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The future container throughput for inland shipping on the traditional Rhine: a SARIMAX approach

Noemi Van Meir[1]
Department Transport and Regional Economics, University of Antwerp, Belgium.

Yasmine Rashed[2]
College of International Transport and Logistics, Arab Academy for Science, Technology & Maritime Transport, Egypt.

Katrien Storms[3]
Department Transport and Regional Economics, University of Antwerp, Belgium.

Christa Sys[4]
Department Transport and Regional Economics, University of Antwerp, Belgium.

Thierry Vanelslander[5]
Department Transport and Regional Economics, University of Antwerp, Belgium.

Edwin van Hassel[6]
Department Transport and Regional Economics, University of Antwerp, Belgium.

Inland container shipping is confronted with significant challenges, both on the demand and supply side. In line with the 2019 Green Deal's ambitious goals and 2020 Sustainable and Smart Mobility Strategy, the European Commission presented an 'Inland Waterway Transport Action plan 2021-2027' with the target of shifting more freight across inland waterways. However, the COVID-19 pandemic together with the low water level raise interest in how these could impact the throughput for container transport on the inland waterways. In this research, the scope is on the container throughput for inland container transport on the traditional Rhine. This study first identifies the market drivers for

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[1] A: Prinsstraat 13, 2000 Antwerpen, Belgium E: Noemi.vanmeir@uantwerpen.be
[2] A: El Moshir Ismail St., 2033 Elhorria, Cairo, Egypt E: yasmine.rashed@aast.edu
[3] A: Prinsstraat 13, 2000 Antwerpen, Belgium E: katrien.storms@uantwerpen.be
[4] A: Prinsstraat 13, 2000 Antwerpen, Belgium E: christa.sys@uantwerpen.be
[5] A: Prinsstraat 13, 2000 Antwerpen, Belgium E: thierry.vanelslander@uantwerpen.be
[6] A: Prinsstraat 13, 2000 Antwerpen, Belgium E: edwin.vanhassel@uantwerpen.be

containerized inland navigation in the medium run and then selects the SARIMAX method to analyse Inland Waterway Transport (IWT) volumes. The model application shows that the throughput for inland container transport on the traditional Rhine is impacted on by periods of low water and the weakening of the economy caused by COVID-19. The results of the study suggest that if the IWT container market is impacted by the identified factors, the throughput for containerized IWT is expected to decline by 8.9% in 2023 relative to the volumes in 2020. The research might act as a decision support tool for analysis, management and planning for policymakers and stakeholders.

Keywords: *Inland container shipping, time series, modal shift, forecasting, Rhine river, SARIMAX.*

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1. Introduction

The European Commission has focused on the modal shift with funding programs towards inland shipping since 1993. Reinforced by initiatives by the ports, the transported volume of containers to and from the ports via inland shipping grew. However, a significant change of choice of transport mode, in favour of inland navigation, did not occur. In 2019, the European Commission launched its *EU Green Deal* plan (EGD), consisting of three goals. Firstly, it intends to bring the net greenhouse gas emissions (GHG) to zero by 2050. Secondly, it stimulates economic growth without resource depletion. Thirdly, the Green Deal has the intention that no person or region will be left behind. Furthermore, the modal shift potential of inland navigation is a crucial part of the Green Deal to reduce GHG emissions (European Commission, 2019).

In line with the EGD's goals (European Commission, 2019), the European Commission presented in 2020 its Sustainable and Smart Mobility Strategy (SSMS) aiming to create a sustainable, smart, and resilient European transport system (including inland navigation). This was followed by the 'NAIADES III - Inland Waterway Transport Action plan 2021-2027' (European Commission, 2021a) with the target of shifting more freight to inland waterways. More specifically, the European Commission sets out the milestone to increase the share of inland waterway transport and short sea shipping by 25% by 2030 and by 50% by 2050 compared to 2015 (European Commission, 2021a).

Despite the many initiatives by the European Commission, the inland shipping sector faces challenges. These challenges appear both on the demand side and supply side. On the demand side, factors such as competition from other transport modes (road or railway transport), fluctuation in the world economy, in full transition to attract new cargo segments etc. all play a major role. Parallel, the supply side faces challenges such as climate change and more specifically lower water levels (Wilkes et al., 2022), pressure to become green (alternative fuels) (CCNR, 2021a), skilled crew availability, prediction of fleet development, etc. All these challenges, reinforced by the COVID-19 pandemic and the 'Fit for 55' ambitions of Europe to reduce net GHG emissions by at least 55% by 2030, create uncertainty for the throughput of containerized IWT and thus also to achieve the desired mode shift (European Commission, 2021b). In addition to the challenges, the sector faces shocks; random and unpredictable events that have a significant impact on the sector. This leads to the following two research questions:

1. Is there a shock in the trend of the throughput of containerized cargo transport on the traditional Rhine?
2. If there is a shock in the trend, by which amount is the container throughput on the traditional Rhine impacted on?

The outcome of this research is relevant for both barge operators who may use this information to (re)evaluate investment decisions, as well as governments, who may measure the effect of previously introduced regulations.

The traditional Rhine is studied as this river is the most vital waterway in Europe per volume of goods transported (tons), with a share of about two-thirds of the total freight transport on European inland waterways (CCNR, 2018; Sys & Hellebosch, 2021). Moreover, the data was limited to this specific part of the Rhine. In addition, the Rhine plays an essential role for the two largest ports in Europe, viz. the port of Rotterdam and the port of Antwerp; unlike the port of Hamburg, where the dominant mode of transport is rail transport. The share of containers transported (15 million tons) is 9.37% of the total transported freight on the traditional Rhine (160 million tons) (CCNR, 2021c). The term 'traditional Rhine' in the research question refers to the stretch between the Swiss-German border (Rheinfelden) and the Dutch-Germany border (CCNR, 2018) as shown in figure 1.

Figure 1. *Rhine river map*
Source: own composition from CCNR, 2019

A three-step research approach is followed to address these questions (Figure 2). In this approach, an overview of the academic literature regarding forecasting and modelling approaches for inland waterway transport (IWT) is given. The aim is to study previously performed analyses for inland shipping to identify possible market drivers. The second step focuses on collecting data and selecting the appropriate method to answer the proposed research questions. In this step also the identified explanatory variables are tested to determine whether they can be used in a modelling approach. In step 3, the empirical part of the research, the analysis is conducted, in which different breakpoints are identified, along with the possible quantification of the impact on container throughput before and after the shock.

The paper is structured in the following way. Section 2 starts with a literature review. In section 3, the paper sets up the analysis framework that covers the research scope, the data collected, a breakpoint analysis, forecasting models, and the model selection. Section 4 deals with the empirical analysis and discusses the results. Section 5 covers the conclusion of the research.

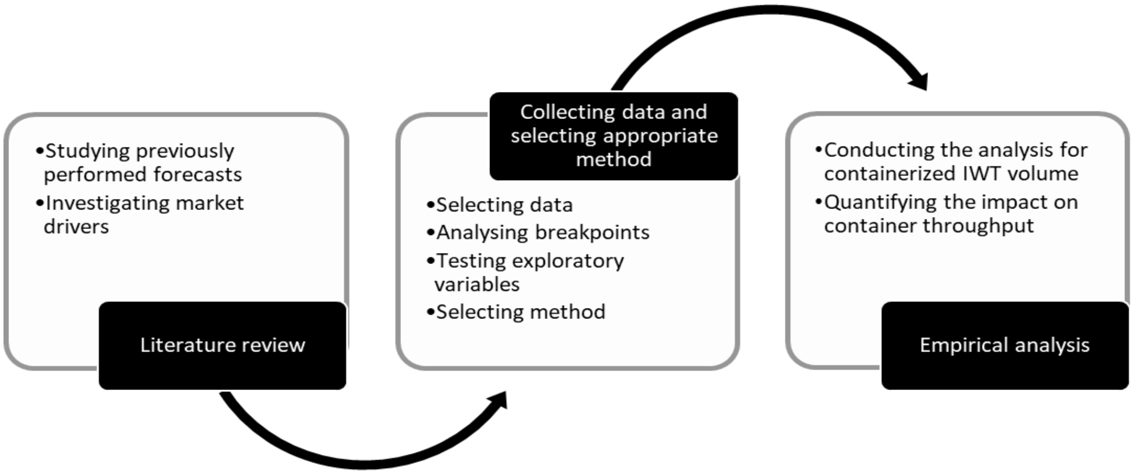

Figure 2. Research outline
Source: own composition

2. Forecasting and modelling studies for inland shipping: a literature review

The first step in the research approach is to conduct a literature review of sources in which a forecast for inland navigation was made. This allows gaining insight into the different types of forecasting models used, the forecasting period covered, the data sources used, the geographical scope, for which sub-markets of inland shipping, and which variables were included in the regressions. The literature review explores prior relevant academic papers published until 2021. Furthermore, the academic literature was expanded with the grey literature published publicly by government departments and agencies (i.e. the Vlaamse Waterweg nv), non-governmental organisations (i.e. Central Commission for the Navigation of the Rhine (CCNR) and consultants (i.e. Panteia). For the grey literature, the literature review search was filtered on reports published between 2016 and 2021, covering a five-year period due to the fact that in this period the methodology used by these institutes did not change.

Table 1 shows the details of the publication, forecasting period/method, the product and geographical scope, and the variables used in papers with estimations (or a model) for future inland navigation in North-Western Europe.

This overview shows that a limited number of studies are executed on forecasting in the inland navigation sector. Moreover, the models are mainly based on aggregate macroeconomic variables (gross domestic product (GDP) and population) and focus on dry or liquid bulk, except for CCNR (2017) and Rashed et al. (2017). The studies are briefly explained below.

Babcock & Luis (2002) provide a forecast for inland navigation on the Mississippi River. The paper focuses on a different geographical scope: North America. However, this can give interesting insights into the method used and the forecasting period. The forecasting period is a short period forecast of one year and three months. The research uses sample forecasting to test the performance of the forecast by using an ARIMA and ARIMAX model. The paper focuses on the dry bulk segment.

Table 1. Forecasting papers inland navigation

Author	Publication year	Title	Sub-segment	Forecasting period	Forecasting method	Geographical scope	Variables used
Babcock & Lu	2002	Forecasting inland waterway grain traffic	Inland navigation, dry bulk (grain)	1989:1-1999:4	Time series model: ARIMA, ARIMAX and dummy variables	Mississippi river	Grain tonnage
Luo & Yang	2013	Study on the Imbalance of Shipping Demand and Supply of Inland Water Transportation of Yangtze River	Inland waterway freight volumes	2002-2025	Regression analysis, output value of coefficient method, elastic coefficient method, time series analysis and the weighted combination of those methods	Yangtze River	GDP per capita, investment in fixed assets, import and export volume of foreign trade, electric energy production and steel production
Legeay, Kriedel, Espenhahn, Fahrner &, Arriola, Kraemer	2017	Annual report 2017 (p. 138 - 142)	Inland navigation container transport, econometric model	Concept (used for reports 2020 and 2022)	Statistical tests, log-log type, ordinary least squares method (OLS), multi-collinearity tests method (OLS), multi-collinearity tests	Rhine	GDP, container transhipment port of RTM, transport of containers by German railways, exchange rates US, exchange rates China, oil price
de Leeuw van Weenen, van der Meulen, & van der Geest	2018	Medium-term forecast for inland navigation	Focus on dry bulk, liquid bulk and barges	2018-2022	PRISMA calculation, trend-analysis	The Netherlands	Demography, world economy, oil price, currency fluctuations, sector development, import & export of products
de Leeuw van Weenen, van der Geest, Hindriks & Grijspaardt	2020		Focus on dry bulk, liquid bulk and barges, predictions with COVID-19 scenarios)	2020-2025	PRISMA-D calculation (renewal/update of PRISMA),		Demography, world economy, oil price, currency fluctuations, sector development, import & export of products
van Hassel & Rashed	2020	Analyzing the tank barge market in the ARA – Rhine region	Inland tank barge market	2016-2020	Error correction model, scenarios	ARA - Rhine region	GDP development, industrial production of the chemical sector, the Brent oil price, the trade fuels in the ARA ports and the low water surcharge

Source: own composition

Luo and Yang (2013) make a forecast of the demand for transport on the Yangtze River. The paper focuses more on the imbalance between supply and demand in inland navigation. They use the following variables in their paper: GDP per capita, investment in fixed assets, import and export volume of foreign trade, electric energy production, and steel production. This research will make a forecast also based on a time series analysis. Legeay, et al. (2017) provide a conceptual model to test variables and see if they can predict what will happen in the inland container navigation market on the Rhine. The model uses log-log to interpret the coefficients as elasticities assigned to each explanatory variable produced via a regression using the ordinary least squares (OLS) approach. The paper statistically assesses the significance and multi-collinearity of these factors; considering the following variables: the GDP, container transshipment in the port of Rotterdam, transport of containers by German railways, exchange rates of the US, exchange rates of China, and the oil price. Legeay et al (2017) used this conceptual model to make their forecasts for the inland navigation container throughput in their reports for 2020 and 2021.

De Leeuw et al (2018) provide an annual forecast for 2018 until 2022, while de Leeuw et al (2020)contains a market prediction from 2020 to 2025 for inland navigation in the Netherlands. In contrast to CCNR (2017), Panteia (2018 and 2020) focuses on the general market (all market segments) and gives a more detailed description of the dry bulk, liquid bulk, and push barge markets. Panteia (2018) uses a macro-sectoral model (PRISMA) and a trend analysis, while Panteia (2020) applies an updated forecast based on the PRISMA-D model. Both papers by Panteia include macroeconomic variables such as demography, world economy, oil prices, currency fluctuations, sector development, and the import and export of products.

Van Hassel & Rashed (2020) make a forecast for the tank segment for the ARA region (referring to the port area of Amsterdam, Rotterdam and Antwerp). Their paper works with specified variables such as the development of the GDP, the growth of the chemical sector, the Brent oil price, the trade fuels in the ARA ports, and the low water surcharge.

Given the above, the purpose of the present paper is to provide a support tool for strategic decisions in relation to the operations of inland navigation actors and to uncover potential issues that may occur. Therefore, following van Hassel & Rashed (2020) and enforced by uncertainties in the inland navigation market (COVID-19, energy crisis, etc.) the research opts for a medium-term forecast.

Reviewing these six papers results in an overview of the market drivers for this research. Firstly, the container port throughput of the port of Rotterdam turns out to have an important influence on the container throughput on the Rhine (CCNR, 2017). The port of Antwerp is not significant, according to the report of the CCNR (2017). Port throughput of the ports within the scope of the research is tested to see which ports influence the container throughput of the Rhine.

The second market driver that should be taken into account is industrial production. Industrial production includes the output of industrial products such as mining, manufacturing, electricity. These segments have an important role in the share of inland navigation on the Rhine. For example, in 2020, the iron ore segment on the Rhine accounted for 18.5 million tonnes. Furthermore, approximately 8 million tonnes of metals were transported via the Rhine and approximately 17 million tonnes of coal (CCNR, 2021c). Moreover, Meersman & Van de Voorde (1999) show that up until the early 1990s, the demand for freight transport in Europe was driven by industrial production rather than the GDP.

The third market driver is the water level. The report of CCNR (2021b), on behalf of the CCNR and European Commission, indicates that the Rhine is highly dependent on rainfall and ice of the Alps, which causes low water levels and high water levels. The classical seasonal water flow or discharge curve on the Rhine is a bell curve. The peak in this bell curve appeared in summer, not in winter. This bell curve is being changed by climate transformation and climate change to some degree. The source of water for the Rhine exists for 50% of rainfall. Due to global warming, there is a higher probability of longer periods of no rainfall, making there will be longer periods of low water (Stahl et al., 2016; Sys & Hellebosch, 2021; Shobayo et al., 2021). Extreme drought and a lack of rainfall are likely to come back year after year due to global warming (Jonkeren et al., 2007 & Ellyatt, 2019). The extremely low water levels caused a reduction in the load capacity of inland vessels, which in its turn impacted the supply of transport capacity. Consequently, freight prices increased and thus affected the transport volume of the inland navigation market negatively (Van Dyck, 2021).

In addition to identifying the variables, the literature was also used for mapping the methodological approaches that were used in the papers. Babcock & Luis (2002), van Hassel & Rashed (2020), and Legeay et al. (2017) all use a time series approach in which different independent variabels are considered. One paper was found that deals with an ARIMA and ARIMAX approach, namely Babcock & Luis (2002). with grain transport in the US and not with container transport in Europe. Therefore, based on the literature study, it was also concluded that a univariate forecasting model for containerized transport on the traditional Rhine is not available.

3. Empirical framework

The empirical analysis aims to provide a medium-term forecast. This section starts by delineating the scope. Next to that, the data is identified, analysed, and the most suitable forecasting method is selected.

3.1 Data selection for analysis

Based on the literature review, three independent variables are identified to explain changes in the throughput[7] for containerized IWT volume on the traditional Rhine (dependent variable). During the data collection of these selected independent variables, it quickly became apparent that data related to inland shipping exists but is collected by different institutes using different definitions and methodologies to measure or collect data. Other challenges were linked to the confidential nature of the required data, limited availability of open access to data, no (access to) longer time series, gaps in the collected time series, different levels of frequency (monthly, quarterly, annually), and level of aggregation with other data sets obtained. Table 2 gives an overview of the data obtained from different sources used in this research.

Firstly, the dataset of the containerized Rhine inland navigation throughput is obtained from Destatis via CCNR. All statistics series related to the water level of inland navigation on the Rhine come from Generaldirektion Wasserstraßen und Schifffahrt (WSV). The ports receive this data from the barge owners active on the Mannheim-Rotterdam corridor. Inland navigation operators must report the port of the final destination. Based on this input, Destatis assigns the presumably followed waterway. Secondly, the container port throughput is collected from the respective statistics published by the port authorities. The study measures the inland navigation throughput and container port throughput in twenty feet equivalent units or TEUs, the standard unit of statistics with respect to loading and unloading activities, all port operations, and ship capacity (supply). The container throughput was obtained every year. Thirdly, the industrial production of Germany (index) was collected by the Institut für Wirtschaftsforschung (Ifo). Lastly, three gauge stations are selected to take the phenomena of the low water levels in periods of extreme drought into account. CCNR (2021b) indicates that Kaub is an essential gauge station as an indicator for low water level conditions on the Rhine, especially for container transport. Additionally, two other gauge stations were added; one located north of Kaub, at Duisburg, and one south, at Maxau (encircled in Figure 1).

[7] Throughput in this research is the result of both the demand (reflected in the industrial production) and supply (reflected by the water level) sides.

Table 2. Data used in the analysis

#	Variable	Definition	Sample	Unit	Frequency	Source
1	Inland navigation	Traditional Rhine container throughput	01.1994-07.2021	TEUs	monthly	Destatis, CCNR
2	Container port throughput	Container throughput Antwerp	1985-2019	TEUs	annually	Port of Antwerp
	Container port throughput	Container throughput Rotterdam	1985-2019	TEUs	annually	https://www.portofrotterdam.com/en/our-port/facts-and-figures/facts-figures-about-the-port/throughput
3	Industrial production	Industrial production (2015=100)	01.1994-11.2021	index	monthly	https://data.oecd.org/industry/industrial-production.htm
4	Water level	Water level: Duisburg, Kaub & Maxau	01.2000-12.2020	centimeters	monthly	WSV, Rhineforecast.com

Source: own composition

3.2 Breakpoint analysis

In order to understand the behaviour of the time series data generating process, a breakpoint analysis is conducted. From this analysis, since 1994, container cargo transported on the Rhine was growing by an average annual growth rate of 6% until 2017. The lowest growth rate was about -10% in 2008/2009, attributed to the global financial crisis, and -10% and -4.4% in 2017/2018 and 2018/2019 due to the significant low water level in 2018, respectively.

The monthly container throughput measured in TEUs on the Rhine is shown for the period from January 1994 till July 2021 (sample size; n=321 observations) in Figure 3.

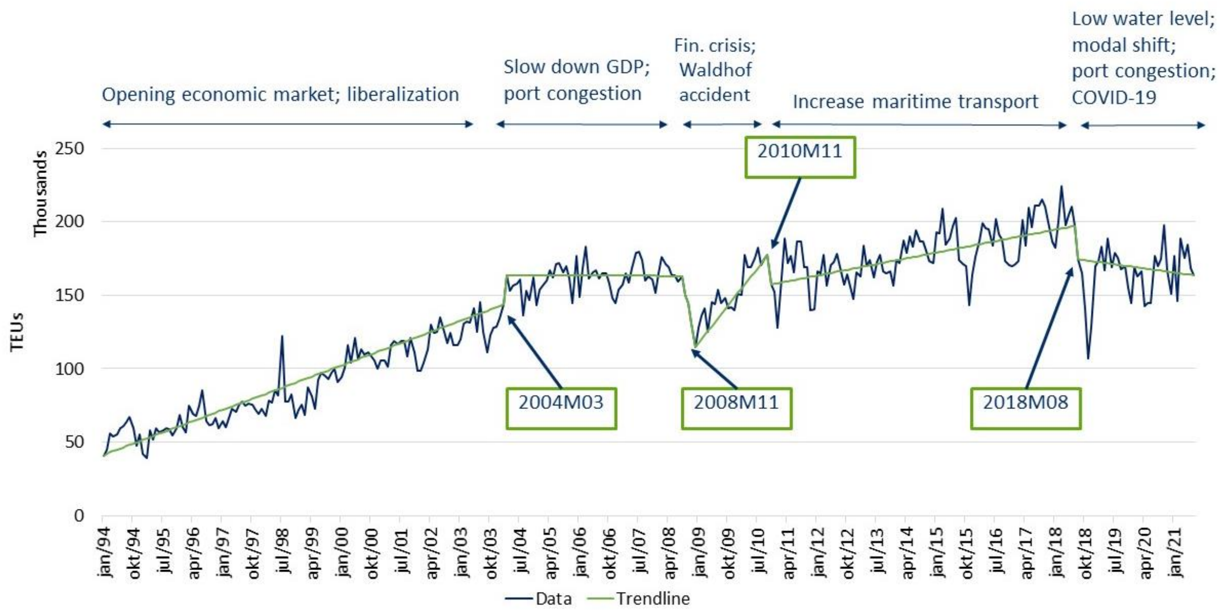

Figure 3. The monthly development of the container transport (TEUs) on the Rhine.
Source: own composition from Destatis (2021); CCNR (2005, 2011, 2017, 2019)

The significant break dates 2004m03, 2008m11, 2010m11, and 2018m08 were determined using the Bai-Perron sequential breakpoint methodology (Bai and Perron, 1998). The estimation is shown in Appendix A.1.

Error! Reference source not found. gives an overview of the different breakpoints in the time series. In addition, the month-over-month average growth rates of Rhine traffic for each period are shown. Furthermore, the reason(s) that might have led to the changing behaviour are enumerated.

Table 3. Average growth rates between breakpoints and reasons for change

No.	Period	Sample (#month)	m/m Av. growth	Reason
1	1994M01 - 2004M02	122	2.7%	Opening Economic market (1993), liberalization of inland navigation market (1998-2000), growth inland container transport in line with growth in the port of Rotterdam and Antwerp (CCNR, 2005)
2	2004M03 - 2008M10	56	0.3%	Slowing down of GDP growth in Europe, container growth follows the dynamics noticed in the seaports. This trend also resulted from congestion problems in the port of Rotterdam and, to a smaller extent, in the port of Antwerp. (CCNR, 2005)
3	2008M11 - 2010M10	24	1.1%	The reduction marked by the financial and economic crisis turned in increased containerized traffic linked to the recovery in global trade, however, impacted again by the closure of the Rhine (Jan. 2010) due to the 'Waldhof' accident (CCNR, 2011)
4	2010M11 - 2018M07	93	0.5%	Benefit from the increase in maritime container transport. However, more competition from other transport modes was experienced; volumes were not affected by low water levels; as of 2017 declining industrial production (CCNR, 2017)
5	2018M08 - 2020M09	26	0.3%	Volumes were largely impacted due to low water levels in the second half of 2018, in combination with the modal shift towards road and rail transport; congestion encountered in the seaports as well as weakening of the global economy due to the COVID-19 pandemic and ports in China closed or experienced a relapse (CCNR, 2019). Furthermore, the impact of the volumes is related to unreliable schedules of deep-sea vessels and port congestion.

Source: own composition based on CCNR (2005), CCNR (2011), CCNR (2017) and CCNR (2019)

From the analysis, it can be concluded that a significant change in average growth rate occurred from 2018M08 onwards, caused by the low water level and port congestion. The data sample size after the post-breakpoint (>2018M08) is too small (39 months) to analyse whether this changing behaviour has a temporary or permanent effect. Hence, it is yet unclear whether the inland container shipping market will recover. Therefore, two forecasts (in- and excluding 2018M08 breakpoint) for the inland container volume are estimated. The development of these models is given in the following sub-section.

3.3 Model development

The model is a time series regression econometric model based on measuring the past relationships among the identified variables, and then forecasting how changes in some variables will affect the future course of container demand. Based on the literature review, three variables are identified as potential for the forecasting model.

The selected independent variables are tested to validate if they have an impact on the throughput for containerized IWT volume. Figure 4 provides the framework for this testing.

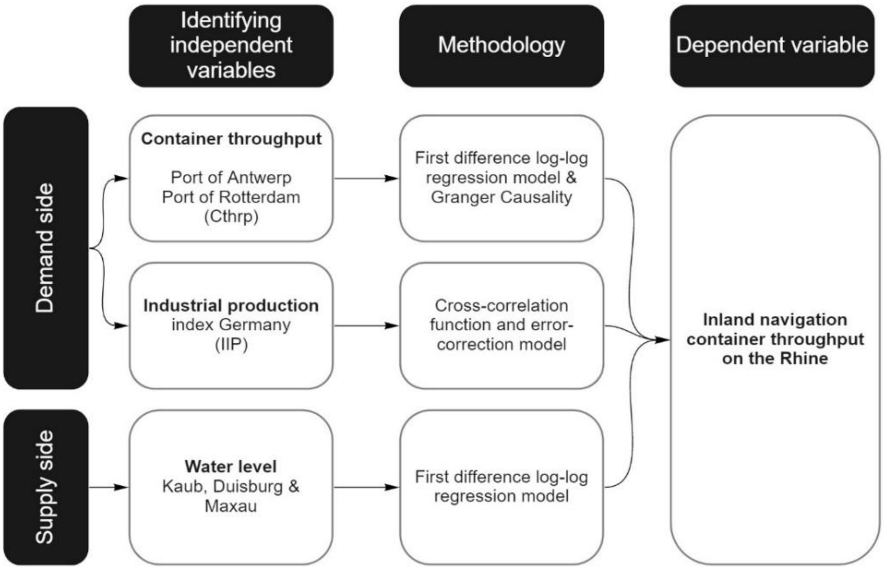

Figure 4. Framework of selected variables impacting the throughput for IWT
Source: own composition

Appendices A.2 to A.5 show the results from the different tests. The significant impact of the port of Antwerp and Rotterdam on the IWT is tested in Appendix A.2A, showing that both are significant as expected since the container throughput is expected to be highly correlated on the traffic at the gateway ports of Antwerp & Rotterdam. Since the models are in natural logarithm, the elasticity is high, 1% change in the container throughput in the ports of Antwerp and Rotterdam will cause 0.77% and 0.65% change in the IWT, respectively. In Appendix A.2B, the Granger Causality test is used to validate the direction of the relationship, as the results show that the IWT container throughput depends on the container throughput at the ports of Antwerp and Rotterdam. For the industrial production, the cross correlogram is used to identify the lead-lag relationship between the industrial production and the IWT container throughput. As shown in Appendix A.3, the IP leads the inland container with four months. In Appendix A.4, the cointegration relationship is estimated. The water level is tested in Appendix A.5 which shows the significance of the Kaub station. From this analysis, it can be concluded that all the selected independent variables as in Figure 4 have a statistically significant impact on the IWT container volumes, which means that these parameters represent a potential leading indicator.

Table 4. Variance Inflation Factors

Variance Inflation Factors
Sample: 1994M01 2015M12
Included observations: 192

Variable	Coefficient Variance	Uncentered VIF
PORT	1.51E-05	13.15552
IP_DE	1785.113	14.91870
KAUB	28.59642	2.181655

Source: own composition

If included in a model, they should improve the forecasting accuracy. The reasons why water level and port throughput as exogenous variables will be excluded from a forecasting model are twofold. First, the water level causes the residual to be serially correlated. Second, the Variance inflation factor (VIF) as shown in Table 4, indicates multicollinearity between the exogenous variables.

Uncentered VIFs greater than five for port throughput and industrial production suggest the presence of moderate to strong multicollinearity (see Gujarati and Porter, 2009, pg. 340). Multicollinearity is a statistical phenomenon in which two or more explanatory variables in a regression model are highly correlated, which causes problems when estimating the model and interpreting the results of the model.

Therefore, this research opted to develop a univariate forecasting method including a seasonal effect and one exogenous variable (Industrial production in Germany). From appendices A.2 to A.5, it can also be seen that the IP in Germany has the strongest link to the throughput for container transport on the traditional Rhine. In this model, the effects of port throughput and water levels variations are incorporated in the seasonal operator. This *Seasonal AutoRegressive Integrated Moving Average model with eXogenous variables (*SARIMAX), an extension of a univariate time-series model, is the addition of explanatory variables or leading indicators (Clements & Hendry, 2004) that also reflects the structural changes of the analysed process (Utnik-Banaś, 2021).

The model is represented in Equation (1)

$$\emptyset_P(B)\Phi_p(B^s)\Delta^d\Delta_s^D Y_t = \theta_q(B)\Theta_q(B^s)\alpha_t + \beta_i x_t^1 \tag{1}$$

Where:

- Yt is the time series at level t
- B is the lag operator
- ΔDs is the seasonal differencing operator, equal to (1−Bs)D
- Δd is the non-seasonal operator defined as (1−B)d
- ∅p(B) is the non-seasonal autoregressive operator of order p defined as (1−∅1B−∅2B2−…−∅pBp)
- θq(B) is the nonseasonal moving average operator of order q defined as (1−θ1B−θ2B2−…−θqBq)
- Φp(Bs) is the seasonal AR operators of finite orders P
- ΘQ(Bs) is the seasonal MA operators of finite orders Q
- αt is the white noise, assumed to be independently identically distributed with 0 mean and variance σ2.
- x_t^1 is the exogenous variable (IP of Germany) in time period t
- β_1 is the coefficients of the exogenous variable

The SARIMAX will be based on the seasonal autoregressive integrated moving average approach that builds on generating a forecast based on the historical pattern accounting for the seasonal variation certainly present in inland shipping. Rashed et al. (2017) applied a similar approach to forecast the container throughput at the Hamburg-Le Havre range ports. Moreover, referring to the breakpoint analysis in Section 3.3, the 2018m08 breakpoint is relatively at the end of the sample (observation no. 296 out of 331 observations), which is not included in the experimental set. Consequently, a dummy variable will be introduced in the SARIMA model. Three models are estimated, and the forecast accuracy is evaluated (see section 3.5).

In order to develop the above-mentioned models, the following steps are taken:

1. Time series modelling requires the system to be stationary. The stationarity of data was evaluated using the augmented Dickey–Fuller (ADF) test (1979).
2. The Box–Jenkins systematic procedure is adopted for identifying, estimating, and verifying the SARIMA models (Box et al., 1976).
    a. The model identification is conducted by applying an autocorrelation function (ACF) and a partial autocorrelation function (PACF).
    b. The model selection and estimation among the different tentative models is based on using the Akaike Information Criterion (AIC) and the Bayesian information criterion (BIC). The lower the AIC or BIC, the better the model.
    c. The diagnostic and validation checking for the selected model is based on the goodness of fit of the estimated model: no serial correlation in the residual using Ljung & Box test and that the model is stationary and invertible.
3. The SARIMAX model involves an additional step of selecting the exogenous variables.
4. The forecasting accuracy is evaluated using the mean absolute percent error (MAPE), it is scale invariant expressed in percentage as in equations 2.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\frac{|y_t - \hat{y}_t|}{y_t} \tag{2}$$

Where y_t is the actual value in period t; $\hat{y}_t$is the forecasted value; and n is the number of observations in the validation set. The lower the value of MAPE, the better the forecasting accuracy of the model.

3.4 Model selection

To select the most appropriate model specification, the model with the lowest MAPE value should be used. In order to calculate the MAPE, the sample data is split into two sub-samples: as shown in table 5 (i) the experimental or the training set; that represent about 80% of the sample size, and is used to estimate the models. (ii) the validation set or the holdout sample representing about 20% of the sample size, and is used to evaluate the accuracy of the out-of-sample forecasting performance of the proposed models. In the SARIMA model with dummy, the sample was split to 90% training set and 10% holdout sample, this is attributed to including the impact of the breakpoint in the data generating process. The detailed results of the estimations of the three estimated models (SARIMA, with and without 2018M08 dummy and the SARIMAX) can be found in Appendices A.6 until A.8.

Table 5. The model identification and forecasting evaluation.

Model	Model specifications	MAPE	Experimental set	Validation set
SARIMA	$(3,1,4)(1,0,1)_{12}$	17.08%	1994m01-2015m12 (265 obs.) 80% of sample	2016m01-2021m07 (67 obs.) 20% of sample
SARIMAX	$(3,1,4)(1,0,1)_{12}$	9.08%		
SARIMA with 2018M08 dummy	$(4,1,4)(1,0,1)_{12}$	9.75%	1994m01-2018m12 (300 obs.) 90% of sample	2019m01-2021m07 (31 obs.) 10% of sample

Source: own composition

From Table 5, it can be concluded that the SARIMA model without the 2018M08 dummy has an autoregressive lag of three months, an integration of term of one (one degree of differencing to obtain stationarity) and an order of four for the moving average term. In the seasonal part of the model, there is one month of time lag and an order of one for the moving average term. If the dummy is added, the time lag of the autoregressive part changes from three to four months. For the SARIMAX, it can be seen that the specification of the SARIMA part is equal to the initial SARIMA model.

In Figure 5, the results of the three models are plotted and can be compared to the observed container transport (IWT). The full line refers to the real container throughput, while the broken lines represent the results of the three estimated models.

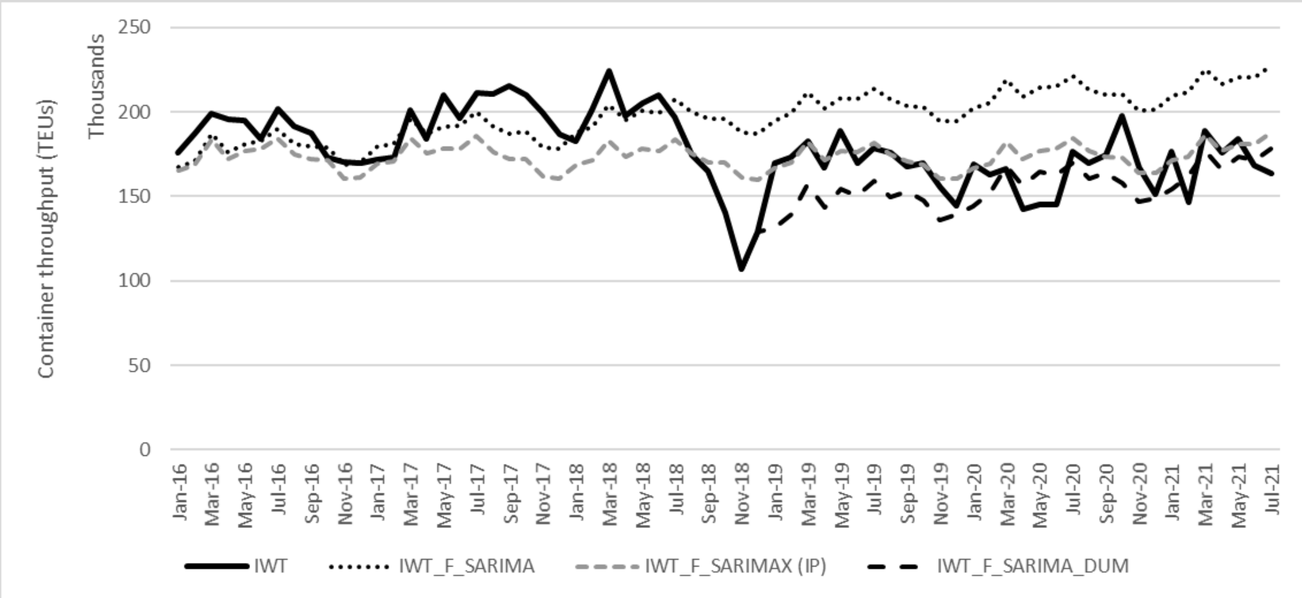

Figure 5. The forecast evaluation for the estimated models
Source: own composition

If the different MAPE scores are compared, the SARIMAX has the lowest value, which means this model will perform the best of the three models. Consequently, the SARIMAX model is used to assess the impact of the 2018M08 breakpoint on the future development of the container throughput on the traditional Rhine. This is further elaborated in the next section.

4. Empirical analysis

In the empirical analysis, the impact of including or excluding the 2018M08 breakpoint is researched for the period up to the end of 2023. To do this, first, a projection of the IP for Germany needs to be created. Hereafter, the forecast of the container throughput volumes is created by using the SARIMAX model that was selected in the previous section. The SARIMAX approach only allows to develop relatively short forecasting periods. This is however relevant as the outcomes of the analysis can serve as input for policy makers and policy evaluation, especially if a modal shift to waterborne transport is needed urgently.

4.1 Forecast of the IP

The forecast of the IP of Germany is created based on the forecast values provided by Trading Economics (2022) (Figure 6). This forecast is used in the SARIMAX model to quantify the throughput of container transport on the traditional Rhine up to 2023.

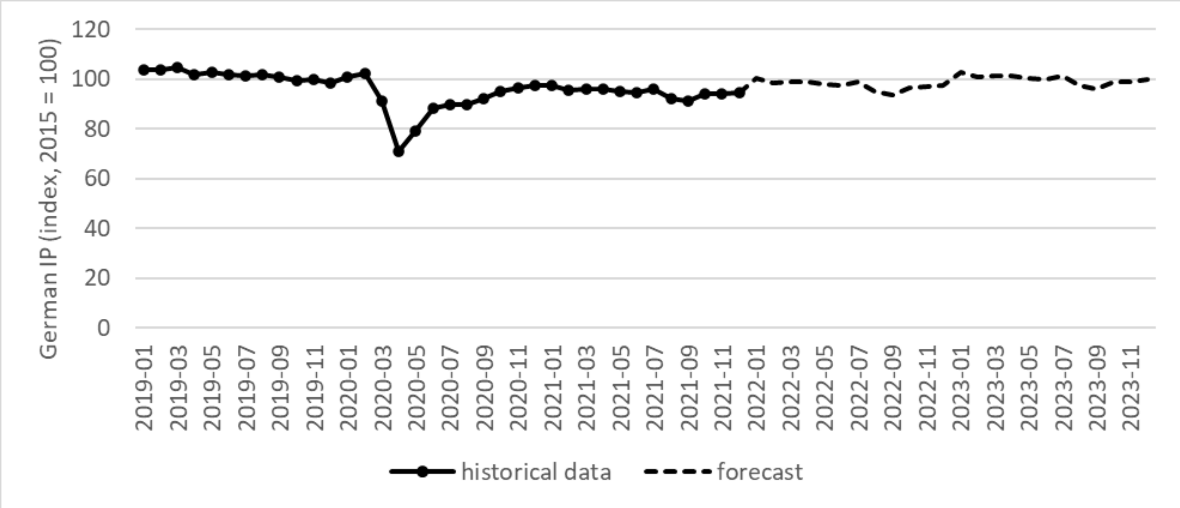

Figure 6. Forecast IP Germany (2019, 2021 historical data, 2022-2023 forecast)
Source: own composition based on Trading economics (2022)

4.2 Forecasting results

If the forecasting result of the German IP is used, it becomes possible to analyze the impact of the latest breakpoint on the container volumes on the traditional Rhine for the period up to 2023. The forecast will be made by using the SARIMAX(3,1,4)(1,0,1)$_{12}$ model. This model is estimated based on the data from 1994M01 till 2015M12. If the model is used to create the forecast, then the structural changes that have entered the IWT market since 2018M08 are not taken into account. This means that this forecast assumes a return to the market situation as it was before the last breakpoint period. Because more data is available (1994m01-2021m07), a new model estimation is created based on this full data set. For this model, the model structure is (4,1,2)(1,2,1)$_{12}$. The specifications of this model can be found in Appendix A.9. In this model, the full impact of the last breakpoint (2018M08-2020M09, see also Table 3), which took place in the added data period, is incorporated. This means that using this model, the forecast will include the trend of the last breakpoint. The main forecasting result of the container volume on the traditional Rhine can be found in Figure 7.

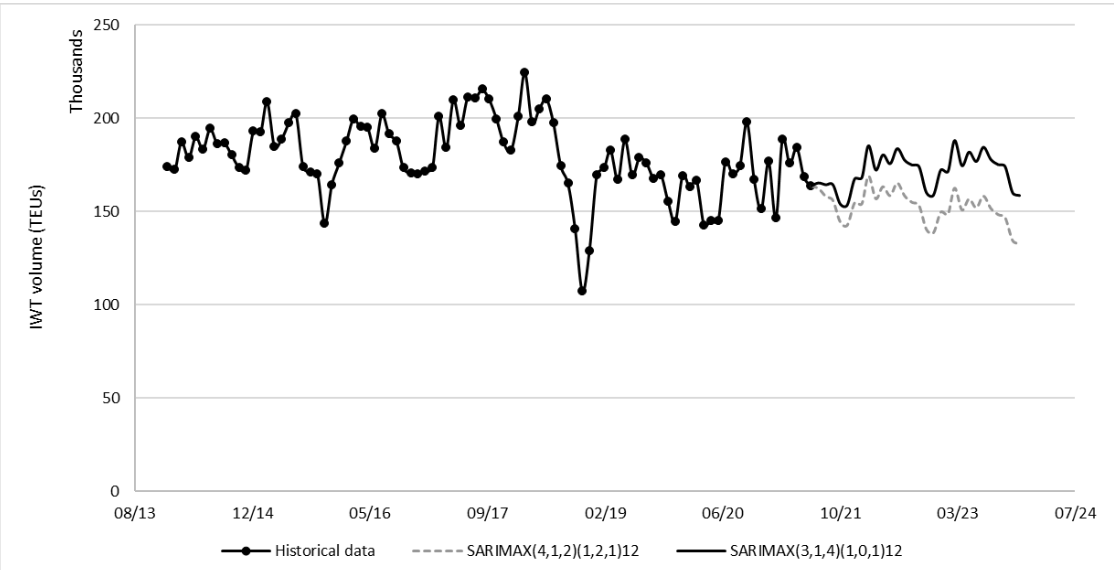

Figure 7. Forecast results of the SARIMAX models
Source: own composition

The results of the two forecasting models indicate that container throughput on the traditional Rhine has a different course. The highest forecast is linked to the SARIMAX(3,1,4)(1,0,1)$_{12}$[8], with a maximum of 187,000 TEUs and a low of 153,000 TEUs. The lowest forecast (dashed line) is linked to the SARIMAX(4,1,1)(1,2,1)$_{12}$ with a maximum of 170,000 and a minimum of 133,000 TEUs per month. This difference between the two forecasting models is due to the inclusion of the period 2016M01 to 2020M07 in the SARIMAX(4,1,1)(1,2,1)$_{12}$[9] model. The last "break period" is taken along by including this part of the data. In this period, the throughput of containerized IWT on the traditional Rhine diminished due to low water levels in the second half of 2018; congestion encountered in the seaports and weakened the global economy due to the COVID-19 pandemic (see also Table 3). When the monthly forecasted volumes are converted (i.e. are added-up) the relative growth to 2020 can be calculated. 2020 is used as a reference year as this year is the last year with complete observed data. The growth impact of the two SARIMAX models can be seen in Table 6.

Table 6. Growth impact of the two SARIMAX models

	SARIMAX(4,1,2)(1,2,1)$_{12}$		SARIMAX(3,1,4)(1,0,1)$_{12}$	
	Yearly container throughput	Growth relative to 2020	Yearly container throughput	Growth relative to 2020
	[TEU]	[%]	[TEU]	[%]
2020	1,967,384		1,967,384	
2021	1,966,615	-0.04%	2,004,547	1.89%
2022	1,867,242	-5.09%	2,077,579	5.60%
2023	1,792,059	-8.91%	2,094,670	6.47%

Source: own composition

From Table 6, it can be derived that if the last break period is included in the SARIMAX model, the IWT container volume will drop to 1,792,059 TEUs in 2023, which is a decrease of almost 8.91% compared to 2020 volumes. For the model in which this breakpoint period is not included, the IWT container volume will increase by 6.47% compared to 2020. This means that if the IWT container market does not recover from this "break" in 2018M08, the throughput of containerized IWT will decline. Even if the market falls back to the structure before the break period, the throughput of containerized IWT will increase, but it will be 11.60%[10] lower than the yearly volume in 2017 (2,133,698 TEU).

Based on the developed forecast, it can be concluded that the medium-term forecast shows that the throughput of inland waterway container transport on the traditional Rhine will not recover, in the short run, to the same levels as 2017. Also, if the structural break found in 2018 is not ending, the demand will decline even further.

5. Discussion and conclusion

This paper developed a model to demonstrate the impact of the changed circumstances in the IWT market on the throughput volumes. The insights obtained from the modeling results can serve as input for policymakers and different IWT stakeholders. Inland waterway barge operators may use this information to (re)evaluate investment decisions. Governments may measure the effect of previously introduced regulations. Inland navigation carriers could utilize the outcome to develop

[8] Model based on the trend excluding the last breakpoint period.
[9] Model based with the trend of last breakpoint period.
[10] 2017 was the highest volume that was observed in the data set.

business plans, hire staff or plan equipment levels. Furthermore, port authorities will be able to estimate port utilization use.

The research focused on container inland navigation transport on the traditional Rhine. The research questions were formulated as: *Is there a shock in the trend of the throughput of containerized cargo transport on the traditional Rhine?* Ans *if there is a shock in the trend, by which amount is the container throughput on the traditional Rhine impacted on?*

A model was developed to answer these questions. In the model, the 2018 low water period is incorporated, along with other structural changes in the same period such as the first period of the COVID-19 pandemic. This provides insight into the data generating process after this structural break and quantifies the impact on container throughput during and after the shock.

In order to analyze the impact of this breakpoint, two specific versions of the SARIMAX model were estimated. For the first one, the model was specified which did not include the trend of the new breakpoint period. In the second model, the last break period was fully included, which means that the impact of low water levels in the second half of 2018, in combination with the modal shift towards road and rail transport; congestion encountered in the seaports, as well as weakening of the global economy due to the COVID-19 pandemic, were included in the trend.

This approach allows for a minimum-maximum change in volume, i.e. a range between which the volumes are expected to evolve. The forecast based on the full dataset (including the last breakpoint) suggests that the IWT container volume will drop to +/- 1,800,000 TEUs in 2023, which is a decrease of almost 9% compared to 2020 volumes. Unlike the forecast where the last breakpoint is not included, the IWT container volume will increase by 6.5% compared to 2020. This means that if the containerized IWT market does not recover from this "break," the throughput for inland waterway container transport will decline.

This decline in throughput for inland container transport on the traditional Rhine will impact on the freight rates of IWT. In the short run, the transport capacity offered by the different barge owners is constant as the number of vessels is not decreasing, hence resulting in lower freight rates and possibly making IWTmore attractive. However, some other trends are noticeable. First of all, there is still a large waiting time for barges at the deep-sea terminals in Antwerp and Rotterdam (Shobayo et al 2021). These barge waiting times impact on the perceived reliability of barge transport. Furthermore, there is the competition of the other modes of transport (rail and road). If, especially road transport, can offer a better transport service, also in terms of ecological footprint, a reverse model shift could be expected. Therefore, a decrease in the freight rates mainly impacts the barge owners leaving with a reduction in revenue. When the fuel cost increases, this could put some extra pressure on the profitability of barge owners who operate in the container transport market on the traditional Rhine. One element that could counter the reduction in profitability is a long low water period. In such a case, the low water surcharge could become large enough, in combination with a reduction in supply to increase the freight rates to create a loss-making situation into a profit-making one (van Hassel & Rashed, 2020 and van Hassel, 2013). From this, it can argued that the profitability for the IWT container sector becomes more dependent on water levels, which makes these barge owners' financial well-being more uncertain.

Future research could extend the model and modify it to adjust to the specificity of other cargo segments. More research is required in the competition between railway and road transport for goods transported via inland navigation on the Rhine (e.g. Jonkeren et al., 2011). The study could be extended for a more extended time period forecast and broadening the geographical scope. Last, inland navigation companies are also experimenting with adjusting the fleet to the low water levels (e.g. Demirel et al., 2011). More research could be done to see whether this could solve the low water problem and its influence on the inland navigation throughput. All this should support operators and policymakers in taking suitable strategic and tactical decisions to avoid losing market share to other modes of transport. A reverse mode shift would go against all European climate and mobility objectives and is, therefore, to be avoided by all means.

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Appenidix A.1: Bai-Perron test

Breakpoint Specification
Description of the breakpoint specification used in estimation
Equation: EQ_TR_BREAK

Summary
Estimated number of breaks: 4 Method: Bai-Perron tests of L+1 vs. L globally determined breaks Maximum number of breaks: 5 Breaks: 2004M03, 2008M11, 2010M11, 2018M08
Current breakpoint calculations: Multiple breakpoint tests Bai-Perron tests of L+1 vs. L globally determined breaks Sample: 1994M01 2020M09 Included observations: 321 Breaking variables: @TREND+1 C Break test options: Trimming 0.05, Max. breaks 5, Sig. level 0.05

Sequential F-statistic determined breaks: 4
Significant F-statistic largest breaks: 4

Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	167.9185	335.8370	12.89
1 vs. 2 *	42.66523	85.33046	14.50
2 vs. 3 *	15.90112	31.80224	15.42
3 vs. 4 *	11.94340	23.88680	16.16
4 vs. 5	7.439157	14.87831	16.61

* Significant at the 0.05 level
** Bai-Perron (Econometric Journal, 2003) critical values.
Estimated break dates:
1: 2004M03
2: 2008M07, 2018M08
3: 2004M03, 2008M09, 2018M08
4: 2004M03, 2008M11, 2010M11, 2018M08
5: 2004M03, 2008M10, 2011M11, 2015M08, 2018M08

Appendix A.2A: The model estimation of the relationship between container volume at ports of Antwerp and Rotterdam and inland traffic

Method: Least Squares
Sample (adjusted): 1995 2019
Included observations: 25 after adjustments

Antwerp

Dependent Variable: DLOG(IWT)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(ANT)	0.767833	0.202363	3.794334	0.0009
C	-0.006723	0.018929	-0.355162	0.7257

R-squared	0.384977	Mean dependent var	0.044909
Adjusted R-squared	0.358237	S.D. dependent var	0.082125
S.E. of regression	0.065790	Akaike info criterion	-2.528070
Sum squared resid	0.099552	Schwarz criterion	-2.430560
Log likelihood	33.60088	Hannan-Quinn criter.	-2.501025
F-statistic	14.39697	Durbin-Watson stat	1.551380
Prob(F-statistic)	0.000936		

Rotterdam

Dependent Variable: DLOG(IWT)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(ROT)	0.650055	0.258149	2.518134	0.0192
C	0.014164	0.019229	0.736581	0.4688

R-squared	0.216114	Mean dependent var	0.044909
Adjusted R-squared	0.182032	S.D. dependent var	0.082125
S.E. of regression	0.074275	Akaike info criterion	-2.285466
Sum squared resid	0.126886	Schwarz criterion	-2.187956
Log likelihood	30.56833	Hannan-Quinn criter.	-2.258421
F-statistic	6.340999	Durbin-Watson stat	1.526908
Prob(F-statistic)	0.019209		

Appendix A.2B: Pairwise Granger Causality Tests

Sample: 1994 2019
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.	Decision*
D_ANT does not Granger Cause D_IWT	24	9.61488	0.0054	Reject H_0
D_IWT does not Granger Cause D_ANT		0.12110	0.7313	DNR H_0
D_ROT does not Granger Cause D_IWT	24	11.1067	0.0032	Reject H_0
D_IWT does not Granger Cause D_ROT		0.25414	0.6194	DNR H_0

*Decision is based on 5% significance level, DNR: do not reject.

Appendix A.3: Cross Correlogram of Inland container and IP of Germany

Sample: 1994M01 2020M09
Included observations: 320
Correlations are asymptotically consistent approximations

D_IWT,D_DE(-i)	D_IWT,D_DE(+i)	i	lag	lead
		0	0.2015	0.2015
		1	-0.0076	-0.0593
		2	0.0566	0.0512
		3	-0.0599	-0.0665
		4	-0.0921	0.1213
		5	0.0148	0.0104
		6	0.0045	0.0110

Appendix A.4: The long and short- term cointegration relationship

Dependent Variable: LOG(IWT)
Method: Least Squares
Sample: 1994M01 2020M09
Included observations: 321

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(IP_DE(4))	2.694346	0.076789	35.08757	0.0000
C	-0.295168	0.344004	-0.858036	0.3915

R-squared	0.794212	Mean dependent var	11.76996
Adjusted R-squared	0.793567	S.D. dependent var	0.396093
S.E. of regression	0.179965	Akaike info criterion	-0.585902
Sum squared resid	10.33153	Schwarz criterion	-0.562404
Log likelihood	96.03732	Hannan-Quinn criter.	-0.576520
F-statistic	1231.138	Durbin-Watson stat	0.377855
Prob(F-statistic)	0.000000		

Dependent Variable: DLOG(IWT)
Method: Least Squares
Date: 09/08/21 Time: 14:08
Sample (adjusted): 1994M03 2020M09
Included observations: 319 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004893	0.005106	0.958281	0.3387
DLOG(IP_DE(4))	0.614724	0.221793	2.771608	0.0059
DLOG(IWT(-1))	-0.238154	0.053513	-4.450419	0.0000
ect	-0.128788	0.029943	-4.301083	0.0000

R-squared	0.147925	Mean dependent var	0.004261
Adjusted R-squared	0.139810	S.D. dependent var	0.098118
S.E. of regression	0.091001	Akaike info criterion	-1.943426
Sum squared resid	2.608589	Schwarz criterion	-1.896214
Log likelihood	313.9765	Hannan-Quinn criter.	-1.924571
F-statistic	18.22852	Durbin-Watson stat	2.020149
Prob(F-statistic)	0.000000		

Appendix A.5: Model estimation of Kaub gauge station

Dependent Variable: DLOG(IWT)
Method: Least Squares
Sample (adjusted): 2000M02 2020M09
Included observations: 248 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(KAUB)	0.029537	0.014788	1.997318	0.0469
C	0.002545	0.005267	0.483200	0.6294

R-squared	0.015958	Mean dependent var	0.002468
Adjusted R-squared	0.011958	S.D. dependent var	0.083436
S.E. of regression	0.082935	Akaike info criterion	-2.133479
Sum squared resid	1.692055	Schwarz criterion	-2.105145
Log likelihood	266.5514	Hannan-Quinn criter.	-2.122073
F-statistic	3.989278	Durbin-Watson stat	2.477988
Prob(F-statistic)	0.046892		

Appendix A.6: SARIMA model

Dependent Variable: D(IWT)
Method: ARMA Maximum Likelihood (BFGS)
Sample: 1994M02 2015M12
Included observations: 263
Convergence achieved after 182 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	491.3290	218.7860	2.245706	0.0256
AR(1)	0.198334	0.040750	4.867047	0.0000
AR(2)	-0.229644	0.041523	-5.530564	0.0000
AR(3)	0.926106	0.040353	22.95006	0.0000
SAR(12)	0.980101	0.023801	41.17933	0.0000
MA(1)	-0.763318	5.899853	-0.129379	0.8972
MA(2)	0.397391	1.291973	0.307585	0.7587
MA(3)	-1.132118	9.331405	-0.121323	0.9035
MA(4)	0.498044	6.906433	0.072113	0.9426
SMA(12)	-0.840121	0.071793	-11.70203	0.0000
SIGMASQ	75970329	3.42E+08	0.222354	0.8242

R-squared	0.429280	Mean dependent var	469.8973
Adjusted R-squared	0.406632	S.D. dependent var	11559.46
S.E. of regression	8904.296	Akaike info criterion	21.12742
Sum squared resid	2.00E+10	Schwarz criterion	21.27682
Log likelihood	-2767.255	Hannan-Quinn criter.	21.18746
F-statistic	18.95475	Durbin-Watson stat	1.969867
Prob(F-statistic)	0.000000		

Appendix A.7: SARIMAX with dummy

Dependent Variable: D(IWT)
Method: ARMA Maximum Likelihood (BFGS)
Sample: 1994M02 2018M12
Included observations: 299
Convergence achieved after 118 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	387.5899	1262.836	0.306920	0.7591
D_2018M08	-38257.18	6974.063	-5.485637	0.0000
AR(1)	-0.802819	0.155912	-5.149193	0.0000
AR(2)	-0.690045	0.170047	-4.057977	0.0001
AR(3)	-0.733457	0.188743	-3.886006	0.0001
AR(4)	0.078232	0.116874	0.669370	0.5038
SAR(12)	0.981893	0.018817	52.18161	0.0000
MA(1)	0.281510	0.134843	2.087691	0.0377
MA(2)	0.287121	0.141258	2.032608	0.0430
MA(3)	0.350445	0.139983	2.503481	0.0129
MA(4)	-0.571285	0.102604	-5.567885	0.0000
SMA(12)	-0.830100	0.067069	-12.37688	0.0000
SIGMASQ	85335472	6585167.	12.95874	0.0000

R-squared	0.412016	Mean dependent var	295.1706
Adjusted R-squared	0.387346	S.D. dependent var	12067.29
S.E. of regression	9445.335	Akaike info criterion	21.23255
Sum squared resid	2.55E+10	Schwarz criterion	21.39344
Log likelihood	-3161.267	Hannan-Quinn criter.	21.29695
F-statistic	16.70067	Durbin-Watson stat	1.998856
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00	.86+.50i	.86-.50i	.50+.86i
	.50-.86i	.10	.03-.92i	.03+.92i
	.00+1.00i	-.00-1.00i	-.50+.86i	-.50-.86i
	-.86-.50i	-.86+.50i	-.96	-1.00
Inverted MA Roots	.98	.85+.49i	.85-.49i	.63
	.49-.85i	.49+.85i	.03-.96i	.03+.96i
	.00+.98i	-.00-.98i	-.49-.85i	-.49+.85i
	-.85+.49i	-.85-.49i	-.97	-.98

Appendix A.8: SARIMAX (IP Germany) [1994M02 2015M12]

Dependent Variable: D(IWT)
Method: ARMA Maximum Likelihood (BFGS)
Sample: 1994M02 2015M12
Included observations: 263
Convergence achieved after 62 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3167.644	831.0005	3.811844	0.0002
IP_DE	-30.94150	9.641471	-3.209209	0.0015
AR(1)	0.150015	0.056798	2.641218	0.0088
AR(2)	-0.265843	0.049251	-5.397750	0.0000
AR(3)	0.879512	0.049663	17.70966	0.0000
SAR(12)	0.983241	0.021425	45.89326	0.0000
MA(1)	-0.737370	5.598606	-0.131706	0.8953
MA(2)	0.390641	1.252555	0.311875	0.7554
MA(3)	-1.125257	9.200578	-0.122303	0.9028
MA(4)	0.471986	6.428138	0.073425	0.9415
SMA(12)	-0.858052	0.069472	-12.35100	0.0000
SIGMASQ	73588064	3.33E+08	0.220816	0.8254

R-squared	0.447176	Mean dependent var	469.8973
Adjusted R-squared	0.422949	S.D. dependent var	11559.46
S.E. of regression	8781.015	Akaike info criterion	21.10711
Sum squared resid	1.94E+10	Schwarz criterion	21.27010
Log likelihood	-2763.585	Hannan-Quinn criter.	21.17261
F-statistic	18.45753	Durbin-Watson stat	1.980167
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00	.91	.86-.50i	.86+.50i
	.50+.86i	.50-.86i	.00+1.00i	-.00-1.00i
	-.38+.90i	-.38-.90i	-.50+.86i	-.50-.86i
	-.86-.50i	-.86+.50i	-1.00	
Inverted MA Roots	1.00	.99	.86+.49i	.86-.49i
	.49-.86i	.49+.86i	.47	.00-.99i
	-.00+.99i	-.37-.93i	-.37+.93i	-.49-.86i
	-.49+.86i	-.86+.49i	-.86-.49i	-.99

Appendix A.9: SARIMAX (IP Germany) [1994M02 2021M07]

Dependent Variable: DLOG(IWT,2)
Method: ARMA Maximum Likelihood (BFGS)
Sample: 1994M03 2021M07
Included observations: 329
Convergence achieved after 94 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IP_DE_BASE	-4.76E-07	1.71E-07	-2.790207	0.0056
AR(1)	0.459890	0.053615	8.577619	0.0000
AR(2)	0.131272	0.053812	2.439474	0.0153
AR(3)	0.171978	0.067515	2.547252	0.0113
AR(4)	-0.113516	0.055687	-2.038458	0.0423
SAR(12)	0.982691	0.014472	67.90379	0.0000
MA(1)	-1.941331	0.004336	-447.6752	0.0000
MA(2)	0.941332	0.003760	250.3553	0.0000
SMA(12)	-0.862230	0.058190	-14.81753	0.0000
SIGMASQ	0.006034	0.000400	15.08079	0.0000

R-squared	0.767932	Mean dependent var	-0.000382
Adjusted R-squared	0.761385	S.D. dependent var	0.161491
S.E. of regression	0.078886	Akaike info criterion	-2.153707
Sum squared resid	1.985120	Schwarz criterion	-2.038325
Log likelihood	364.2847	Hannan-Quinn criter.	-2.107678
Durbin-Watson stat	1.989783		

Inverted AR Roots	1.00	.86-.50i	.86+.50i	.66
	.50+.86i	.50-.86i	.50	.00+1.00i
	-.00-1.00i	-.35+.47i	-.35-.47i	-.50+.86i
	-.50-.86i	-.86-.50i	-.86+.50i	-1.00
Inverted MA Roots	1.00	.99	.94	.86-.49i
	.86+.49i	.49-.86i	.49+.86i	.00+.99i
	-.00-.99i	-.49-.86i	-.49+.86i	-.86+.49i
	-.86-.49i	-.99		