havre range or other ports that share about the same hinterland or compete to serve a specific region, overcoming the problem of data availability.

From the empirical application perspective, if more detailed data is available, other variables will be included in the models and the scenarios. It is interesting to examine further if possible data or indices are available, which reflects the impact of changes in the oil prices, the increasing size of the container vessels on maritime freight transport, the developments in the supply chain networks and logistics activities and the hinterland connections. Moreover, the scenarios may be developed to include not only the economic growth scenarios but also scenarios for the trade routes changes.
APPENDICES

Appendix A: Software

All the data analysis, graphical representations, model estimation and forecasts were performed using the statistical software packages; EViews 9 and SAS 9.3. The data may be provided upon request with the exception of the monthly container throughput of the Port of Antwerp.

Appendix B: Mathematical notation

The following list defines the operators used within the context of the thesis (Sargent, 1987, Chap. 9):

- $Bx_t = x_{t-1}$
- $B^m x_t = x_{t-m}$
- The difference operator: $\triangle x_t = x_t - x_{t-1} = (1 - B)x_t$
- $\phi(B) = 1 + \phi_1 B + \phi_2 B^2 + \ldots$
- $\phi(B)x_t = x_t + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots$
- $(1 - B)x_t = x_t - x_{t-1} = \triangle x_t$

Appendix C: Unit Root Tests

Unit root tests are used to test the stationarity of the time series. If the series is non-stationary, then, the persistence of shocks will be infinite, will lead to spurious regression and the standard assumptions for asymptotic analysis will not be valid. In the context of this thesis, stationarity is defined as weak stationarity, where the mean, variance and covariance at equal displacements are constant. A data generating process - as defined by (see Charemza and Deadman, 1997, p. 84) - is stationary if the joint and conditional probability distributions are both invariant with respect to time displacement. Two kinds of tests are illustrated, in Section 5.4, the convention ADF test without structural breaks and the DF with structural breaks in Section 5.4.
Conventional unit root tests

The basic objective is to test the null hypothesis ‘$H_0 : \rho = 1$’, i.e. $H_0$: the series is nonstationary—contains a unit root. Against the one-sided alternative hypothesis ‘$H_a : \rho < 1$’, i.e. $H_a$: the series is stationary, in Equation 5.1

$$Y_t = \alpha + \beta t + \rho Y_{t-1} + \epsilon_t$$  \hspace{1cm} (5.1)

The augmented Dickey-Fuller test as in Equation 5.2 allow for serial correlation in $\epsilon_t$ (Pindyck and Rubinfeld, 1997)

$$Y_t = \alpha + \beta t + \rho Y_{t-1} + \sum_{j=1}^{p} \lambda_j y_{t-j} + \epsilon_t$$ \hspace{1cm} (5.2)

Structural break unit root test

Perron (1989, p.1364-65) proposed a modified DF unit root test procedure that incorporates a dummy variable of a known single structural break in the trend function. This approach allows three scenarios to test for the unit root on the full sample that permits different types of structural break effects; (A) a change in the level of the series, (B) a change in the rate of growth (slope), and (C) changes in both level and growth rate. The following regression equations 5.3, 5.4, and 5.5 correspond to the models respectively:

$$y_t = \mu^A + \dot{\theta}^A D t + \beta^A t + \lambda^A D(TB)_t + \alpha^A y_{t-1} + \sum_{i=1}^{i=k} \epsilon_i \Delta y_{t-i} + \epsilon_t$$ \hspace{1cm} (5.3)

$$y_t = \mu^B + \dot{\beta}^B t + \dot{\gamma}^B D T^*_t + \lambda^B y_{t-1} + \sum_{i=1}^{i=k} \epsilon_i \Delta y_{t-i} + \epsilon_t$$ \hspace{1cm} (5.4)

$$y_t = \mu^C + \dot{\theta}^C D U_t + \beta^C t + \gamma^C D T_t + \lambda^C D(TB)_t + \alpha^C y_{t-1} + \sum_{i=1}^{i=k} \epsilon_i \Delta y_{t-i} + \epsilon_t$$ \hspace{1cm} (5.5)

where $TB$ refers to the time of the break,
Appendix

\[ DU_t = \begin{cases} 
1, & \text{if } t > TB \\
0, & \text{otherwise} 
\end{cases} \]

\[ D(TB)_t = \begin{cases} 
1, & \text{if } t = TB + 1 \\
0, & \text{otherwise} 
\end{cases} \]

\[ DT^*_t = \begin{cases} 
t - TB, & \text{if } t > TB \\
0, & \text{otherwise} 
\end{cases} \]

\[ DT_t = \begin{cases} 
t, & \text{if } t > TB \\
0, & \text{otherwise} 
\end{cases} \]

The following restrictions are imposed under the null hypothesis of a unit root: \( \alpha^A, \alpha^B, \alpha^C = 1; \beta^A, \beta^B, \beta^C = 0; \theta^A, \gamma^B, \gamma^C = 0; d^A, d^C, \theta^B \neq 0 \). Under the alternative hypothesis of trend-stationary process, the following is expected: \( \alpha^A, \alpha^B, \alpha^C < 1; \beta^A, \beta^B, \beta^C \neq 0; \theta^A, \theta^C, \gamma^B, \gamma^C \neq 0; d^A, d^C, \theta^B \approx 0 \).

Appendix D: Evaluating the forecasting error

To evaluate the forecasting accuracy by estimating the error measures in the estimation period and hence the forecasting power of the models, the following criteria are used throughout the different chapters to measure the ex-post forecasting accuracy are:

1. The mean square error (MSE): it depends on the scale of the dependent variable
\[
\frac{1}{n} \sum_{t=1}^{n} e_t^2.
\]
2. The root mean square error (RMSE): it is measured in the units of the dependent variable, defined as
\[
RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} e_t^2}.
\]
3. The mean absolute percentage error (MAPE): it is scale invariant expressed in percentage, defined as
\[
MAPE = \frac{1}{n} \sum_{t=1}^{n} \frac{|e_t|}{y_t} \times 100.
\]
4. The Theil inequality coefficient: it is measured as
\[
U = \frac{\sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - f_t)^2}}{\sqrt{\frac{1}{n} \sum_{t=1}^{n} y_t^2} + \sqrt{\frac{1}{n} \sum_{t=1}^{n} f_t^2}}.
\]

It lies between 0 and 1, where zero indicates a perfect fit. It compromises 3 proportions (Pindyck and Rubinfeld, 1997, pg. 210-4):

(i) The bias proportion tells us how far the mean of the forecast is from the mean of the actual series.

(ii) The variance proportion tells us how far the variation of the forecast is from the variation of the actual series.

(iii) The covariance proportion measures the remaining unsystematic forecasting errors.
Remark: Although there are many measures to evaluate and compare the forecasting accuracy of the different models, the MAPE is the preferred measure used throughout the thesis. Since, it is reported in a percentage, hence it does not depend on the measured units of the variables.
References


OECD (December 2009). Interpreting OECD composite leading indicators (CLIs). Technical report, OECD.


References


