# The Relationship between Trade and Container flows

**Paresa Markianidou**

University of Antwerp
Faculty of Applied Economics
**Department of Transport and Regional Economics**

Flemish Ministry of Mobility and Public Works
**Research Centre Commodity Flows**

14 February 2012

## ACKNOWLEDGEMENTS

First and foremost, I would like to thank my parents who have encouraged and supported me in pursuing my dreams. Special thanks go to my brother whose approach to research adds a different perspective to my way of thinking. I am also particularly grateful for the day to day support of Filipe who had to go through the PhD process together with me while helping me to prepare for the future. I also express my gratitude to my friends for their patience, especially Monica and Marjan who shared their thoughts with me on a daily basis and Polina who encouraged me during the last difficult months.

I am most grateful to my principal supervisor, Prof. Hilde Meersman, for her help, support, advice and guidance which have been invaluable throughout and particularly during the last year. Her profound knowledge of the fields of both transport and trade has been instrumental.

To my internal commission members, Prof. Eddy van de Voorde, Dr. Tom Pauwels and Dr. Thierry Vanelslander I would like to express my gratitude for their regular input and constructive criticism to my work. I would also especially like to thank Dr. Tom Pauwels for his support on a personal level.

My sincere thanks goes to the members of my external commission Prof. Werner Rothengatter, Dr. Heather Mac Laughlin and Dr. Jan Blomme for their valuable comments and suggestions for possible improvements.

Further, it would not have been possible to complete this doctoral thesis without the help of Dr. Arie Weeren, of the core facility for Statistics of the University of Antwerp, STATUA. I am most grateful for the support and discussions held during the last two years at both the academic and personal levels.

I would also like to thank Prof. Honore Paelinck for sharing with me his thoughts and expertise in the field of transport. His deep knowledge of the markets' practices adds particular value to the work of researchers in the field.

Finally, I would like to acknowledge the financial support of the Flemish Minister of Mobility and Public Works, Hilde Crevits.

## SUMMARY

The role of freight transport in transportation science and policy has been steadily increasing mainly due to the increase in the sheer volumes and the more pronounced impact freight transport can have on economic activity. In particular, one of the most applied blocks of research has been the understanding of freight transport demand. Within this field of research, given the importance of the container as a facilitator of transport activities as practiced today, it is important to incorporate the movement of containers in addition to the traditional product-based approach.

The objective of this research is to provide an alternative approach to investigating transport demand, as expressed by freight transport volumes and containerized flows. The distinguishing factor from the traditional approaches is that the modeling of transport demand is no longer limited to freight data. Instead, it uses the more extended in coverage trade databases. The use of trade data for transport research means easier access to data and addition of detail in terms of origin destination data and product categories disaggregation. What is anticipated is that more sophisticated modeling exercises can be constructed.

The way the suggested approach is put in practice is twofold. Firstly, the modeling of trade is made in volume units, as opposed to the common approach of modeling trade in value. In this way the output becomes readily usable for transport stakeholders. Secondly, the link between trade volumes and container flows is quantified. The focus in particular on the container segment is stimulated by the lack of research quantifying the link between containers and goods. Given the importance of gaining insight into the most widely used unit of transport, the container investigation is performed on two levels, disaggregated (specific goods categories) and aggregated (total trade).

The applications of modeling trade flows use trade in volume measurements where the country groups and product categories defined reflect transport considerations. The level of complexity and detail involved is also accordingly adjusted. It is in particular avoided that an excessive level of complexity is introduced in the models, since replication by transport stakeholders is a desired property. The segment of transport demand under investigation is the growth, variability and forecasting of trade volumes.

The investigation of the link between trade and container volumes is performed with two alternative approaches, depending on the desired level of aggregation, hence addressing the needs of either product specific studies or studies on the level of total trade. The former is performed in a rather "technical" way through the construction of a step-by-step methodology. The latter relies on econometric estimations using time series.

This PhD provides evidence that it is possible to link trade to transport volumes and to container flows using a stepwise methodology which can be converted into a complete tool in the hands of transport stakeholders.

# 1. Setting the Framework

Chapter one lays out the framework of the research. It does so by describing the research fundamentals in terms of motivation and focus in chapter 1.1, followed by the objective and its formulation as a research question in chapter 1.2.

## 1.1 Motivation and Objective

The central role freight transport plays in modern society is demonstrated by the number of studies commissioned on the national, regional and international level and the diversity in scope of those studies. Interest in performing such studies is expressed by a number of players including governments, academia, international organizations, consultancies or the industry itself. What is noticeable is the increasing sophistication of the methodologies employed. In particular, one of the most applied blocks of research has been the understanding of freight transport demand. In the majority of studies it is typically the starting point of the investigation, whether quantified internally or assumed as given.

Tools are thus constructed which capture the trends forming transport demand. Such tools provide for the necessary output typically expressed in ton or vehicle kilometers. Such tools are expected to reflect the dynamic nature of trade and the common practices of an in effect fragmented transport sector. To increase the sophistication of those tools typically many more resources especially in terms of model output and data input are required. One of the most common barriers to fulfilling the latter expectations is the amount and quality of data available for transport studies.

Furthermore, given the dominance of the container as a facilitator of transport activities as practiced today, it is important for those tools to incorporate the movement of containers in addition to the traditional product-based approach. Concerning the container unit in particular, data barriers are much more pronounced given the lack of information on the origins and destinations of container flows and the actual content of the containers. This problem is present on both international flows connecting ports and hinterland flows. In particular in Europe, this problem is accentuated for both product-based and container flows due to the creation of the single market where customs no longer register transit flows (re-imports/re-exports) between the countries of the European Union. Consequently, detailed model output is not readily available, at least on the container unit which is required in transport-related studies.

The current two major approaches in capturing freight transport demand can be broadly categorized as either the trade (value) or freight (volume) perspective.

The difference lies in the unit being investigated. More specifically in the former case, trade studies typically model on the unit of value (or certain volume indices) not volume, nor containers. Hence, while the level of sophistication is on average high the input cannot be directly plugged into transport-related studies. Furthermore, the limited coverage in terms of the countries being modeled in the available studies and hence the available Origins and Destinations (ODs) of the trade flows also hinder the direct use of such models. This is a consequence of the type of transport models constructed, which typically require an extended OD coverage.

Transport studies on the other hand which correspond to the freight approach are subject to limitations in acquiring a satisfactory amount of data given transport's fragmented nature, a result of the abundance of transport agents. For international transport flows, what is typically used is port throughput data where container data are directly available. Such data however are limited in time series coverage, do not record specific OD's, nor do they include any information on the container's content. Such exclusive trade or container applications do not thus far link with each other. As a consequence, it is not directly possible to draw inferences on container flows on the basis of the far more extended trade data and modeling outputs.

The objective of this research is to transform trade data directly in volume units and to link shipped freight volumes to container flows. This research hence provides an alternative approach to investigating transport demand. In particular the applications made, investigate the variability and future growth of freight transport volumes and containerized flows. The modelling on the level of trade volume, as opposed to the common approach of modelling trade in value, provides for output readily usable for transport stakeholders. This is because transport demand studies require the input in physical units rather than monetary units. Furthermore, the focus on the container segment addresses the lack in linkages between containers and product categories or total trade. Such lacking information currently hinders trade modelling output from being directly understood by transport stakeholders. The applications made are hence built with transport stakeholders as targeted final users. As a result of the choices made, this PhD consists of a complete tool for applications in the transport field.

The underlying curiosity finally forming the motivation and objective as described in this work is the questioning of today's economic paradigms and the sustainability of current trends. Since 2008 both the financial and debt crises have hit western societies hard. Talks on rethinking drivers of fiscal and monetary policies, on ways to balance sovereign and bank balance sheets are now more than ever in the forefront of policy making. Freight transport demand is a quantifiable "barometer" of economic activities and as such is subject to the volatility and risks implied by today's transitory period. Given hence the impact of such events on transport demand, potentially significant changes in current supply chain routines can be expected. Current tools need thus to be reinforced by incorporating the necessary information, through the addition of detail in their model structures.

What is anticipated is that this work will reinforce the quantitative support in the hands of the interested stakeholders, be it policy makers or the industry itself. In particular policy makers are expected to benefit from this research either directly or indirectly. Some examples include the following aspects of policy making:

- Assess future investments of freight transport infrastructure by estimating future growth of container trade flows per country or entire region;
- Evaluate whether to stimulate economic growth through freight transport related actions;
- Assess sector specific relevance generating transport flows by applying the step wise approach for specific product categories of relevance to the national or regional economy;
- Evaluate whether to strengthen cooperation with neighboring countries or other European countries or other trading partners oversees;
- Assess possible negative externalities which are caused by the transport of goods/ containers;
- Assess most appropriate location of logistics platforms, as part of competitiveness considerations and relative positioning of the country/region.

On the other hand the relevance of this work extends from the policy maker to transport industry stakeholders. Examples of possible applications within the transport industry include the following:

- Provision of freight volumes per supply chain that can be used by logistics platforms. Efficiency gains can thus be realized for entire supply chains and for individual agents especially with respect to the consolidation of flows;
- Contribution to the long term planning strategies through in particular market analyses: combine and compare the data on own-performance with total potential of the specific services and assess new markets.

## 1.2 Research Question and Focus

The research question posed is:

“Could **Trade Data** be used to capture **Patterns in Transport Volumes**

&

**Containerized Freight Flows**?”

The answer to the latter is pursued through an investigation on the following levels:

- Are existing studies directly usable by transport stakeholders, in particular policy makers and the transport industry? (chapter two)
- How could insights on the variability and future growth of freight transport/container flows be obtained by the use of trade data? (chapter three)
- Do available trade data in terms of coverage and quality suffice? (chapter four)
- What is the most appropriate growth model of trade volumes? (chapter five)
- What is the most appropriate forecasting model of trade volumes? (chapter six)
- How could a link between trade and container data be quantified? (chapter seven)
- Does trade model output translate into container units? (chapter eight)
- What is the societal and sector specific relevance and possible implementations? (chapter nine)

The chapters reflect the order of keywords referenced in the research question: the trade aspect precedes the transport perspective, which is introduced, in two ways: Firstly by the quantification on volume and secondly by the translation to the container unit TEU.

The investigation starts by the existing literature in chapter two and explores whether studies in the field of either explicitly the container trade or trade in general could become directly usable by final users like the transport industry and policy makers. The focus is on studies related to growth and variability and especially the ones incorporating forecasts of flows. When looking in more detail at pure trade studies the intention extends to realizing the potential of using such approaches for trade volumes and container applications.

Having gained insight on existing applications chapter three suggests an alternative methodology, differentiated from the traditional approach by the starting point of investigation. It thus emphasizes the use of trade instead of freight input.

Due to the work being heavily empirical and hence dependent on the quality of data a fully dedicated chapter on the issues of coverage and data quality is provided for in chapter four.

Illustrations of applications modeling trade volumes suitable for transport stakeholders with the intention of adding value to decision making processes are described in chapters five and six.

In chapter seven, two different methodologies are proposed for providing the link between trade data and containerized units. They are distinguished according to aggregation level of the input data in order to serve the needs of different transport stakeholders.

The three last chapters come together in chapter eight where the model output of chapters five and seven on the level of trade volume is translated into container units.

The final chapter, chapter nine focuses on the impact of this research for both the transport sector and society, positioning the work within a broader framework for future implementations.

In defining the focus of this research attention was given to the quality and reliability of the output, the practical applicability of the results obtained and the transferability of the methodologies used. In particular, the focus is split in terms of trade composition, trade direction and time span.

Regarding trade composition trade flows are split per level of aggregation. Two levels in particular are defined, the aggregated and disaggregated. On the disaggregated level the goods categories looked into are the manufactures while the aggregated refers to total trade. The different levels of aggregation serve in providing a wide spectrum of applications according to the needs of the different transport stakeholders. Such a choice additionally reflects the curiosity in investigating whether more reliable results are obtained when disaggregating flows.

The direction of flows includes i) total trade and ii) imports only of goods of European countries. The trading partner is the world. In this case the choices made are defined according to the specificities imposed by the different applications made in this PhD. The reasoning followed is that as a consequence of the unbalanced nature of the direction of trade between Europe and its trading partners, each direction (inbound, outbound, total) requires a separate investigation.

The time span covers the medium to long term periods. This is the result of the annual intervals of the available data.

Finally it is interesting to note that the transferability of the output has been taken into account by the use of methodologies which can be replicated across product categories and trading partners.

# 2. Insights from existing literature

Chapter two includes the literature review which incorporates the focal theory, the background and the context relevant to this thesis. The theory which is the basis of both background and context is trade theory. The background refers to the notion of derived demand in transport and forecasting as a tool commonly applied by transport stakeholders in their decision making processes. The context, describes the sources of growth figures and forecasts

The background is laid out in chapter 2.1. It should be noted that trade theory has been and still is extensively researched and debated leading to a vast body of literature. However, since this is not a trade exclusive thesis, only limited reference to this literature is made. More emphasis is therefore directly placed on the specific background which makes a direct link to the specificities of this thesis and even more so to the context given the nature of transport as derived demand. The context in particular is described in chapter 2.2 and is split in two parts: A purely transport part and a selection from within the trade and macro-economics literature. This part, the trade and macro-economics which is explained in substantial more detail, prepares the reader for what is presented in chapter three, the thesis' methodological choices while it anticipates the contribution of this work. This chapter concludes with a summary and discussion of the main findings in chapter 2.3.

## 2.1 Background: Derived Freight Transport Demand and Forecasting

Trade theory explains why goods are added or subtracted from the stock of material resources of a country by entering (imports) or leaving (exports) its economic territory. As such this movement of goods implies the use of transportation. Understanding hence why countries trade is instrumental in understanding transport demand

Freight transport demand is derived demand. Derived demand is defined in economics as the demand which arises or is determined indirectly from other type of economic activities.. Examples in economics include the demand for foreign currency which is derived from demand for foreign goods, bonds and so forth, or more relevant to this thesis the demand for import of a homogeneous good is derived from domestic demand and supply (Deardorff, 2010).

Specifically freight transport's derived nature of demand is related to the volumes of goods produced, traded and consumed. It is also related to the location of suppliers and consumers. Moreover freight flows shift with new sources of and uses for materials, new locations for manufacturers and retailers and new products and specialized transport (Ben Akiva, 2008). Once again the links to trade theory are made explicitly.

Forecasting is a process applied in both the policy field and in the industry and is highly valued as a complementary tool in decision making processes. Although very technical in nature, the forecasting of future values of economic variables is often viewed as art. Moreover often times, forecasts are wrong while the longer the time horizon the lower the accuracy (MITSLOAN, 2011). Despite these caveats, forecasting applications remain very popular and continuously undergo improvements as a result of both academic interest and expanding range of possible applications. The two basic approaches are the structural and time series. In the former case the model built typically describes the relationship between the variable of interest and other economic variables. The model is subsequently used as the basis for forecasting. On the other hand in purely time series approaches the current values are related to past values. Hence forecasts are made on the basis of the information in past values of the variable of interest.

An important discussion between macroeconomists since the 1970's has been the distinction between trends and cycles of economic activity. This discussion is prominent to this analysis given its impact on the future projections. The argument used to be that trends and cycles in economic activity are investigated as distinct economic phenomena and should be explained with different models or at a minimum, with different impulses or sources of shocks. Departures from this traditional approach integrate the study of trends and cycles.

The latter studies investigate the extent to which economic cycle fluctuations are understood as the result of one or more common unobserved stochastic trends. Shifts hence occur as a result of shocks to the stochastic trends (King, Plosser, Stock and Watson, 1987). This discussion largely continues in extensions from the univariate to the multivariate setting with a discussion on the cointegration concept and the presence of common stochastic trends. In the making of forecasts these considerations need to be considered.

The question that arises is how are trade theory and freight transport demand captured in the empirical literature and how if at all are they linked to each other. This is further investigated in the next chapter.

## 2.2 Context: the availability and suitability of existing applications

The context of this thesis is described in two parts. The transport part in chapter 2.2.2 investigates applications explicitly dealing with the forecasting of international flows. As such it hence targets maritime reports either commercial ones, or reports produced by international organizations and academic papers. Within these reports the case of container flows is of prime interest. These reports perform forecasting or present figures of growth of international trade which require a deep sea leg of transport. The trade and macroeconomics part in chapter 2.2.3 is reviewed in search of the type of output which could directly serve the transport sector. In addition, it represents the platform of trade applications which could contribute to the existing literature of transport applications.

The macro economic standpoint hence investigates the forecasting and scenario techniques applied in the literature. Before the description of the core parts, a clarification on the output sought within the literature and the time span implications is explained in chapter 2.2.1.

### 2.2.1 Desired Output: Time Span Implications

The time span of the output can vary from short, to medium or long term depending on the type of decision making it is meant to support. Depending on whose view point is being considered, the importance carried by each of the different outputs (the three time horizons) varies according to the strategic behavior of the core player under consideration.

For example, policy makers or port authorities in consideration of future investments might benefit more from information on the long term bilateral trade. Logistic/ freight forwarding /liner companies, which benefit from their responsiveness to change, could make additional use of short term trade flows guidance. Given the dynamics and the current structure of for example the maritime market a port authority tends to focus on the longer term strategic planning of the port while short term action is rather beyond its influential power. In the medium term the dynamics are more complicated and synergies between port authorities and interacting players are more common. The structure and scope of co-operation agreements in the maritime sector is a complicated and dynamic topic addressed in detail by Heaver et al. (2000). The understanding of trends, is nevertheless crucial for any type of cooperation or competition-based strategies of the players.

In the investigation of the available types of output provided by the maritime and macro-economics literature the availability of all the differentiated timing spans is accounted for. However the core focus of this research is the medium to long term future given the availability of yearly data or rather the lack of data of shorter intervals.

### 2.2.2 Direct applications: International Flows - Maritime

The impact of growing uncertainty in the maritime sector, led to the realization of the need for systematic solutions. Such concerns, materialized through the creation of several specialized “products” from a diverse set of actors. The core issues addressed include forecasting maritime flows and port throughput. A list of the “products” is summarized in a non-exhaustive list, in tables 2.1 and 2.2. Table 2.1 lists the non academic contributions within international organizations, consultancies and port authorities, while table 2.2 concentrates on academic output. The main observations drawn from table 2.1, focusing primarily on timing and methodology are the following:

- International Organizations like the United Nations Conference on Trade and Developement (UNCTAD, 2010) offer descriptive reviews published yearly. An interesting application is made by the United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP, 2007) which primarily driven by development targets, performs forecasts that are region specific. This publication dates back to 2007. The methodology is based on linear relationships between container volumes and GDP. It should be noted that detailed information on the methodologies utilized is not specified;
- European organizations like the European Seaports Association (ESPO, 2010) publish a yearly report and a statistical report published quarterly based on a system initiated by ESPO itself called Rapid Data Exchange System (RES). The latter includes European port data disaggregated per type of freight. It does not include forecasts.
- The European Commission developed a project named WORLDNET, aiming at refining the European transport network model regarding freight and intermodal transport on a global basis. It is linked to the modeling and scenario making performed within TRANS-TOOLS and TRANSFORUM. The objective for the maritime block is to construct a database for maritime freight flows. The main source is port data and the desired output is to collect information on the country, the port and the cargo volumes per shipment mode (general dry bulk, liquid, bulk, container, ro-ro).
- National organizations like the Dutch central plan bureau, based on the project "Welvaart en Leefomgeving een scenariostudie voor Nederland in 2040" projected container throughput for the Dutch ports in 2006. The time span was based on a previous study called "Four futures of Europe" corresponding to four different scenarios for 2020 and 2040. The core model used was the SMILE+ (Strategic Model Integral Logistics and Evaluation). Given the adjustments performed by technical experts to the model's output no documentation of the exact techniques is available;
- Established consultancies within the field offer a variety of specialized publications with both global and region-specific coverage, often on a half yearly but also monthly basis. To the knowledge of the author the forecasting techniques applied are mainly based on GDP and/or exchange rate movements, which determine the rate of change in demand.

  An exception is MDS transmodal whose forecasts are based on a database with detailed country origin-destination matrices on a product level. Although the last publication was in 2007 with forecasts until 2015, the database has been updated and forecasts are extended to 2020. In these cases too detailed information on the methodologies are not specified;
- Port Authorities are evidently interested in monitoring their own growth and make projections of their traffic. Some ports develop in-house forecasting tools like e.g. the port of Rotterdam. The approach is one of a product level monitoring of flows. However in this case too, neither detailed methodological information is available nor is a detailed forecasting report publically available. The port of Antwerp relies on linear regressions per cargo type using indicators like indices of GDP and Industrial production. Elasticities are additionally calculated ;

- Shipping companies too typically develop in-house schemes with the purpose of monitoring their growth per loop and consequently adjust their capacity utilization. In this case too these tools are confidential.

Table 2.1: Maritime Transport – Commercial and non commercial products

| Type | Source | | Output | Coverage | Forecast |
|---|---|---|---|---|---|
| **International organizations** | UNCTAD | Review of Maritime Transport | volume of merchandise trade (exports and imports) | World, EU 27, North America, Africa, Middle East, America (South, Central) , Asia, China | |
| | UNESCAP | Regional Shipping and Port Development | annual growth rate for container trade volumes | Global, ESCAP economies | 2015 |
| | | | share in world container (exports and imports) | ESCAP member economies, East Asia share of ESCAP | |
| | | | route trade volume | Asia-Europe | |
| | | | trade imbalance | Transpacific, Transatlantic,Europe-Asia, Europe-MidEast, Asia-MidEast | |
| | ESPO | RES Statistics | port traffic | European ports | |
| | EC | WORLDNET | extended maritime freight origin-destination database | Global | Transtools applications |
| | | | web tool for accessing the information | | |
| **National organizations** | CPB | CPB Memorandum: Aanpassing WLO scenario's voor het containervervoer | container turnover deep sea | Dutch ports | 2020, 2040 |
| | | | container turnover feeder | | |
| | | | Container turnover sss | | |

Table 2.1(continued): Maritime Transport – Commercial and non commercial products

| | | | | | |
|---|---|---|---|---|---|
| **Consultancies** | Drewry | Container forecaster | Container traffic | World | 2010-2013 (quarterly) |
| | | | container activity (change in total port handling & TEU) | North America, Europe (North, West, South, Eastern), Far East, Middle East, Latin America (Caribbean, South), Asia (South East, South), Africa | |
| | OSC | East Asian container port markets to 2020 | Container port demand forecasts | North East Asia, South East Asia, East Asia | 2020 |
| | | | (non) transshipment container handling demand | | |
| | | The European and Mediterranean container port markets to 2015 | container handling demand (exports and imports) | North Europe, South Europe and Mediterranean | 2015 |
| | | | transshipment demand | | |
| | | World Container port Outlook to 2015 | container handling demand (exports and imports) | East Asia, China, North Europe, South Europe/Med, America, Middle East, Sub Saharan, Australasia | 2015 |
| | | | total container port demand | | |
| | | | container transshipment demand | | |
| | MDS | World Freight Model | quarterly loaded TEU | Asia-Europe/Med, Transpacific, Transatlantic, to/from Sub-Saharan, to/from Australasia excluding Americas | 2014 |
| | | China trade briefing-January 2010 | loaded TEU | China | 2011 |
| | | China's cargo growth: how long will it last? | route growth rate | Asia-Europe | 2012 |
| | Clarkson | Container Intelligence quarterly | Container trade | Global, Far East-Europe, Transatlantic, Other | 2009-2010 (quarterly) |
| | | | container exports and imports | Global, Europe (NW, Med), Asia, America (North, Latin America & Caribbean), Australia & New Zealand, per route | |
| | | | container exports and export growth | Europe (NW, Med, Central/Eastern, Baltic, CIS), Asia, America (North, Latin, Central & Caribbean), Australasia, Middle East, Africa | |
| | | | port throughput | World, Europe (North, Med), America North, Asia | |
| **Port Authorities** | Rotterdam | Summary Port vision | port throughput | port of Rotterdam | 2010/2020 |
| | | Havenplan 2020 | goods flows | dry bulk, crude oil & petrochemicals, base products, containers, roro, general cargo | |

Source: own compilation based on indicated sources

Notes

(1) This is a non-exhaustive and indicative list. Forecasts are developed by a number of other consultancies (for example AXS Marine among others ), port Authorities (for example Hamburg, Antwerp among others).

(2) Country level disaggregation in the column of coverage is not provided in the table.

(3) Drewry offers similar products for the other maritime markets i.e. Tanker, Dry Bulk, LPG, Chemical forecasters.

(4) OSC offers similar products for i.e. port markets in the Middle East, the Americas, and for the other maritime markets i.e. LPG, LNG, Bulk, Chemical, Tanker prospects and more specialized product categories i.e. fertilizers and refrigerated trade prospects.

Evidently tools do exist, providing trend indication which can be directly used by either the industry or policy makers. However, in most cases the methodologies are not documented i.e. consultancies' publications or meant for internal use i.e. the case of the port of Rotterdam. The majority of those publications rely on a one-to-one relationship with GDP. As such, they become useful during times of "Business As Usual" (BAU). The more sophisticated approach applied by MDS transmodal does not provide for regular timely updates readily utilizable by the interested stakeholders. The trade off between the sophistication of the methodologies used in a report and the timing intervals of their publications is hence well illustrated.

With respect to the publications for which some methodological information is obtainable, further remarks can be made.

In particular, the UNESCAP methodology's underlying economic assumptions rely primarily on the IMF projections of GDP growth, which estimate major economies only. As such the spectrum of countries is limited to the countries modeled by the IMF. Furthermore the economic growth is defined externally and is build under the assumption that there will not be a major, prolonged economic slowdown. The conversion of economic growth rates to projected full container volumes is based on import and export volumes independent equations for individual countries only (for which no details are given). Regressions are the main tool and no reference to dynamic approaches is made. The WORLDNET model on the other hand is based on container flow data for a number of ports for a single year. No time series estimations are therefore possible on the level of container flows. The approach of the DUTCH CPB is based on the model SMILE+ incorporating uncertainty on the macroeconomic level by the use of scenarios. Unfortunately the translation of the economic output of the four scenarios in freight is not available. It would appear that the aforementioned missing information of for the rest well documented methodologies and the more anticipated confidentiality assumed by the consultancies (like MDS transmodal) is because of the high value, conversion factors have for the respective institutions or companies.

The academic world has also dealt with the topic of forecasting maritime flows. Within these contributions, the approach followed varies according to the objective. A substantial part of the investigations are descriptive but in this table (see table 2.2) only an indicative list of papers utilizing quantitative techniques are considered. The main observations drawn from table 2.2 are the following, focusing primarily on the different types of methodologies:

- In the model developed by the Imperial University in the UK, "Container World", forecasting maritime flows is treated separately within a sub-model. It is in particular a multi agent model. The logic is one of systems dynamics whereby information is passed on to the other sub-models through feedback loops. However details on the methodologies are unknown. Similarly, Levine (2009) et al treat flows separately by incorporating in their analysis a gravity model for the transportation of international sea containers based on container data for the year 2004;
- Schade (2005) further developed the ASTRA-D model time-path simulation or dis-equilibrium model with primary objective the integration of socio- economic, transport and environmental assessment of European Transport Policy in the long term. As such it incorporates a population macro-economic, a regional economic and foreign trade module among other modules. These modules are constructed as structural models and they use trade data of imports and exports in values.
- The ones dealing exclusively with the topic i.e. Meersman et al (2003) and Veenstra (2000), make use of sophisticated time series techniques, in particular Vector Autoregressive (VAR) or Vector Error Correction (VEC) models which are known for their longer term forecasting properties. Furthermore De Langen (2003) calculates the growth of containers based on seven variables and provides qualitative scenarios. It is an interesting study explaining the reasons of container growth;
- Luo and Grigalunas (2003) developed a simulation model, as an alternative to econometric methodologies to estimate container port demand wherein a conversion algorithm is used to convert trade data to TEU. The estimation of container port demand assumes that the demand for international trade of containerized goods is fixed. ;
- In the "Worldwide container model" Perrin et al. (2008) estimating maritime flows makes part of a wider objective, the routing of worldwide container flows. As in the case of Luo and Gragalunas demand for containerized goods is fixed which allows to mainly build on the container routing investigation;

Table 2.2 Freight Transport – Academic contributions

| Year | Author | Title | Objective | Methodology |
|---|---|---|---|---|
| 2009 | Levine et al. | Estimating an Origin-Destination Table for US Exports of Waterborne Containerized Freight | Estimate number of containers that flow from origin country o to destination TAZ d | Multi-modal origin–destination table estimation problem as a linear program<br>Gravity Equation |
| 2008 | Perrin et al. | Worldwide Container model | Model the routing of worldwide container flows, including the choice of service, port and route in a network of service lines | Macroscopic; Routing container flows; Shortest path Algorithm<br>Logit route choice model-current<br>Path size multinomial logit-future |
| 2008 | Meersman et al. | The relationship between economic activity and freight transport | Study of the stabilty of the freight elasticity over time | Panel data estimations<br>Fixed effects method |
| 2005 | Schade | Strategic Sustainability Analysis: Concept and application for the assessment of European Transport Policy | Depict long term developments paths towards sustainability of European Transport | System Dynamics integrating models for population, macro-economy, trade, regional-economy, transport activity, vehicle fleets and environment |
| 2004 | Woods et al. | Container World | Improve strategic modeling of the container transport system | Complex Multi Agent Simulation<br>International Trade Model<br>Distribution Model |
| 2003 | Luo and Grigalunas | A spatial-economic multimodal transportation simulation model for US coastal container ports | Assess the potential demand for container ports and related multimodal transportation | Spatial, economic multimodal container transportation demand simulation model |
| 2003 | Meersman et al. | Port throughput and international trade: have port authorities any degrees of freedom left? | Estimate relation between economic and port activity-relation between the port of Antwerp and international trade | Multivariate Time Series<br>Unrestricted VAR |
| 2002 | Meersman et al. | Forecasting potential throughput | Forecast iron ore traffic and container loadings and unloadings | VECM |
| 2000 | Veenstra and Haralambides | Multivariate autoregressive models for forecasting seaborne trade flows | Long term forecacts of four commodity markets trade flows | VAR |
| 1996 | Kavussanos | Highly disaggregated models of seaborne trade. An empirical model for bilateral dry-cargo trade flows in the World economy | Construct an empirical model estimating bilateral dry cargo seaborne import flows | Seaborne trade Constant Ratio of Elasticities of Substitution Homogenous/ Homothetic CRESH |
| 1987 | Dagenais and Martin | Forecasting containerized traffic for the port of Montreal (1981–1995) | Long term forecasting by commodity, by origin and by destination | Export/ Import functions |
| 1982 | Eriksen | The demand for bulk ship services | Isolate the effect of freight rates and commodity prices on trade pattern, for iron ore, coal and crude oil | Relative demand functions |

Source: own compilation based on indicated sources

The main conclusion from the preceded academic literature review is the existence of several practical tools for the estimation of future demand. Past applications concentrated on freight data directly and single time series techniques. More recent applications incorporate demand in their analysis which precedes the core analysis. In these models three major approaches are distinguished: 1) the use of growth factors, 2) the use of gravity models and 3) the use of economic activity models. The latter is the most complex approach which requires a substantial amount of data in order to simultaneously model the economy, land use, and freight demand. The gravity models are typically used in 4-step models within the distribution step. Growth factors predict supply and demand from a region using growth factors (MIT, 2011). Typically the models are estimated using observations for one year across countries or regions (cross section data). This reflects the difficulty in obtaining long enough series to estimate the demand especially in the case of using freight data directly and even more so in container data. Furthermore in modeling transport demand exclusively on the level of tons a similar methodology as for trade is used (see chapter 2.3.3.2) based on value to weight ratios per commodity. This is typically applied for a reference year. In the majority of freight models the analysis remains on the level of tons and does not address the container segment.

Finally, as regards the incorporation of container flows, the main conclusions on the literature of freight demand either on the more commercial or academic applications can be summarized to the following:

- When the quantification is made on containers directly, the models for freight demand are built on data for one year only like in the case of the WORLDNET (2009). Data on the level of container are difficult to obtain and the coverage of geographic areas on a global scale is a problem. Additionally, such databases are typically restricted to port-to-port data;
- When the quantification can be made on tons, the approach of dividing tons to the design weight of the container is an (over) simplistic approach that can only be used as a very rough approximation. One of the major problems of this approach is the inability to differentiate between heavy and light goods. When the tons are a result of port data in this case too they are only available for port-to-port flows;
- When the quantification is made on tons no conversion mechanism to containers is explained in detail like in the case of UNESCAP (2007) or the CPB-NL (2006).

Judging from the reviewed literature, there is a lack of research in providing estimations of container flows on the basis of historic series while there is no detailed information on how the conversion from tons to TEU is made. In particular there exists no study on the link between trade and container flows.

In order to explore the potential regarding the estimation of freight demand from a trade perspective and the use of econometric techniques, further literature is being sought in the trade and macro-economics field. In the latter field of research, tools have extensively been constructed to address uncertainty on a macroeconomic level only not explicitly made for the transport sector. This topic is addressed within the second part of the literature review.

### 2.2.3 Indirect applications: Trade

Traditional trade applications are now explored as a consequence of the nature of derived demand for transport. The investigation within the trade and macro-economics literature is prepared in function of the definition of desired output. The reason is that the models described are not meant to be evaluated on the basis of their properties or their applications since they have been constructed for different purposes. The commentary is based on their suitability for transport applications on the basis of their current output range. In sub-chapter 2.3.1 some preliminary explanations are added to assist in the understanding of the subsequent descriptive analysis.

#### 2.2.3.1 Introductory notes

The analysis is based on table 2.3. It includes trade and macro economic reports/working papers from several sources. The items reported in the table include reliability, output (composed of the report, trade projections and coverage), methodology (composed of the title and/or the specific model, the year of last publication and the features), forecasting (composed of application and time-spam), scenarios and documentation. These items are identified as the key elements which contribute to the assessment of the techniques most useful for transport applications. Further information on the content and the reasons for the aforementioned choices include:

- Reliability is measured according to perception in terms of reputation, quality of reporting and expertise in the field. In this case it means that only major international organizations and national institutes are considered i.e. European Commission (EC), European Central Bank (ECB), Organization for Economic Cooperation and Development (OECD), International Monetary Fund (IMF), World Trade Organization (WTO), the Deutsche Bundesbank (DB) and the Central Plan Bureaus (CPBs) of Belgium and the Netherlands;
- Trade projections are sought in order to check whether the models' outputs could be utilized for the purpose under investigation;
- Coverage contributes to the above stating the countries/regions for which the output becomes available;
- The methodology applied is viewed with the purpose of classifying models in structural models, with or without long term attributes, or time series models;
- Some models are highlighted since they do not directly provide for the desired output but given their interesting properties it is judged necessary to include them;
- The addition of the presence of forecasting exercises or not is evidently added mainly for the clarification of the time span for which forecasts are applied;

- Scenarios are considered to the extent that they can be assumed as the basis for the creation of maritime related forecasts. However at this stage no further information on the type of scenarios is given;
- The column of documentation evaluates the possibility for future replication(s) of the selected model(s).

Detailed commentary on table 2.3 is found in chapter 2.3.2. A general observation is that all institutions/organizations rely on macroscopic models which generally converge in terms of methodologies. The line of thought is similar with the majority of such models incorporating scenarios while stating that forecasting does not represent the core output and use of such models. They are built according to General Equilibrium modeling (GEM) practices which are however increasingly re-evaluated especially in the light of disequilibrium models which prove to reflect the workings of the economies more realistically. In particular, in current times more than ever complexity economics, which avoid the assumption that the economy is a system in equilibrium, are gaining momentum and are expected to be made use of by policy makers in the near future.

A critical look regarding the potential use of the models described in table 2.3 for the current research is discussed in chapter 2.4. It should however be stressed once more that the purpose is not to evaluate these models on their scientific value, but to evaluate them on their potential usefulness for the purposes of this research.

### 2.2.3.2 Descriptive Analysis

For each of the main publications listed in table 2.3, a description is added highlighting each time the following elements: i) publications, ii) timing, iii) output reporting, iv) methodology and v) a personal assessment of suitability for transport applications. The reason why this description is extensive is because it is meant to evaluate the potential advantages in terms of added information gained as a result of trade being the starting point for the making of trade volume and container inferences. In particular the specific publications are quoted together with their issuance timing given the importance of timely input for especially the transport industry. The latter emphasizes on the actual output provided by these publications, bearing in mind the difficulties in publishing sophisticated and detailed studies in regular intervals. The assumption made is that the current output serves the needs of the transport sector. This is however mainly under investigation. The methodology used in each study is important especially in the case where replication is under consideration. According to the pre-described four elements a personal assessment and a final choice is made.

Table 2.3 – Trade & Macro-economic Modeling

| Criteria 1: Reliability | Criteria 2: Output | | | Criteria 3: Methodology | | | Criteria 4: Forecasting | | Criteria 5: Scenarios | Criteria 6: Documentation |
|---|---|---|---|---|---|---|---|---|---|---|
| **Source** | **Report** | **Trade projections** | **Coverage** | **Title/Model** | **Year** | **Features** | **Application** | **Timespam** | | |
| **EC** | European Economic Forecast | 1) Exports (goods and services) 2) Imports (goods and services) | EU27 Croatia, FUROM, Turkey, US, Japan, Russia, China, EFTA | | 2009 | 1) statistical methods of varying degrees 2) performed by country desks 3) judgemental forecasting models 4) Three times iterative process | yes | 2 years ahead | yes | No |
| | | 3) import growth | World | | | | | | | |
| | | 4) Export market growth | Extra EU | | | | | | | |
| | | 5) Trade Interactions/shock responce | EU15, US, Japan, Canada, Australia, Switzerland, Norway | QUEST III | 2008 | DSGE for an open economy | yes | medium-long term | yes | Average |
| | Interim forecast | Same as above | Germany, Spain, France, Italy, the Netherlands, Poland, UK | | 2009 | 1) indicator based 2) judgemental forecasting models | yes | Current year | no | No |
| | Quarterly Report on the Euro Area | Same as above | EMU | | 2009 | based on Economic and Interim forecast | yes | 2 years ahead | no | No |
| **ECB** | ECB staff macroeconomic projections for the Euro area | 1) Exports (goods and services) 2) Imports (goods and services) | EMU | An Area-Wide model (AWM) for the Euro Area | 2001 | 1) long run properties consistent with a basic neoclasical steady state 2) short run dynamics specified in traditional "ad hoc" form, estimated on the basis of historical series | yes | 2 years ahead | yes | Full documentation |
| | | | | Multi-country model of the European System of Central Banks (ESCB) | 2002 | | | | | Full documentation |
| | | | | Leading indicators and judgemental methods | | based on technical experts | | | | No |
| **OECD** | OECD economic outlook | 1) Exports (goods and services) 2) Imports (goods and services) | OECD, World, Estonia, Slovenia, Israel, Chille, China exc Hong-Kong, India, Indonesia, Brazil, South Africa | INTERLINK* | 1987 | 1) combination of semi annual macro-econometric models | yes | 2 years ahead | yes | Average |
| | | | | Trade linkages and Trade matrices in the OECD INTERLINK | 2001 | set of trade matrices summarizing the geographical nature of global trade relations | | | | Average |

Table 2.3 (continued) – Trade & Macro-economic Modeling

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **OECD** | | | | The new international trade model | 2005 | behavioural equations with long-run equilibrium-correction terms estimated for volumes and prices | | | | Average |
| | | | OECD, China, Dynamic Asia, Other Asia, Africa,Middle East, Latin America, Eastern & Central Europe | Modeling Manufacturing Export Volumes Equations | 2000 | logarithmic dynamic error correction form equations estimated as a system | Yes | 2 years ahead | yes | Average |
| | Main Economic Indicators | 1) Exports (goods) 2) Imports (goods) | OECD, China, Brazil,India, Indonesia, South Africa, Russia | | 2009 | | No | no | no | |
| | | | EMU, US, Japan | Small Global Forecasting Model | 2002 | 1) demand side model 2) S-style output relationship 3) Phillips curve Inflation basis | Yes | 18 months | yes | Average |
| **IMF** | WEO | 1) Exports (volume of goods) 2) Imports (volume of goods) | Advanced, emerging and developing economies, Fuel/non fuel exporters | Aggregated projections from individual country desks | 2009 | | Yes | 2 years ahead | no | No |
| | | 3) Trade in Goods | World | | | | | | | |
| | | 5) Trade Interactions shock responce | | GEM | 2004 | 1) stochastic dynamic general equilibrium 2) microeconomic structure 3) standard functional forms 4) flexible modular structure | Yes | 2 years ahead | yes | Average |
| **WTO** | **ITS** | 1) Exports (merchandise) volume 2) Imports (merchandise) volume | Advanced, developing economies Euro area | | 2009 | | Yes | Current year | yes | No |
| | | 3) Merchandise Trade volume | World | | | | | | | |
| | | 4) Exports (goods and services) 5) Imports (goods and services) | OECD, EMU | Forecasting Trade | 2006 | 1) time series forecasting model 2) univariate AR 3) multivariate ADL/VAR/GARCH | Yes | 6-18 months | no | Full documentation |

Table 2.3 (continued) – Trade & Macro-economic Modeling

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **WB** | Prospects for the Global Economy forecasts | 1) Exports of goods and non-factor services 2) Imports of goods and non-factor services | World, 152 countries, High income, EMU, Developing, East Asia/Pacific, Europe /Central Asia, Latin America /Caribbean, Middle East/North Africa, South Asia, Sub-Saharan Africa | | 2010 | 1) aggregated country-specific forecasts 2) driven by the international investment cycle, macroeconomic policy considerations and other cyclical forces | Yes | 3 years ahead | yes | No |
| **Bundesbank** | Outlook for the German Economy-macroeconomic projections | 1) Exports (goods and services) 2) Imports (goods and services) | Germany | MEMMOD | 2009 2000 | 1) macro-econometric 2) neo classical long run properties 3) backward/ forward-looking expectations | Yes | 2 years ahead | yes | Full documentation |
| **CPB-NL** | Newsletter | 1) Exports (goods volume) 2) Imports (goods volume) | World, Advanced economies, Emerging economies, Asia, Latin America, Transition countries, Africa & Middle East, EMU, EU15 (all), C&E Europe (all), US, Japan, Canada, Australia, New Zealand, China, Turkey, Switzerland, Norway, Iceland | SAFFIER | 2009 2006 | 1) multipurpose model 2) combination of short (JADE) and medium term (SAFE) dynamics | Yes | 2 years ahead | yes | Average |
| | | 3)Trade in goods | World | | | | | | | |
| | | 4) Trade Interactions shock responce | | WORLDSCAN | 2006 | 1) stochastic 2) Dynamic General Equilibrium 3) micro-founded 4) open economy model | Yes | 20-40 years ahead | yes | Average |
| **CPB-BE** | Economic Forecasts | 1) Exports (goods and services) 2) Imports (goods and services) | EMU, Non EMU western MS, Non EMU eastern MS, USA, Japan, rest of the world | NIME | 2001 | 1) macro-econometric )Gauss-Saidel simulation type | Yes | 2 - 6 years ahead | yes | Average |
| | | 3) Trade Interactions shock responce | | NIME and NEMESIS | 2004 | 1) macrosectoral econometric model 2) framework model | | 25-50 years ahead | | |

Source: own compilation based on indicated sources

The EC provides three different types of publications which include trade forecasts: the core Macroeconomic Forecasts, the Interim which updates the former and the Quarterly publication. The time frame for the economic forecasts in terms of frequency is four times a year with two comprehensive spring and autumn forecasts and two smaller interim forecasts in February and September. The quarterly report is released at the end of March, June, September and December (Melander, 2007). The trade projections report on export and import values for goods and services taken together as well as a World import growth figure and an Extra EU export market growth figure. The methodologies employed for the trade projections are not documented in detail given their nature as largely a compilation of "in-house" work of the relevant country desks and their type (judgmental iterative techniques). The simulations run with QUEST III[1] applications have not, to the knowledge of the author until now (autumn 2009 last published), been reported for scenarios that involve trade directly. Clearly the output provided by the EC does not give much insight into trade projections readily usable for maritime applications. It could however be consulted as a trend indicator and/or for the collection of indicators which influence global trading conditions. Given aforementioned reasons of in-house estimations and lack of detailed documentation on the techniques utilized, the EC approach is not going to be considered as a replication option.

The OECD publishes the Economic Outlook twice a year and maintains a database of the Main Economic Indicators (MEI) which incorporates monthly data within its time series. The former is published in June and December while the latter is a monthly publication. The readily available output of the Economic Outlook provides for aggregated figures of exports and imports of goods and services. The reported projections are not solely based on one model (INTERLINK) but they rely on a series of modeling techniques and experts opinions. Despite the fairly common disadvantage of aggregation the OECD modeling activities include a variety of techniques which provide for a platform to modeling alternatives also for volume of trade flows. Some of the applications are less resource intensive, requiring less data while the documentation of the modeling is relatively good. The MEI which does not provide for forecasts has been exceptionally included in the table given its monthly nature. The view point argued in this research is one where the simultaneous monitoring of a set of carefully chosen indicators could act as a complement to any type of forecasting exercise. The disadvantage is the time lag between published and real time data (around 6 months).

The IMF's World Economic Outlook is released in April and September/October each year. Trade is reported in terms of goods volume of imports and exports resulting from aggregation of projections made by individual country desks, an approach followed by the EC as well. Although the type of output is more suitable for the current investigation and unquestionably a useful indicator its level of aggregation and unidirectional nature does not fully suffice for the provision of a complete

[1] QUEST is a CGE model developed by the EC. QUEST I (1991) and QUEST II (1997) preceded QUEST III (2008) which is the latest version. The two initial versions differ with respect to their theoretical structure where, QUEST I follows the Keynesian tradition of econometric modeling, while QUEST II is based on dynamic optimisation techniques.

international trade volume flow oriented indication. In addition, the documentation for the models used is not sufficient for replication purposes.

The WTO publishes its own forecasts within a press release in April which updates the International Trade Statistics released earlier in October. The type of output includes aggregates of volumes while the model used internally produces forecasts for goods and services. The reported methodology utilizes time series modeling for the making of forecasts. Given the complete documentation of the latter, replication of such an established technique (see Meersman and Veenstra in table 2.2) for this research's application could be considered as an option within the non structural approaches.

Within the international and national banking sector three cases are examined: the European Central Bank, the World Bank and the German National Bank[2].

The ECB publishes one document on the organizations staff macroeconomic forecasts. It becomes available twice a year, in June and December. The projections made, report values of goods and services together, as does the EC hence also making it less suited as an option for a direct application. The methodology utilized follows the trend set by the major international organizations (see table 2.3 IMF and OECD) applied on each of the European Monetary Union (EMU) countries separately which are linked together through trade equations. The exports and imports equation however do not differentiate between intra and extra flows supporting its rejection as a model suitable for international trade volume considerations for transport applications. Nevertheless given the ECB's core focus on Europe, its methodological transparency and detailed documentation of the models utilized it is advisable that any forthcoming improvements on those models could be monitored.

The World Bank's main forecasting publication, Prospects for the Global Economy is published twice a year once in December/January within the Global Economic Prospects, and in April/May within the Global Development Finance. The type of output includes export and imports for goods and non factor services for three years hence a year extra as compared to the OECD and the IMF. In addition the long term prospective is being reported namely through a baseline, deeper recession and stronger growth scenario expressed by means of GDP. Despite the lack of documentation on the methodologies applied, the free access to its extended country/region forecasts on trade complemented by product prices forecasts provides for a satisfying source of general trend monitoring which can regularly at the time of publication be checked by any interested party.

The Bundesbank publishes a monthly report for the German economy wherein it forecasts export/import values of goods and services. Its complete documentation and modeling properties (in

[2] The choice of the latter, a national bank although it could be extended to include other countries as well like for example the UK it has been limited to one for practical purposes while the specific choice has been made due to its usage for maritime purposes (forthcoming J. Pruyn, 2010).

terms of total number of equations which are substantially less than other macroeconomic models) make it an interesting choice for replication.

National planning offices also perform research of that scale. Here, two cases are being examined the Dutch and Belgian case.

The Central Plan Bureau of the Netherlands releases a newsletter four times a year. The forecasts reported in it are based on the Central Economic Plan (CEP) and the Macro Economic Outlook (MEV) published simultaneously with the newsletter twice a year, in April and in September. Two more newsletters become available in June and December. The projections of trade in goods are recorded in volumes making them directly applicable for maritime consultations. The models and their updates are well documented but represent, as all previously mentioned macro-econometric models, a resource overwhelming task. Additionally the study "Four Futures' is worth mentioning due to its widespread quotation and its direct use in maritime projections (see chapter 2.2). In particular, it elaborates on long-term policy challenges within a European context, driven by social and international trends.

The Central Plan Bureau of Belgium publishes short term forecasts twice a year, in September and February which cover from four to six quarters. The mid term forecasts are published once a year typically in May. The output is reported in values for goods and services. The macro-econometric models used follow the same principles of that specific scale of modeling but with a less comprehensive coverage. Same reasons hold true in this case too when it comes to the specifics of this investigation.

It should be noted that despite the lack of readily available output in volumes for merchandise trade only (instead of goods plus services aggregated), by the majority of organizations, the trade literature for converting values in volumes is based on value and price series. This is in particular the case in the WTO's International Trade Statistics (ITS). The import hence for a country equals the import value divided by the import price and the same is done for exports. The aggregated for total trade is additionally calculated in order to obtain world trade volumes which is defined as the arithmetic average of world exports and world imports. Such methodology relies on the calculation of prices of goods which unless calculated as unit values it can quickly become a tedious process with substantial issues of data availability across countries.

The individual preceding descriptions, demonstrate common trends within the field of macro-economic modeling on a global scale. These are summarized to the following:

- Most organizations use partly a multi country macro econometric model complemented by some kind of judgmental methodology;

- The majority of the organizations apply GEM models which might however in the future loose their dominant position to disequilibrium models;
- Most models are resource intensive and demand huge amounts of data;
- The methodologies used and especially the sub-models of those sophisticated large scale models have interesting properties that could be considered for replication within this research;
- The time series models directly model the variable under consideration, are less resource intensive and demonstrate a good level of forecasting performance;
- Forecasting within the structural models is not their core purpose;
- The applied structural methodologies partially converge.

What is observed is that the spectrum of tools utilizable for international trade volume applications for transport purposes is vast including both econometric methodologies and indicators. The ideal output readily utilizable by the transport industry does not exist although several types of output can be regularly consulted like for example the output of the CPB of the Netherlands, the World Bank and the MEI of the OECD. It is therefore not possible to rely on the modeling output of existing models and as a consequence a modeling approach needs to be designed.

According to Borges (1986) in a study commissioned by the OECD the GEM approach is only justified in the case of policies with sufficient impact on the overall economy to warrant the utilization of such a powerful and costly tool. It is seldom the case that sectoral policies, with limited feedbacks, need a general equilibrium approach. Since in this paper no cross sector approach is considered replicating a GEM model is not considered as a suitable option.

Furthermore, in this thesis, special attention is given on the construction of models, which are easy to apply, update and replicate by a number of players in the transport field. Macro-economic applications require expertise in applying such complicated techniques like GEM and substantial time to make the necessary yearly updates of such a model with what is typically quite an extended number of variables. The flexibility and speed often required within the transport sector would thus be compromised if such models are not properly maintained. Moreover the excessive volume of information implied by the GEM approach might exceed the information actually needed by transport stakeholders.

## 2.3 Main literature review findings

The combined findings from the two parts of the literature review reveal several intriguing points. In particular the final user could benefit from the fact that:

- The commercial reports provide timely trend indications and the output is directly measured in freight/maritime units;

- Although the commercial techniques are not as sophisticated as the ones from the international organizations up until before the crisis the relation to GDP has roughly given good estimates of future growth;
- There is ample choice of forecasting output from organizations which is freely available like the forecasting performed by the WB which offers a good coverage of regions, a particularly relevant issue for maritime players;
- Although typically the output is reported in values and goods and services are combined there are organizations which report in volumes like the CPB;
- Given the ample choice of indicators provided by international organizations like the OECD (although a subscription is needed) final users could create their own monitoring mechanism by selecting indicators which they anticipate influence their future business growth;
- Time series techniques are easy to replicate given the "limited" resources they require and their flexibility as tools for both industry and policy makers given the span of possible specifications.

On the other hand the main limitations when opting to reduce or rather cope with uncertainty within a transport framework are interpreted in the following way:

- The commercial tools mainly provide direction under Business As Usual (BAU) conditions;
- More sophisticated tools lack in practicality due to the irregularity or scarce timing of their publication. This is a reasonable consequence of the trade off between the level of detail and timing of such publications;
- Trade and macro-economic models do not provide for the output which can be readily translated into a transport context;
- The forecasting power of those models is treated with caution;
- The dynamics of structural approaches are very complex and restricted by data availability;
- The build in of scenarios in the econometric models although very useful cannot be regularly consulted as forecasting tools while shock effects are frequently tested after the shock has already taken place to validate and often calibrate existing models;
- Time series, even highly sophisticated techniques, are criticized for their lack of theoretical underpinnings and lack of adequate observations for the making of reliable forecasts.

As previously mentioned there is a vast variety of tools and models available to the final user. In this research it is believed that an attempt to replicate (after appropriately adjusting for the output) any of the macro-econometric models is neither feasible due to resource constraints nor desirable due to the unnecessary level of detail. Reducing the level of complexity by simplifying a structural model is not a desirable methodology while subject to a risk of delivering poor added value to the transport sector and the policy makers.

The alternatives according to this research need to be sought through a combination of time series modeling techniques, applied with trade data and translated into transport information. In other words based on this literature, the intention is to strive for the sophistication of trade applications of single series and panel data techniques. In particular the panel data setting is a field which has substantially grown in applications in the recent years exactly due the possibility to increase the sample size. This is a particularly desired property in economics research in which limited number of observations is common. The higher level of detail which is fed into the panel model translates in meaningful information regarding the volume of trade and also the containerized trade. As such existing trade applications using time series are being considered for applications in this research. The direct use of output from existing time series and structural models is not considered given the lack of the desired output unit, volumes of trade. The suggested framework is further described in chapter three.

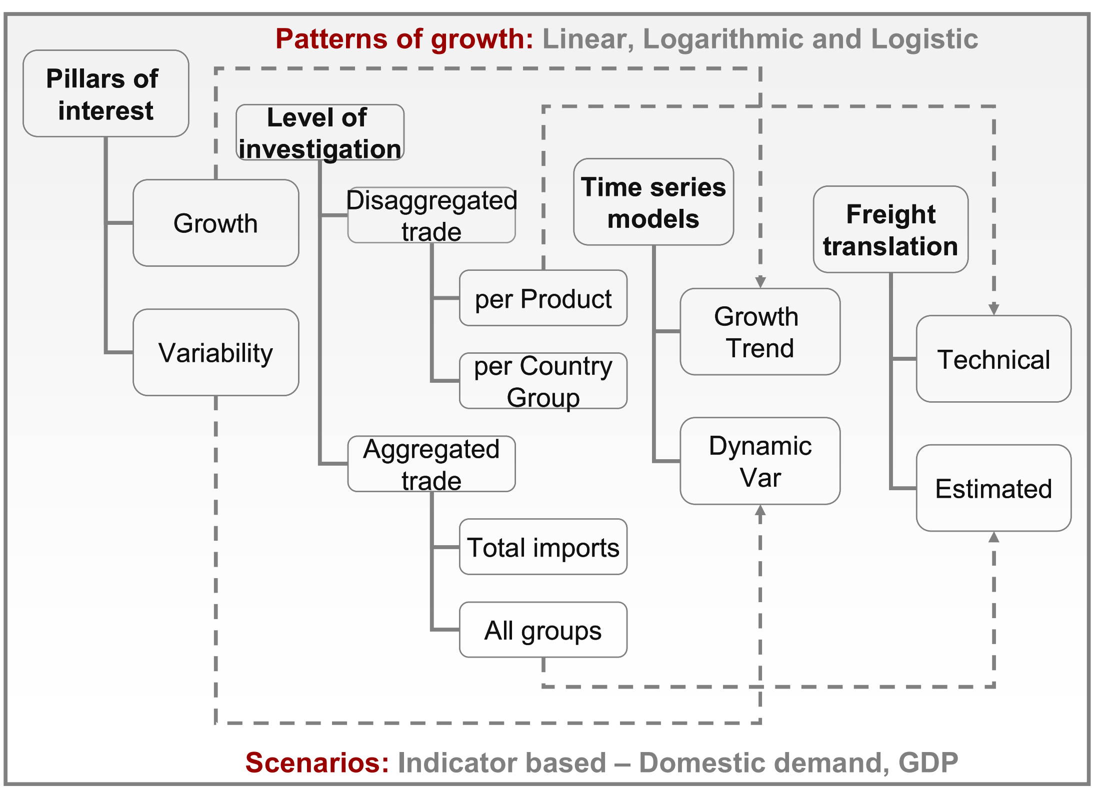
# 3. Methodological Choices

Chapter three describes the suggested methodology for capturing patterns in transport volume and containerized freight flows when the starting point of analysis is trade. It describes the methodological choices made. This is done by a description of the core components and their links. In chapter 3.1 the core components and the reasons supporting each choice are given. The links between the core components described in chapter 3.2, show how the core components combined answer the research question posed. This description is followed by the explanation of two critical points of this research and in particular the choices supporting the aggregation level and the choices made for the data mining process. They are found in chapters 3.3 and 3.4 respectively. The justification of the more technical choices made in the empirical part of this research: i) growth patterns, variability, trend projection, ii) dynamic forecasting exercises and iii) the link between trade and container flows are explained in the separate chapters (chapters 5, 6 and 7).

## 3.1 Core components

The core components are illustrated in figure 3.1 below which is split in four axes, their corresponding blocks and the links between the blocks.

Figure 3.1: Core components



The pillars of interest in the first axis are defined as growth of trade and variability of trade. They are investigated through growth models and dynamic/single series VAR models respectively, as shown in the fourth axis. The alternatives for each of the two are defined on the basis of different growth specifications and indicators for the investigations on growth and variability. The second axis refers to the level of investigation which varies in four ways: disaggregated trade per product, disaggregated trade per geographic group of countries, aggregated trade of all products and aggregated trade of al the different geographic groups (all the countries) in one group. The link between trade and container flows is labeled "freight translation" and distinguishes between a technical approach, which results from the disaggregated analysis and the estimated which is linked to the aggregated analysis.

The reasons supporting the above choices are explained by means of questions in the following way:

**1. Why model trade growth and its variability for transport?**

The interest in modeling trade growth and its variability for transport is due to its relevance for decision making processes regarding the strategic planning of policy makers and transport agents. An example of the demand for such input is evident in studies using the so called four stage freight models (with the inherent estimation of transport demand). Other applications can be found within environmental studies with final output the calculation of $CO_2$ emissions from freight transport, or in welfare studies wherein the impact of transport-related policy measures on societal welfare is being assessed. Finally transport agents typically base strategic decisions of expansion, be it organic or through Merger and Acquisition (M&A) on future growth anticipations. A more complete description of the impact of this work can be found in chapter nine.

**2. Why distinguish per level of investigation?**

The different levels of investigation serve for the coverage of a wide spectrum of applications according to the needs of the different transport agents. This is explained in detail in chapter 3.3.

**3. Why is the freight translation needed?**

The freight translation is needed in order to gain a better understanding of the link between trade and container flows. This investigation should lead to alternative ways in converting trade from weight to volume and subsequently TEU. Particularly this issue addresses the lack of existing literature on the topic as established in chapter two. It particularly refers to the possibility of estimating container flows using time series. More details on the specifics are given in chapter seven.

**4. Why model in the first place and not translate to freight from available output of trade models?**

The reason why the modeling is a necessary step in this research is because the existing output of trade models cannot be directly used for the purpose of this research.

In particular the modeling process is performed in this research with the purpose of firstly modeling trade in volume directly instead of modeling trade in values which is the standard approach in the majority of the applications within trade. Secondly in order to create country groups and product categories according to freight transport considerations. Thirdly it allows one to choose the level of desired/necessary model complexity especially when considering the fact that the available GEM models would be redundant as a methodology for transport purposes only. Finally it provides for all the necessary steps for the construction of a complete tool for the transport sector. In particular starting from the initial step being the raw database and the data mining, the modeling of trade follows next which finally ends with the step of the conversions of trade to the TEU unit. See chapter two for further support on the aforementioned arguments.

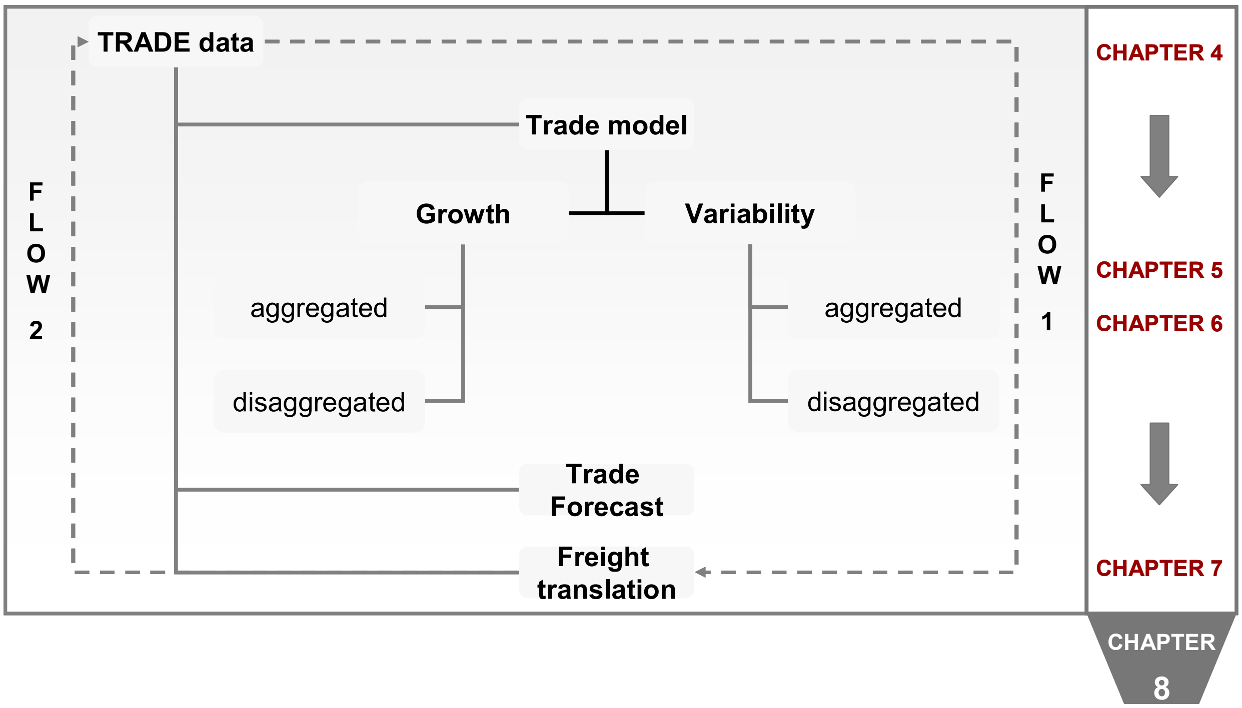
**5. Why use time series techniques**

The selection of time series is made given the objective of performing dynamic forecasts using the available information from the past. Theory is used as a guide to select variables. From a practical point of view through time series one avoids the complexity of alternative techniques like structural models, neural networks, system dynamics techniques which require substantial amounts of data. In particular structural approaches rely on economic theory and are typically used to evaluate policy changes by the use of scenarios. The literature on forecasting has demonstrated that even simple univariate time series models outperform or perform at least as good as large structural models (Stock, 2002; Verbeek, 2008). Furthermore structural models tend to be large as shown in the literature review on trade in chapter two including even hundreds of variables. It is for this reason that the WTO for example does not attempt to design such a model due to the very high resource requirements such models entail. This research in particular is intended for transport stakeholders. This means that the models used should have a low cost of maintenance but assure a good level forecasting performance.

## 3.2 Flow structure

The purpose of the flow structure is to link the core components between them. The two possible flow streams (flow one and flow two) are described in figure 3.2. For auxiliary purposes, a flow chart of the respective chapters where the components are found is added on the right hand side of the figure. The provision of the sketchy links illustrates how the flow of information developed by the core components ultimately addresses the research question. It therefore shows how the use of trade flows can be used to investigate transport demand in ways not possible when following the traditional approach. The latter is in particular demonstrated by a comparison with the traditional exclusive freight approaches.

Figure 3.2: Flow Structure




The approach suggested in this study is described by flow one. The block "Trade Model" illustrates that the process of modeling freight flows starts at the level of trade. Trade is modeled in volume and can therefore serve as direct input in transport studies modeling for example tons of freight. The resulting advantage is the available range of Origins and Destinations (OD's) and of product categories and the availability of long time series. Due to the access to larger amounts of data the range of empirical applications made possible also increases.

The blocks "Growth" and "Variability" illustrate that on the basis of trade data, models are buildt - of different levels of aggregation and for the two different pillars of interest - which can additionally be used to produce forecasts (block "Trade forecast"). Until this point models are based on trade data in volumes as defined by the UNCOMTRADE. This step already represents a transport customized approach in contrast to the majority of applications in trade which use values as a trade flow quantification unit.

However, within the transport sector, besides the traditional bulk products, transport volumes are typically quoted in TEU, the Twenty foot Equivalent Unit, a measure used for capacity in container transportation. It is for this reason that a freight translation step is introduced (block "Freight translation") which allows transport stakeholders to interpret or to use as input detailed data on the unit of TEU. This is illustrated graphically by flow one where the translation happens on the forecasted trade data and is contrasted by flow two where forecasts of freight data are made directly.

In other words while flow one models trade in volume, flow two models freight in TEU. It is hence the freight translation timing that distinguishes flow one from flow two.

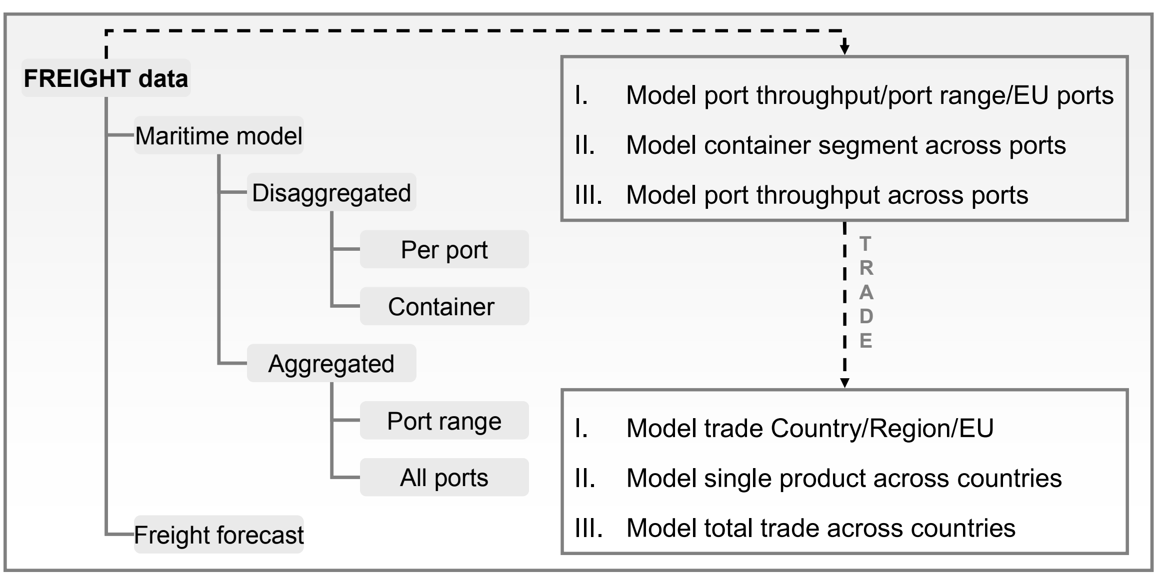
The reason for choosing flow one against flow two is the limitation of bias in the models. This is achieved through the use of "unbiased" trade data compared to freight data - translated from the original trade data - with the additional errors implied by the translation exercise. The introduction of such additional bias in the model would compromise the quality of the empirical results. It should be noted that the data used are subject to some unknown level of bias stemming from the raw database over which there is no control.

Flow one is described in chapters four until seven on the right hand side of figure 3.2. It shows how trade data are sourced and prepared in chapter four, how they are further analyzed for the purpose of modeling transport demand in chapters five and six on the level of freight volume and how the translation to TEU is performed in chapter seven. The output of the individual chapters is combined in chapter eight which delivers the output in the container unit.

The traditional approach considers freight data directly as shown in figure 3.3 which is an example for the maritime sector. The maritime sector reflects international trade flows. Extensions of the maritime example to land freight transport applications in terms of transit flows are not considered. The reasons for the exclusion of the latter are the lack of re-export and re-import data within Europe (see Annex III for further details).

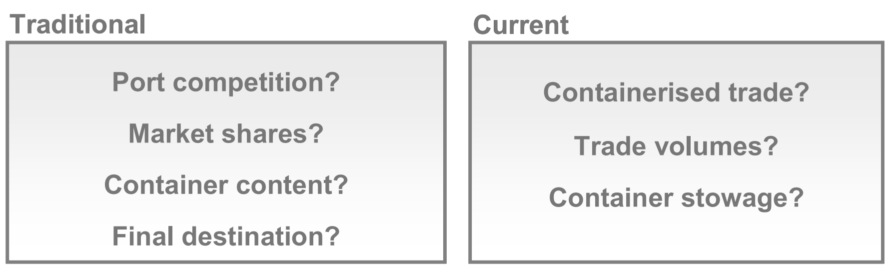
In particular the traditional approach leads to the creation of maritime models on two different levels, a disaggregated and an aggregated.

Figure 3.3: Traditional approach



On the disaggregated level it corresponds to modeling single port throughput and/or market segments across different ports (given the interest of the study the container segment is only mentioned in figure 3.3). The aggregated level includes estimations of total traffic or of the container segment performed for a port range or for the entirety of European ports. In figure 3.3, the choices of models derived from freight data are matched with the equivalent ones derived from trade data. Advantages and disadvantages of the traditional versus the current approach are illustrated in figure 3.4. Each block lists the main bottlenecks identified.

Figure 3.4: Advantages and Disadvantages of transport versus trade approaches




The disadvantage which arises from the modeling of single port throughput - whether on the total traffic or on a market segment - is the additional complication entering in the model as a result of competition with other ports, where assumptions regarding market share need to be properly addressed. In such cases the selection and collection of the necessary indicators and respective data is a tedious process. In the absence however of such element the realism of the application is compromized. In the case of in particular container modeling - across ports or for a single port – the final decision on the model specification is subject to uncertainties arising from the lack of data on the actual content of the container and of its final destination. This type of information is required for the construction of a reliable and robust model that would provide for more insight within the transport setting. Furthermore, the lack of content eliminates the use of such approaches for certain transport stakeholders who are interested in specific product niches. Despite product niches the container data obtained by ports are typically reported as total inflow or outflow. No OD information is provided which limits the impact of the traditional applications for transport stakeholders either transport agents or policy makers. An extended discussion of impact can be found in chapter nine.

The trade data approach on the other hand if free of such transport-related issues of port choice and lack of data on the OD's and content of the containers. The modeling technique is defined according to the selection of countries or country groups and to the level of disaggregation on the product level which can range from total trade to trade per product in one to six digits (depending on the classification) which is a variation of the level of detail in the product classification. In the field of trade research a wide range of models can be applied and the existing literature is vast.

The spectrum of applications represents an advantage in terms of a) model choice options, b) model robustness given the more solid theoretical foundations and the common practice of parameter comparison across different country sets.

It should be noted that port data and trade data are interlinked. However, in particular the trade database used in this research is not influenced by port choice since the data are sourced as imports and not re-imports. This means that the database used includes the imports of the country of final destination of the goods from the original export country and not the intermediate country of the goods entry.

Part of the considerations in the final approach followed is bias minimization. The two raw databases under consideration, port throughput and trade volumes both introduce bias in the model. The former because of double counting (due to flows transshipped not being separately referenced) and the latter because of the coverage in kilograms (due to product characteristics, for example liquid products which are not reported in kilograms). The additional bias due to model specification depends on the selection of the final model. Clearly none of the two approaches is flawless. The final selection of trade data as the starting point is chosen on the basis of a broader spectrum of criteria namely the lack of such approach, the additional information on the level of OD's which is not available in TEU, the general availability of data for the specification of a model on the trade level and the potential for further improvements and possible extensions of the raw trade databases. The latter relate to the intention of the UNCOMTRADE to provide for data in shorter time intervals.

## 3.3 Level of investigation: from disaggregated to aggregated flows

The choice on the level of analysis regarding product categories is decided as one of both a disaggregated and an aggregated level. The aggregated approach is chosen for both practical reasons and for the purpose of making comparisons. The main reason is that through aggregation, patterns are smoothened out which makes it easier when investigating trends and/or making projections. Further reasons supporting the aggregation of trade flows include:

**Transport / Maritime**

- The aggregated information gives transport providers an overall idea on the growth of the transport market. As such it represents future potential which is useful information when drafting medium to long term strategies. For the maritime sector in particular since total trade includes intra trade as well it is a less direct indicator of future potential. For such purposes total trade needs to be split in intra European trade and external trade;
- The majority of shipping lines use FAK (Freight All Kind). This means that charter rates do not vary per product;

**Trade / Technicalities**

- The majority of trade models are estimated on a total trade level. This is done due to the implied simplification of the analysis.

For the disaggregated in particular, the three digits Standard International Trade Classification (SITC), revision two, of the UN is chosen. [3]The justification is that valuable information is lost due to the aggregation of product categories and has hence yet not fully been explored. Further reasons justifying this approach within the field of transport, maritime and trade research include:

**Transport / Maritime**[4]

- Container freight rates are charged on the basis of market conditions and not on the traditional method of "weight or measurement whichever is the greater"[5];
- The type of cargo is an indicator of freight height for some shipping lines, while all shipping lines differentiate rates for heavy goods[6];
- Supply chain corridors differ according to product type;

**Trade**

- Empirical research (gravity, demand estimations, etc.) has often shown that aggregated flows mask or distort the estimated impact of the explanatory variables;
- Demand growth differs per product category;
- Patterns of consumption differ per product category as income level rises;
- Patterns of consumption differ per product category as unit price increases;

**Technicalities**

- Practical reasons for checking the presence of outliers, tracing them back in the database and interpret them accordingly.

However, the purpose of this research is to cover a range of transport stakeholders. The exploration of flows on the digit 3 level only hampers the understanding and communication of the results to final users like for example port authorities. For this reason the following steps are followed:

[3] The choice of revision two was due to the historic coverage of flows.
[4] Based on targeted expert opinion
[5] "Weight or measurement whichever is the greater" is a method for defining the freight rate. It means that the cargo is charged according to weight when heavy and volume when volumous.
[6] However during today's times the behaviour of the market experiences disruptions in its common workings. This is illustrated through the peculiarities in the charging of freight rates.

(1) The SITC-digit 3 database is used to check for discrepancies in the data and obtain a deeper understanding of the patterns;

(2) The SITC-digit 2 database is obtained by aggregating the SITC-digit 3 data. Similarly an analysis on the SITC-digit 2 level is made where differences in patterns can be investigated on a level which is usable by for example shippers or freight forwarders;

(3) The SITC-digit 1 database is obtained by further aggregating SITC-digit 2. This is the level which is further modeled representing the disaggregated application.

Especially with respect to the container unit some additional clarifications are necessary. In particular, a stepwise approach is pursued starting from a disaggregated level of flows in order to address the link to the container unit. This is achieved by classifying products according to their containerization probability. Such classification is based on the containerization degree and splits products according to a high, low or average containerization probability.

The category "high containerization probability" (HP) represents the mature containerized products. The category "low containerization probability" (LP) represents the currently non containerized products. Finally the category "average containerization probability" (AP) represents the products that have occasionally been containerized. The reasoning for the differentiation between the sub-categories HP and AP is the presence of occasional containerization. What is actually observed is that due to unforeseen events goods are occasionally being transported in containers. Especially due to the crisis and the consequent pressures for capacity optimization this tendency has been even more pronounced. An interesting complication relevant to these dynamics is that during times of very high charter rates cargo reverts from containers to general cargo ships or bulk.

The details on the way this approach is applied are found in chapter seven.

## 3.4 Data mining

The data mining performed, uses as input the Origin Destination (OD) trade flows of European countries. Databases are created on the different classifications (SITC, ISIC, BEC) for different levels of aggregation and unit measurements. The final output includes databases which can be further elaborated to provide for the investigation of growth, variability patterns, forecasts and for the unit measurement conversion to TEU. A description of the data mining is shown in table 3.1.

Table 3.1: Data mining

<table>
<tr><th colspan="6">DATA MINING</th><th>PATTERNS</th></tr>
<tr><th>Input</th><th colspan="5">Database</th><th rowspan="3">Output</th></tr>
<tr><th>Flow</th><th>Classification</th><th colspan="3">Aggregation</th><th>Quantity</th></tr>
<tr><th>OD</th><th></th><th>Digit</th><th>Group</th><th>Product</th><th>Unit</th></tr>
<tr><td>Europe ↓↑ World</td><td rowspan="3">SITC</td><td rowspan="3">▪ Digit 4<br>▪ Digit 3<br>▪ Digit 2<br>▪ Digit 1</td><td rowspan="3">▪ EU27<br>▪ HWHSHE<br>▪ HW<br>▪ HS<br>▪ HE<br>▪ Country</td><td rowspan="3">▪ cat6<br>▪ Total</td><td rowspan="3">▪ Kg<br>▪ Ton<br>▪ TEU</td><td rowspan="5">▪ Trend Growth patterns (chapter 5)<br>▪ Dynamic Growth patterns (chapter 6)<br>▪ Container flows (Chapter 7)<br>▪ Lead time (chapter 4)</td></tr>
<tr><td>Europe ↓↑ Partners</td></tr>
<tr><td>Europe ↓↑ Europe</td></tr>
<tr><td rowspan="2">Generic</td><td colspan="5">BEC</td></tr>
<tr><td colspan="5">ISIC</td></tr>
</table>

Source: Own compilation

**Notes**
(1) HW: AU, BE, FR, DE, LU, NL, CH
(2) HS: CY, GR, IT, MA, PT, SL, SP
(3) HE: BG, CZ, HU, PO, RO, SV
(4) HN: DK, ES, FI, IE, LV, LT, SE, UK
(5) SITC: Standard International Trade Classification
(6) BEC: Classification by Broad Economic Categories
(7) ISIC: International Standard Industrial Classification of All Economic Activities

The table is explained below:

Column Input/Flow/OD: The three OD's listed serve different purposes. The OD Europe-World represents the core database with the imports and exports of a sample of European countries from the world. The OD Europe partner is used as a secondary database providing the perspective for the core database. In this research the partner chosen is China. The OD Intra Europe is sourced due to the interest in international flows only and is hence needed in order to be deducted from total imports and result in the so called extra trade of Europe (the trade of European countries with non-European external partners).

Column Database/Classification: The different levels of aggregation are needed on the SITC level. It should be noted that the SITC revision two product category classification is chosen due to the need for historic time series which are available in such older product classification of the UN.

All classifications of the UN can be converted in the newer classifications if necessary in case for example SITC revision two seizes to exist or if for any other reason more recent classifications are preferred. Further data mining included the characterization of the data according to alternative classifications which were meant to provide a broader perspective from an economic and a supply chain point of view. This was done by means of the Broad Economic Classification (BEC) and the International Standard Industrial Classification of All Economic Activities (ISIC) classifications also attainable from the UN classifications.

<u>Column Database/Aggregation/Digit</u>: The digit wise depth of analysis is made for the sourcing of volume units which are only available from digit three onwards.

<u>Column Database/Aggregation/Group</u>: Further disaggregation levels are made for reporters on the basis of country groups, separately and the countries all together in a single database. The country groups made (see notes) are interpreted as geographic divisions which correspond to the UN geographical split.

<u>Column Database/Aggregation/Product</u>: A last level of aggregation involves product disaggregation with total trade contrasting the trade for one product category that of category six, manufactured goods chiefly classified by material.

<u>Column Database/Quantity/Unit</u>: The units attained from the data mining, include the Kg and tons units and the unit created within this research from the trade databases, the TEU unit.

<u>Column Patterns/Output</u>: Patterns of "growth" are identified, explored and modeled to the extent possible. Four different aspects are specified: i) Trend Growth patterns ii) Dynamic Growth patterns, iii) Container Flows and iv) Lead time. They represent the different chapters as specified in figure 3.2.

Only exception is the lead time which is only briefly referenced in chapter four given the low volumes represented by products which are believed to experience a shift from low labor cost countries to locations closer to the final demand. The three different perspectives are explained in more detail in chapter four, were detailed comments on the data mining process and further analysis is added.

The main advantage of carrying out the data mining exercise on a deep level of disaggregation is the quantity of information available which can be directly utilizable in transport analyses. It should be noted again that databases of products in units of volume (kg or tons) are not directly available while typically databases provide for either recent data from 1995 onwards (EUROSTAT, 2010) or volume indices including goods and services aggregated (OECD, 2010).

# 4. Data Mining: description, coverage, quality and relative importance

Chapter four describes the output of the extensive data mining exercise. It initiates the modeling part of this research and represents a crucial step for every such type of empirical analysis. Three main issues are addressed: i) data coverage, ii) data quality and iii) relative positioning of the core data from the transport perspective.

The issue of data coverage although a very technical matter, it is addressed in detail since a negative evaluation of the trade database in volume measurements immediately cancels the approach of modeling freight and containers through trade data.

Data quality assessment on the other hand is a crucial part in every modeling exercise and a particularly difficult process in trade data. In particular, difficulties arise due to the presence of outliers. The process of identifying and interpreting outliers in this research is a tedious but necessary task finally defining whether the data is suitable for further analysis.

Finally, given the targeted final users being transport stakeholders, the data are presented in relative terms. The relative importance of the core data (which are further modeled in subsequent chapters) in terms of volumes and partners is hence further discussed. Inferences of relevance to policy makers and the transport industry are thus also drawn.

The structure of the chapter is as follows: Chapter 4.1 includes an overview of the data and a justification of the chosen case studies. Remarks on the data sourcing process are additionally made. The core data are elaborated in chapters 4.2 and 4.3. Each chapter includes graphical descriptions and the relevant secondary data which provide the perspective. Chapter 4.4 summarizes the main conclusions per aggregation level and is coupled with a discussion on the relevance of each dataset for transport stakeholders. The more technical process of how the data is checked is reported in Annex IV.

## 4.1 Data overview

The data consists of two different blocks, the core and the secondary. The core data are the databases investigated in detail while the secondary data include different sets of databases for the purpose of adding perspective to the analysis. Figure 4.1 provides an overview of the core and secondary data.

On the right hand side of figure 4.1 the two pillars of product level and partner level are distinguished, within which the core data are being positioned. The core data are highlighted in bold, indicating category six, world and extra trade. On the left hand side, the table shows the core disaggregated data, category six, reported on the digit two level for a first familiarization with its content.

Figure 4.1: Core and secondary data

| Code 6 | Manufactured goods classified chiefly by material |
|---|---|
| 61 | Leather, leather manufactures, n.e.s., and dressed furskins |
| 62 | Rubber manufactures, n.e.s. |
| 63 | Cork and wood manufactures (excluding furniture) |
| 64 | Paper, paperboard and articles of paper pulp, of paper or of paperboard |
| 65 | Textile yarn, fabrics, made-up articles, n.e.s., and related products |
| 66 | Non-metallic mineral manufactures, n.e.s. |
| 67 | Iron and steel |
| 68 | Non-ferrous metals |
| 69 | Manufactures of metals, n.e.s. |


Source: UNCOMTRADE, UNCTAD, EUROSTAT

The level product positions category six within the complete manufactured goods category according to the classification of UNCTAD. In particular the remaining manufactures consist of chemicals and related products (category five), machinery and vehicles (category seven) and miscellaneous manufactured articles (category eight).

The level partner positions world and extra European trade among other trading partners. The latter includes a listing of the major trading partners including the most important non European partners of the EU according to the EUROSTAT and major exporters of manufactured goods according to UNCTAD.

The chosen perspective for the disaggregated data is used in such a way as to provide insights on the importance of category six within the entire category of manufacturers in terms of volume. Additionally special cases of partners are considered to highlight the perspective of direction of growth patterns. In particular, China and Intra trade have been judged as being most informative for the purpose of adding the transport perspective.

The chosen perspective for the aggregated data is used with the purpose of illustrating both direction and volume variability of trade growth patterns per partner. In particular intra trade is used for the purpose of adding the transport perspective. This is done by distinguishing between freight trade using land transport (intra trade) and trade necessitating a sea leg of transport (extra trade). In both cases inferences are drawn for transport stakeholders.

### 4.1.1 Choice of case studies

The case studies are chosen on the basis of transport relevance, either of freight flows, or of maritime flows. Choices are needed since the spectrum of possible case studies as a result of trade data availability is vast.

The chosen pilot concerning flow direction is Europe's imports from the world. The reason why imports are chosen is because of the volumes they represent, reflected also in the trade balance of the Euro area, figuring a 1.5 billion euro deficit trade balance with the rest of the world in February 2011 compared with 1.4 billion in February 2010 (Eurostat, 2011). An additional reason for the choice of imports is due to the information they contain on European consumption patterns.

The reason why total trade (imports plus exports) is not taken into account is because of the unbalanced nature of the European trade especially in the Asia-Europe route as demonstrated by the yearly figures in the Review of Maritime Transport (UNCTAD, 2010). Aggregating across the direction of flows disguises important features of trade patterns.

On the other hand exports are not chosen given the view point of this paper being the consumption behavior of Europeans and not the consumption behavior of the world or of a specific trading partner. Additional reasons include the intended added value of this research in terms of inputting this information in models of road traffic like for example the "Freight model Flanders" a four stage freight model (Flemish Traffic Centre, 2006). Practical reasons for the exclusion of exports from the analysis are time and scope constraints.

The chosen case concerning trade partners is the world. The reason why the world is chosen instead of specific trading partners is because of transport considerations, since total incoming freight in Europe would appeal to a wider range of transport players. In this case too however time and scope constraints are practical reasons explaining the lack of further partner investigation.

The chosen case study concerning the disaggregated analysis is category six under the title "manufactured goods chiefly categorized by material". It belongs to the broader category of manufactured goods completed by category five "Chemicals and related products", seven "Machinery and transport equipment" and eight "Miscellaneous manufactured articles". In particular categories eight and the pilot case comprise of the category of "other manufactured goods".

The reason why it is chosen as a case study is because it belongs to the overall sector of manufactures, which is a largely relocated sector from Europe to countries with lower labor costs. Interestingly however category six remains a category which is still produced within Europe and hence included in the intra trade dataset. It is thus viewed as a category which is relevant for the land freight transport sector. At the same time it is seen as representing potential volumes which due to the structural tendencies (relocation of industries in the manufacturing sector) could ultimately be transported from overseas and hence become relevant to the maritime sector.

Lastly, technical reasons leading to the final choice of category six include the quality of the dataset. In particular category seven (Machinery and Transport Equipment) given its nature, it demonstrates erratic disturbances of the growth pattern (when for example planes are ordered), which are not suitable for modeling. Category eight (miscellaneous manufactured articles) on the other hand appears to have systematic errors in the dataset[7]. Category five (Chemicals and related products) is more relevant for exports from Europe and is a rather stable type of trade in terms of share of the total EU trade although interesting for specific countries like Belgium and the Netherlands especially due to the port activities.

Subsequent chapters provide more detailed information on each of the product categories. As in the other two cases of flow direction and trade partner, practical reasons in this case too limited the analysis to one category, that of category six.

### 4.1.2 Data sourcing and points of attention

The data are sourced for the European countries listed in table 4.1. The criterion for creating the country groups is based on geographical considerations as defined by the United Nations classification. HW includes Western European countries while HS and HE Southern and Eastern countries respectively. Sample countries from Northern Europe are not included given the extreme diversity between the countries in their patterns of trade. The geographic division thus makes less sense and it is hence decided to exclude them entirely from the analysis.

Table 4.1: Country groups

| **Flow** | **Groups** | **Countries** |
|---|---|---|
| **Partner/** | HW | AUT BLX CHE DEU FRA NLD |
| **Reporter** | HS | CYP ESP GRC ITA MLT PRT |
| | HE | BGR CSK HUN POL ROM SVN |

During the process of data sourcing problems occurred depending on the provider of data and the definition of the query. In particular differences were observed depending on whether the data was sourced from the UNCOMTRADE or from WITS the system provided by the World Bank. In most cases the differences were minor but in some others substantial differences were noted. This was the case for category 8 which was also the reason why it has not been used in the modeling exercises.

[7] Despite the long discussions and willingness of the helpdesk of the UNCOMTRADE to clarify the issue, it was finally not possible to obtain a workable dataset.

Furthermore alternative query definitions for the same type of data resulted in discrepancies. This was the case of sourcing imports either directly, with reporters the countries of interest and partner the world or indirectly, as exports from the world to the countries under consideration (hence world are reporter and the European countries as partners). The reason why the latter was considered was due to the initial intention of creating a unit price database for which the value of imports had to be recorded in FOB instead of CIF, hence requiring exports and not imports as trade flow. An additional reason for sourcing imports as world exports to the sample countries was due to the inclusion of Eastern European countries. Hence, given the political conditions for those countries until approximately the year 1993, the datasets suffer from missing values and outliers. It was hence decided against sourcing imports with the countries themselves as reporters.

## 4.2 Disaggregated core data: Manufactured goods

The core data consists of imports of manufactured goods and in particular of category six of the sample of European countries from the world. In chapter seven this database is further explored for the purpose of making container transport inferences.

The data are sourced from the UNCOMTRADE using the World Integrated Trade Solution (WITS) a software developed by the World Bank. In particular, the data collected are longitudinal panel data and include the following:

| | |
|---|---|
| Quantity: | the kilograms exported from the world to European countries[8]; |
| Country: | the selected countries of Europe; |
| Group: | the selected countries of Europe grouped per geographic; |
| Product: | the product category in three digits; |
| Year: | the annual observations from 1980 until 2009. |

In order to extract the information needed for the subsequent analysis on pattern explorations and in particular the modeling on import growth and forecasting, category six is subject to a data mining exercise. In practice, as described in chapter three this means 1) disaggregating the category per digit three in order to extract the information measured in weight (kilograms), 2) aggregating back to the level two digits and one digit, 3) splitting Europe in geographic groups and 4) checking for the quality of the attained dataset.

Further data mining includes the characterization of the data according to alternative classifications which are meant to provide a broader perspective from an economic and a supply chain point of view.

[8] For simplicity the wording "total imports of European countries" will be used. The reason why "exports of the world", instead of "imports from the world" has been chosen is because of the forthcoming work of unit values where values are preferably recorded as FOB. Given the current analysis in volumes (weight) the difference between the two (exports from world and imports from world) should according to the UN not vary significantly.

This is done by means of the Broad Economic Classification (BEC) and the International Standard Industrial Classification of All Economic Activities (ISIC) classifications also attainable from the UN classifications. The BEC and ISIC results are independent of the volume of trade and are merely based on the actual classifications.

In particular category six is 81% composed of BEC code 22 products i.e. processed industrial supplies (see Annex III). In significantly smaller percentages the category composes of semi durable goods (in comparison with durable and non durable), capital goods, transport equipment and parts and accessories thereof. On the other hand category six is 27% composed of ISIC code D 17-19 products (see Annex III). In particular the category includes the following items:

---

17 → Manufacture of textiles;

18 → Manufacture of wearing apparel, dressing and dyeing of fur;

19 → Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear.

---

These products include fashion related items which for the purpose of this investigation are viewed as products with a potential tendency to shorter lead times. Further analysis is required in order to estimate the importance of that trade in terms of volume. The latter however goes beyond the scope of the current research.

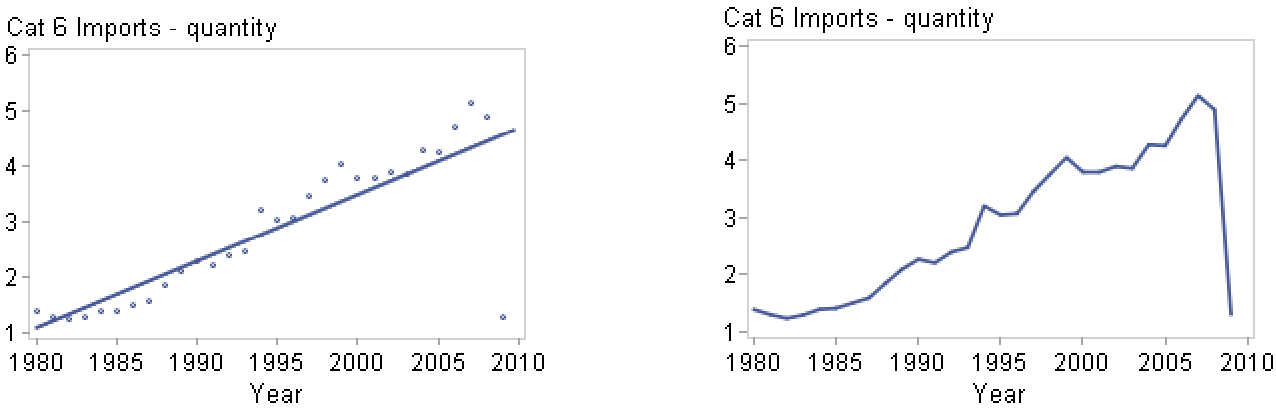
### 4.2.1 Descriptive Statistics: A Graphical exploration

The graphical exploration plots the longitudinal panel data on a one and two digit classification level and on an aggregated scale with sub-products and partners aggregated all together. The line and scatter plots illustrated in this research show the data aggregated in digit one and grouped per geographic group. The patterns on a digit two level and per country are found in annex IV. A complete analysis on the digit two level falls outside the scope of this research but could be performed on request. In particular, the levels of investigation are four: i) product digit one level for all geographic groups aggregated ii) product digit one level per geographic group, iii) product digit one per country and iv) product digit two per country geographic group.

The level -i- is described in graph 4.1. A first rough observation is that fitting a linear trend and extrapolating into the future produces reasonable forecasts. This approach would however only produce reasonable forecasts during the times of growth up until 2008. Nevertheless, given i) the real pattern of growth without the fitted line, which is a clear non-linear pattern, ii) the growth disruption of 2009 due to the global economic crisis and iii) expectations regarding the level of maturity of growth in imports present in the underlying dynamics in the data before 2009, it is likely that the aforementioned practice might no longer describe the growth pattern in a reliable way.

Graph 4.1: Category 6 – Aggregated Imports (kg)

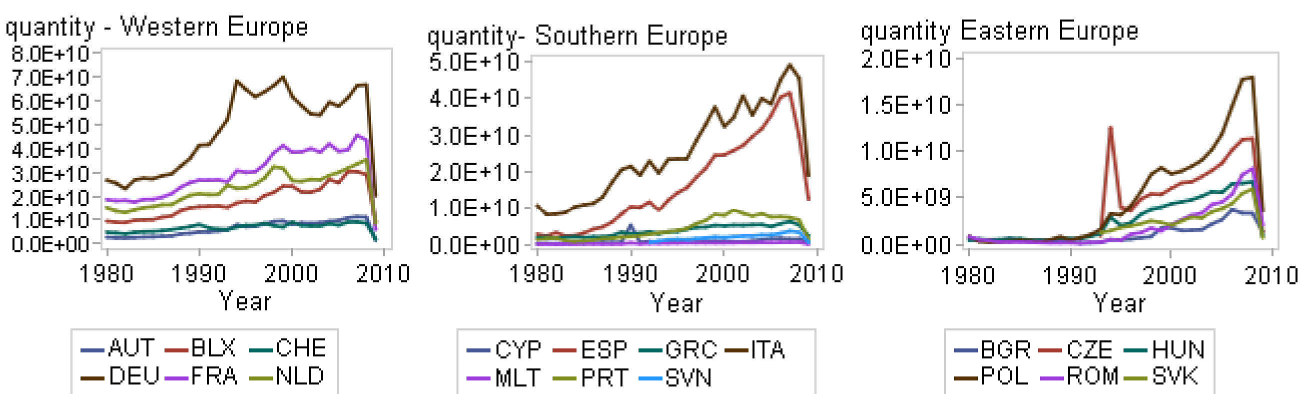
**a) Scatter plot with Linear Trend** **b) Line plot**




Source: own calculations based on UNCOMTRADE data

The latter skepticism regarding the belief in a linear growth pattern and the ambiguity in defining a single trend pattern is confirmed by the examination on the level -ii- , product digit one level per geographic group. This is illustrated in the three plots of graph 4.2 representing each the different groups.

Graph 4.2: Category 6 – Imports per geographic group (kg)




Source: own calculations based on UNCOMTRADE data

What is observed is that the plots exhibit non linear patterns. The growth patterns vary both between and within the geographic groups. The latter is further illustrated by plotting the data individually per country (see annex IV). A more pronounced growth pattern is visible for the groups of HE and HS with the latter being driven by Italy (ITA) and Spain (ESP) in terms of sheer volumes, while group HW shows signs of a more saturated growth pattern. Further investigation is hence needed in the variability of the countries in terms of growth rate and volumes. This is further pursued in chapter six.

What is common to all plots is the effect of the financial crisis on the growth pattern, where steep declines are noted for all groups in the year 2009. The observations for year 2009 have been double checked given the suspiciously extreme declines. The data has additionally been sourced from Eurostat although only for the sum of the categories six and eight, the category of other manufactures as previously mentioned. However it is not possible to establish the nature of the 2009 observations as outliers or errors and the decision taken is to keep them as sourced by the UNCOMTRADE/WITS.

On the level -iii-, product digit two per country group what is observed is that sub-products behave differently among each other, showing variability in growth patterns. In general however, for the majority of sub-products within product category six a pattern of growth is observed. However, between the countries within the group of geographic West (HW) and between the groups of geographic South (HS) and East (HE) differences do exist with respect to the slope, the intercept and the functional form (for an illustrative example see annex II graph 2.2). The core data coverage and quality is assessed in annex IV.

### 4.2.2 Providing perspective

Secondary data which are not investigated in full detail and are hence not modeled are used for the provision of perspective of the core modeled data. On the product level the secondary data assist in the understanding of the composition of the manufactured goods category and the importance in volume of each category. On the partner level the secondary data are used for the making of freight direction inferences. Both volume and direction are viewed from a transport perspective. The modeling of secondary data goes beyond the scope of this research. The methodology used for the core datasets could however be replicated to cover all product categories.

#### 4.2.2.1 Disaggregated data: Product level

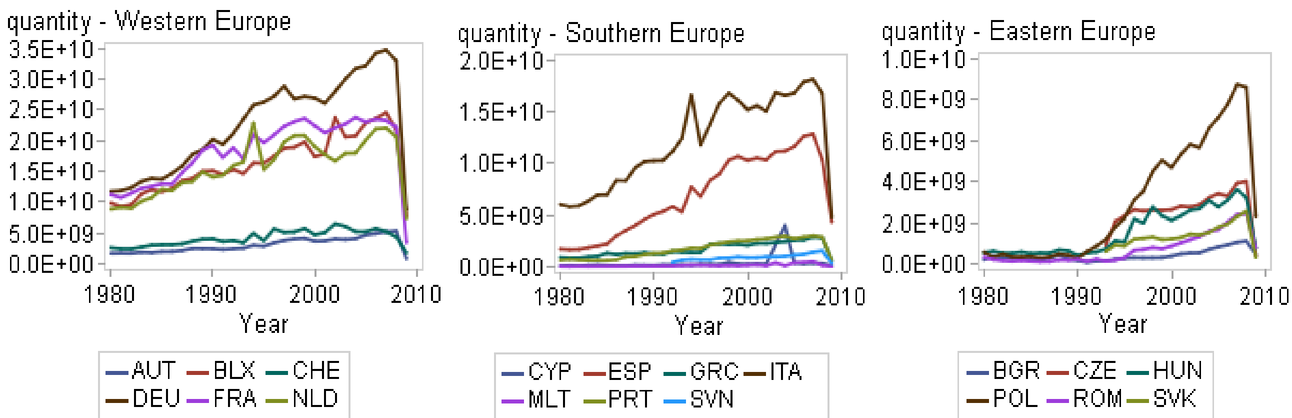
The secondary data include the product categories which complete the manufactured goods category. These are the SITC categories five, seven and eight. In particular and according to the EU, SITC six and eight include heterogeneous products which incorporate basic semi-manufactured products (leather, rubber, wood, paper, textiles, metals, building fixtures and fittings) and labour-intensive products (clothes, shoes and accessories, scientific instruments, clocks, watches and cameras). Within Eurostat they are grouped together as “Other manufactured goods” (Eurostat, 2010). SITC category five represents the chemicals sector while SITC category seven includes machinery and vehicles.

For the extraction of patterns the same data mining exercise as for SITC category six is applied to each of those categories. Hence for each of the categories the growth pattern is illustrated in graphs with the world as partner. This is complemented by a description of the category in terms of ISIC and BEC.

**Category 5-Chemicals and related products**

In category five the EU typically posts a trade surplus (Eurostat, 2010). The growth pattern of imports is one of a steady growth for all EU members as illustrated in graph 4.3. The graphs show total imports and hence intra European trade is included but external sources indicate the USA as the main trading partner (Eurostat, 2010). Tables BEC-5 and ISIC-5 (see annex IV tables 4.1 and 4.2) show the decomposition of this category in ISIC and in BEC terms.

Graph 4.3: Category 5 – Imports per geographic group (kg)




So

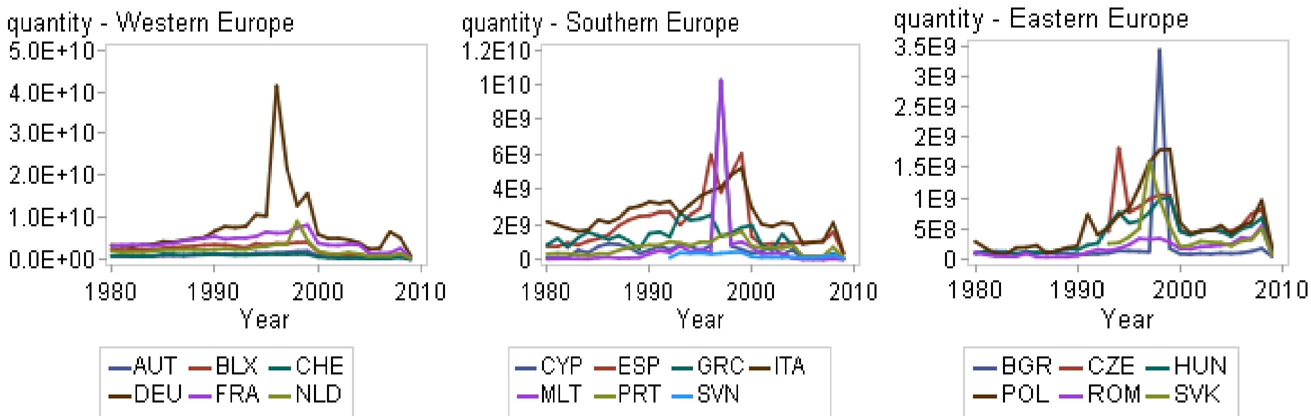
urce: own calculations based on UNCOMTRADE data

In particular category five is 91% comprised of manufacture of chemicals and chemical products in ISIC classification terms and 91% comprised of processed industrial supplies not elsewhere specified in BEC classification terms. These products are inputs for industrial production and are hence influenced by final demand. What is graphically observed is the presence of a similar growth pattern differentiation per geographic group as in the case study, category 6 especially for groups HW and HE. Geographic group HS seems to have a similar pattern to the one of the HW countries demonstrating a slower growth rate.

**Category 7 - Machinery and transport equipment**

In category seven as is the case of category five the EU posts a trade surplus. This category comprises 57% of manufactures of machinery and equipment on the ISIC level. The irregularities observed in the importing profiles of the EU countries illustrated in graph 4.4 cannot be attributed to the existence of outliers resulting from a mishandling of data.

Graph 4.4: Category 7 – Imports per geographic group (kg)




Source: own calculations based on UNCOMTRADE data

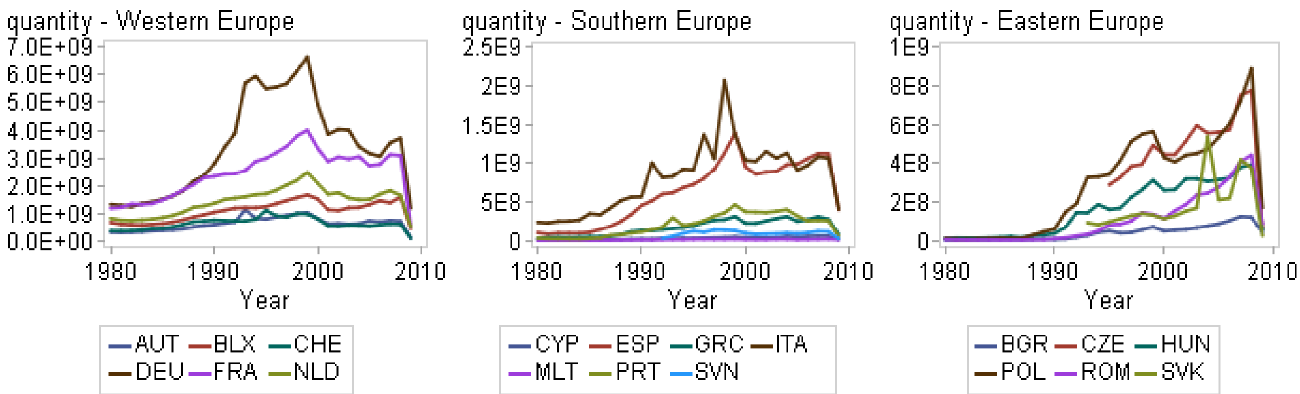
This is supported by an investigation of the spikes in the databases where an extreme value for the category of for example "ships, boats and floating structures" (see Annex IV) measured in weight could result in such volatile patterns. This category is not further explored for the additional reason that its contribution in the modeling of growth patterns part does not add value to this research. Such volatility is better dealt on higher levels of disaggregation and for purposes that go beyond growth specification investigations.

**Category 8 - Miscellaneous manufactured articles**

Category eight belongs to the category of "other manufactured goods" classified by the EU for which the EU posts a deficit. China is the biggest trading partner in this category with the USA in the second place followed by Switzerland and Turkey (Eurostat, 2010). The graphical patterns are illustrated in graph 4.5 where in this case too a similar pattern as in the core data case of category six is visible. This applies across the geographic groups with a similar differentiation as for category six.

In terms of BEC classification category 8 comprises 34.54% of semi durable goods not elsewhere specified while in ISIC terms there is wide variation which in practice means that category 8 is quite heterogeneous. As explained in chapter 4.3 category eight is subject to significant discrepancies between the data sourced by the UNCOMTRADE and WITS while demonstrating a large number of outliers. While it is a category of great interest and it would have been ideal to model either also category eight separately or aggregated together with category 6 it is decided against doing so due to the aforementioned reasons.

Graph 4.5: Category 8 – Imports per geographic group (kg)




Source: own calculations based on UNCOMTRADE data

### 4.2.2.2 Disaggregated data: Partner level perspective

The secondary data on the partner level are meant to add perspective and are only calculated for the core category, category 6. There are two main ways by which the perspective is interpreted. Firstly, in a transport context, maritime inferences are made depending on the geographic location of the chosen partners. This is done, by distinguishing between partners where a deep sea leg of transport is required or not. However, as explained in chapter three this research does not take into account competition from air transport and hence no further differentiation will be made according to type of products which are prone to being transported by either sea or air[9]. The partners of interest which are believed to contribute to the perspective as described above are the intra European partners and China. The main reason supporting the aforementioned choices is volumes of imports for the specific product category and the growth rate respectively.

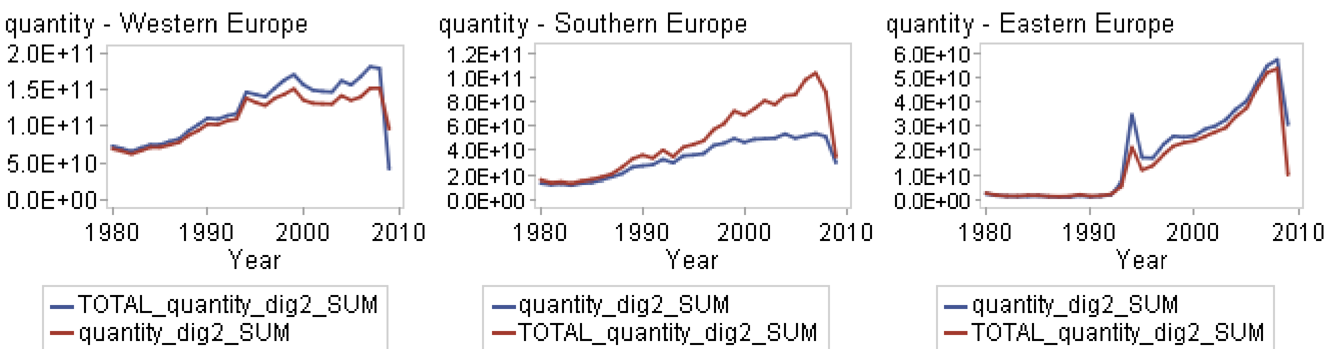
**Partner level - Intra Trade**

Intra trade corresponds to the trade of each European country with all other European counterparts. In particular, this type of trade represents volumes which do not include a deep sea leg. Hence, in order to capture the external trade, these volumes should be discounted from the total trade i.e. imports from world (the pilot case). Additionally, the external trade, largely represents trade volumes imported by trading partners who are located overseas and hence includes a deep sea leg in the transport chain for the imported goods.

[9] The differentiation between products which are carried by sea or air could be made on the basis of their logistic chain characteristics and/or the value of the product in question. This investigation however goes beyond the scope of this research.

The data are similarly as with the partner world, been sourced from the UNCOMTRADE through WITS. The query is build as the exports of category six, on a three digits level (SITC revision 2), of the European countries (EU 27) as reporters, to this study's European countries as partners. Hence, for each partner country the exports of the reporters need to be aggregated in order to lead to a database of only the partner countries with the trade volumes and values from European countries of this study. The choice of flow direction is exports instead of imports. Since the main interest is volumes (measured as weight in kilograms) there is no difference between the two approaches. Reliability of the reporting country is also not an issue. However the final choice being exports is made due to the potential use of values where it is preferred not to have values recorded in CIF terms. The checking of the coverage/quality of the data and the data mining is done in the same way as for the core data. The results of the data coverage/quality are reported in Annex IV. The main results from the data mining, which are graphically illustrated in graph 4.6 are summarized in the following major points:

Graph 4.6: Intra trade versus total trade - per geographic group (kg)




Source: own calculations based on UNCOMTRADE data

Intra trade corresponds to the vast majority of imports of category six of the European countries in terms of volume. Hence, category six as part of the category "other manufactured goods" is sourced from within the EU. From a maritime perspective such a pattern can be viewed from two different perspectives. One which classifies this category as being of minor importance or one that shows future growth potential. The patterns between the country groups are similar for the HW and HE and less similar for the HS group were the difference between total trade and intra trade increases with time after the 1990's.

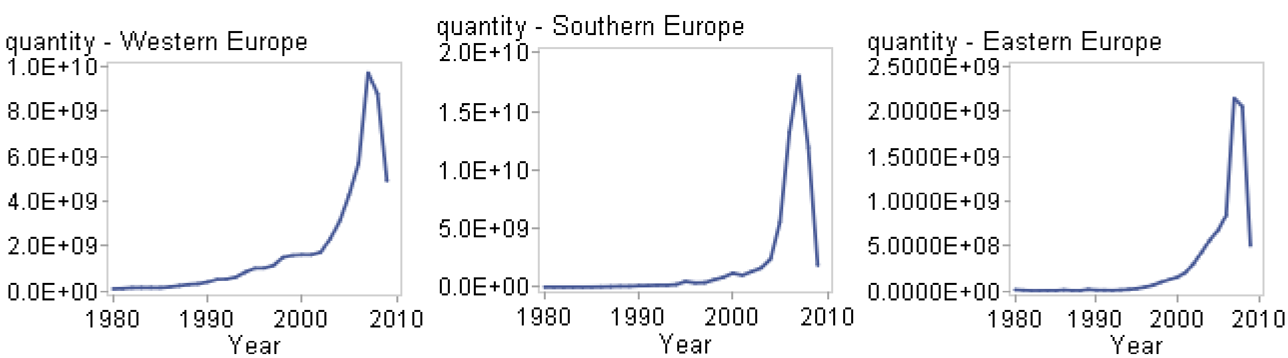
**Partner level – China**

China is explored as a trading partner given its significance in world trade and in its bilateral trade with the European countries in terms of export volumes.

At the same time the geographical location of China necessitates deep sea transport for the trading activity to take place. Yet again, it should be noted that this research does not take into account competition from air transport and hence it will be assumed that all exports of category 6 manufactured goods from China to Europe are transported by sea.

The data for China are similarly as with the partner world, sourced from the UNCOMTRADE through WITS. The query is built as the imports of category six, on a three digit level (SITC revision 2), of the European countries from China. The reasons why imports from China is chosen instead of the exports from China is due to the requirement for long and reliable time series. In particular China did not have any data reported for the early years in the 1980's, while the quality of its reported data has in the past been put in question. The checking of the coverage/quality of the data and the data mining is done in the same way as for the core data and is reported in the Annex IV. The obvious conclusion from the data mining which is graphically illustrated in graph 4.7 is that all groups demonstrate a clear exponential importation growth pattern. In particular 66, 67, 69 are the product categories imported in biggest volumes for all groups (see annex IV). As expected, for all countries 2009 reflects the effect of the crisis.

Graph 4.7: Category 6 – Imports from China per geographic group (kg)




Source: own calculations based on UNCOMTRADE data

It should be noted that the importance of China in the trade of category 6 is currently less important in terms of volumes when compared to intra trade volumes but the exponential growth pattern shows potential for further growth.

## 4.3 Aggregated core data: Total trade, Extra Trade

The aggregated data of total imports includes all goods. According to the SITC classification goods are split in 10 categories from 0 to 9 in the following way:

0 - Food and live animals
1 - Beverages and tobacco
2 - Crude materials, inedible, except fuels
3 - Mineral fuels, lubricants and related materials
4 - Animal and vegetable oils, fats and waxes
5 - Chemicals and related products, n.e.s.
6 - Manufactured goods classified chiefly by material
7 - Machinery and transport equipment
8 - Miscellaneous manufactured articles
9 - Commodities and transactions not classified elsewhere in the SITC

For the purpose of the research of aggregated databases, the categories 0 to 9 are aggregated and investigated for their quality and usability for transport research. In chapter seven this database is further explored for the purpose of making container transport inferences.

The category extra trade is a result of the subtraction of intra trade from total trade. The databases hence include the aggregation of total imports and exports and total intra imports and exports. The specific interest in extra trade is firstly due to its relevance for maritime transport and secondly as an auxiliary database for the maritime translation.

### 4.3.1 Total trade: A Graphical exploration

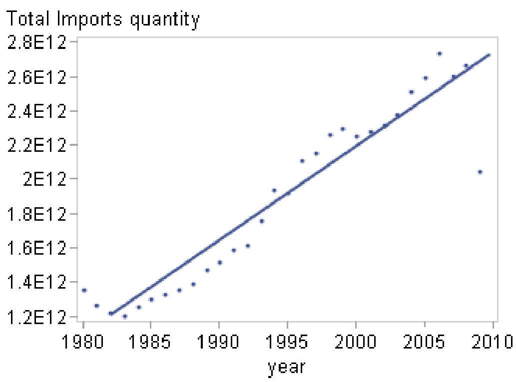
The series for total trade are plotted in a scatter plot with a fitted linear curve and in a line plot, illustrated in graph 4.8.

The main observation from graph 4.8 is that total imports demonstrate a trend of continuous growth. The trend follows a non linear pattern although the linear trend in this case too fits the data reasonably well, given the fact that economic cycles are not incorporated in the analysis and the core interest lies in the trend pattern.

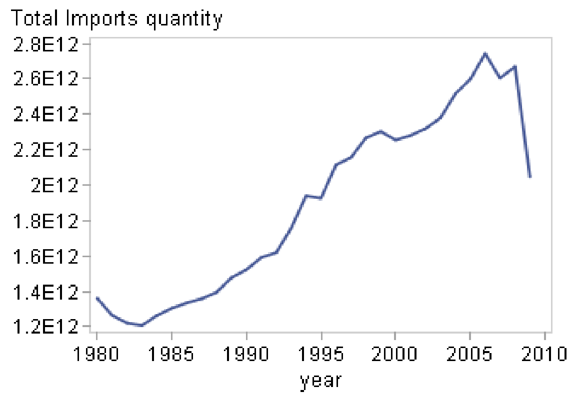
As in the case of category six there is a visible crisis effect in the year 2009 which is however less pronounced than what was observed for category six. This is not unexpected since the different sectors being hit by the crisis must have experienced different degrees of decline, resulting in an overall leveling off of the aggregate decrease of volume.

4.8: Total trade – Aggregated Imports (kg)

**a) Scatter plot with Linear Trend**



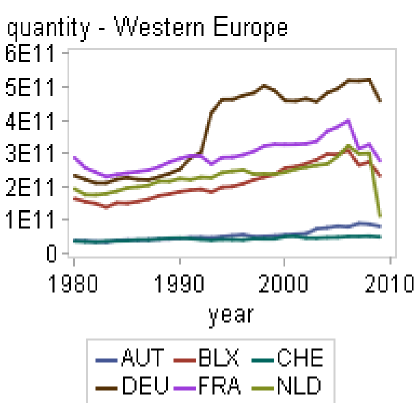

**b) Line plot**

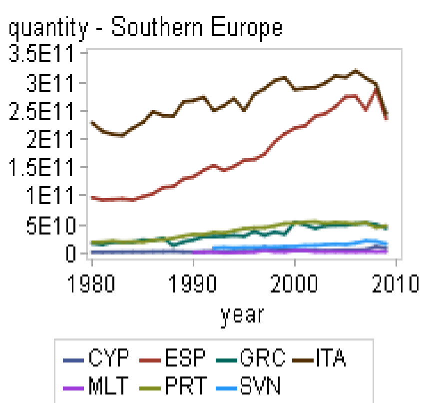


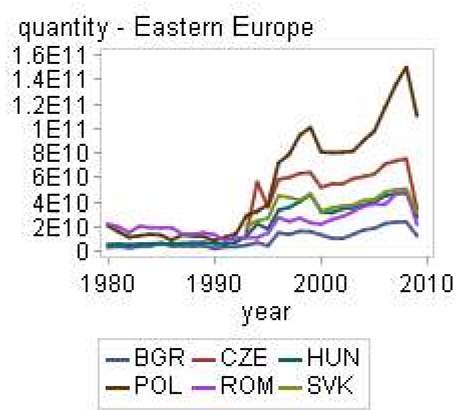

Source: own calculations based on UNCOMTRADE data

The observations on the aggregated plots are further explored and checked for their validity per geographic group in graph 4.9.

4.9: Total trade – Imports per geographic group (kg)




Source: own calculations based on UNCOMTRADE data

What is observed is that the growth patterns vary both between and within the geographic groups. The latter is further illustrated by plotting the data individually per country where both volume and growth rate vary between the countries. In particular a more pronounced growth pattern is visible for the group of HE, while groups HW and HS show signs of a plateau growth pattern. This however is further explored on a per country level for a clear visualization of the growth patterns.

As expected all plots show the effect of the financial crisis on the growth pattern, where steep declines are noted for all groups in the year 2009. For all groups the crisis is however less pronounced than for category six with the exception of the Netherlands.

For this reason has the data been checked by means of comparison with the database of Eurostat. The comparison was only possible on the level of values and it has been applied for NLD and BLX. The analysis showed that the databases were roughly equal with a slightly more pronounced decline reported by the UNCOMTRADE. Additionally within the latter database the decline in value and volume does not signal a disproportionate variation of one against the other which means that there is no justification for a database error as the reason for the steep decline observed for NLD.
An additional database was consulted, in particular the World Economic Outlook (WEO) of the IMF. The indicator chosen to draw inferences on data quality was the volume of import of goods for the sample countries. It is constructed as a percentual change of volume of imports of goods. It refers to the aggregate change in the quantities of imports of goods whose characteristics are unchanged. The goods and their prices are held constant and therefore changes are due to changes in quantities only (WEO, 2011). According to this table the percentual change for the NLD is -10 per cent which is a similar decrease as in the case of DEU and BLX. The data are reported in table 4.2.

Table 4.2: Crisis data quality check: Import volumes per country

| **Countries** | **Import volume of goods (Percent change)** | | **Estimates start after** |
|---|---|---|---|
| | **2009** | **2010** | |
| **AUT** | -15 | 10 | 2010 |
| **BGR** | -26 | -6 | 2010 |
| **BLX** | -10 | 10 | 2010 |
| **CHE** | -8 | 9 | 2010 |
| **CZE** | -15 | 19 | 2010 |
| **CYP** | n.a | n.a | 2010 |
| **DEU** | -10 | 13 | 2010 |
| **ESP** | -19 | 6 | 2010 |
| **FRA** | -11 | 8 | 2010 |
| **GRC** | -18 | -15 | 2010 |
| **HUN** | -14 | 11 | 2010 |
| **ITA** | -18 | 7 | 2009 |
| **NLD** | -10 | 12 | 2010 |
| **POL** | -12 | 10 | 2010 |
| **PRT** | -14 | -5 | 2010 |

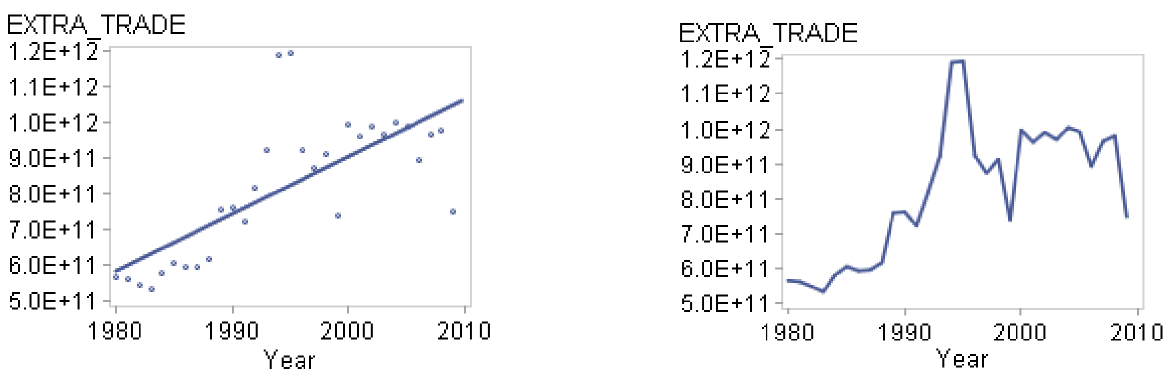
Source: IMF /WEO, 2011

Bearing in mind the above findings and the technical solutions to resolve such an issue for estimations the final decisions on how to treat the data for 2009 are tackled within chapters five and six. Regardless, what is a necessity is that the data sourced by the UNCOMTRADE should be revised when an update will become available.

### 4.3.2 Extra trade: A Graphical exploration

The growth pattern of extra trade is plotted in graph 4.10. A first observation from the graph with the fitted linear curve is the presence of a positive growth pattern. Nevertheless, when observing the plot without the fitted line, there are signs of irregularities. In particular what figure 4.10 shows is that extra trade grew exponentially until the year 1995. In the years 1996 and 1998 however sharp declines occurred and from the year 2000 onwards a plateau growth pattern prevailed until 2008. The year 2009 illustrates the effect of the crisis where as in all cases a sharp decline is reported.

Graph 4.10: Extra trade – Aggregated (kg)



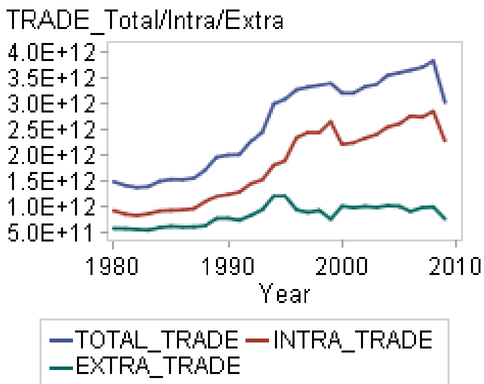

Source: own calculations based on UNCOMTRADE data

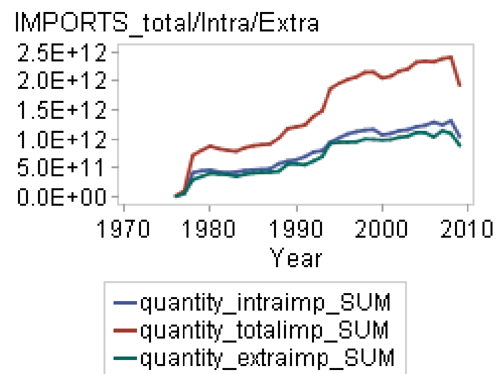
Given the volatility of the growth pattern an evaluation of the quality of the data is crucial. The quality of the data for extra trade can be found in Annex IV. The message from the latter investigation is that while the coverage as in all previous cases is judged as satisfactory there were problems identified in the intra exports database where intra exports exceed total exports from the year 1995 onwards. It is for this reason that the database for extra trade is not pursued further for the modeling exercise of the growth patterns and the forecasting.

### 4.3.3 Aggregated core data: Providing perspective

The perspective for the aggregated datasets is given in figure 4.12 where total, intra and extra trade are plotted together in a single graph.

Figure 4.12: Total, Intra & Extra Trade - Aggregated (kg)




Source: own calculations based on UNCOMTRADE data

In this case exports and imports are aggregated. What is shown is that the majority of the trade volume of the selected European countries takes place within Europe which matches the statistics for trade in values as illustrated by Eurostat (Eurostat, 2009; Eurostat, 2011). In the case of imports Intra and Extra trade each roughly represent half of total imports.

## 4.4 Discussion on disaggregated and aggregated trade data in freight transport research

The main concluding remark resulting from this investigation is that the complete category of manufactures is a category which is quite heterogeneous and hence generalizing conclusions on the basis of total observed trends although useful, does not add much to the understanding of growth patterns. As such the approach followed in this paper addresses the need to look into the patterns per product category with the objective of providing more reliable information on growth patterns and their variability. Furthermore, the category of manufactured goods classified chiefly by material, has proven to be a category worth exploring on a freight and maritime context. Such finding is reflected in part of the data mining output summarized in table 4.3 where key indicators are listed.

Table 4.3: Disaggregated trade output for transport

| Year | Cat_6 tons Imports | Cat_6 Total Imports in total manufactured goods | Cat_6 Total Imports In total imports | Cat_6 Extra Imports in total Category 6 | Cat_6 import Growth from China |
|---|---|---|---|---|---|
| | | % contribution | | | |
| 1980 | 118713950 | 61.17% | 8.72% | 7.21% | - |
| 1981 | 110539992 | 60.01% | 8.74% | 5.85% | 13.20% |
| 1982 | 108531063 | 59.23% | 8.89% | 6.32% | 12.16% |
| 1983 | 114055343 | 58.28% | 9.45% | 6.66% | 6.00% |
| 1984 | 121529511 | 58.49% | 9.62% | 6.16% | 2.39% |
| 1985 | 123760574 | 56.98% | 9.49% | 6.63% | -1.51% |
| 1986 | 130829452 | 57.91% | 9.81% | 7.37% | 28.08% |
| 1987 | 138682486 | 57.04% | 10.21% | 6.93% | 31.27% |
| 1988 | 161702252 | 58.68% | 11.60% | 9.70% | 20.94% |
| 1989 | 185778446 | 60.79% | 12.58% | 11.12% | 12.68% |
| 1990 | 197813280 | 60.77% | 13.00% | 11.56% | 25.89% |
| 1991 | 185459729 | 59.50% | 11.66% | 8.89% | 22.51% |
| 1992 | 198870204 | 60.19% | 12.29% | 9.54% | 7.50% |
| 1993 | 205677646 | 59.94% | 11.70% | 6.77% | 11.67% |
| 1994 | 261172334 | 61.34% | 13.47% | 0.93% | 30.96% |
| 1995 | 310397054 | 66.50% | 16.12% | 7.26% | 39.74% |
| 1996 | 355513215 | 63.69% | 16.82% | 9.64% | -5.39% |
| 1997 | 473537956 | 69.30% | 21.97% | 9.97% | 12.56% |
| 1998 | 321763959 | 61.90% | 14.20% | 12.77% | 39.60% |
| 1999 | 346187043 | 63.33% | 15.03% | 15.01% | 13.77% |
| 2000 | 315156711 | 67.93% | 13.98% | 16.49% | 14.62% |
| 2001 | 317802446 | 70.22% | 13.94% | 16.16% | 0.14% |
| 2002 | 324205099 | 69.06% | 13.98% | 17.89% | 18.49% |
| 2003 | 321870335 | 68.67% | 13.53% | 16.10% | 30.04% |
| 2004 | 356142161 | 70.82% | 14.16% | 17.37% | 38.75% |
| 2005 | 353315498 | 71.58% | 13.60% | 19.28% | 67.06% |
| 2006 | 394624112 | 72.68% | 14.39% | 22.95% | 79.10% |
| 2007 | 422046960 | 72.90% | 16.21% | 22.72% | 53.73% |
| 2008 | 399027507 | 71.96% | 14.94% | 18.71% | -23.49% |

Source: own calculations based on UNCOMTRADE data

What table 4.3 shows is that category six deserves further attention due to i) the sheer volumes category six represents within the total manufacturing goods sector, ii) the large intra trade volumes, iii) the growing importance of China and iv) the composition of the category.

Category six is a category of high volumes in particular representing more than 50% of the total volumes of manufactures. The analysis on the partner level showed that the majority of those volumes are represented by intra trade. On the other hand the volumes of category 6 imported by China although very small in volume as compared to intra trade volumes they show a clear exponential growth until the year of the crisis in 2009.

In all cases investigated within the core and secondary data the setback of the year 2009 is striking although no evidence has been found for the classification of the observations as outliers. Explanation for such a pattern can be explained by the freezing of orders of manufacturing companies in Europe for the entire year. This is however a hypothesis which would require further investigation on the micro scale. As such it goes beyond the scope of this research.

Regarding the composition of category six, it includes items like fashion items which have demonstrated alternative trends in their supply chain characteristics. As such however, current trends of shorter lead time and vicinity to the final demand still represent a niche. In cases however where such products are exclusively imported by specific partners such trends are important. Such conclusions can however only be drawn after an investigation on a partner level.

The discussion on the use of the data mining output of disaggregated data for transportation research in terms of freight is multi-dimensional, varying according to the final user. From a maritime stakeholders' point of view it is less appealing -in terms of product- given the sector's interest in aggregated trends, while being more relevant -in terms of direction- for the purpose of future market analyses. From a land freight transport point of view the disaggregated databases relevance to the sector also results from future market growth analyses. In such applications corridors within Europe in terms of country groups (Western countries, Southern countries, Eastern countries) and in terms of specific products on the desired level of disaggregation depending on the level of transport company specialization are possible.

Lastly, the disaggregated approach available through trade databases provides the opportunity to classify products according to their transport characteristics and particularly their degree of containerization. Despite the fact that the sheer number of product categories and the inherent difficulties in performing such a task are high it nevertheless adds value to future transport research. The extent to which the disaggregated trade approach could provide good estimates of containerized trade is investigated further in chapter seven.

Aggregated data are typically smoother, less prone to sharp fluctuations, then disaggregated data. Problems arise in the presence of outliers since their identification becomes a much more complicated and tedious task. The loss of information accuracy, depth in the understanding of growth patterns is compensated by the ease in providing a first rough impression of the aggregated growth patterns.

Such information is easily understood and utilizable by those transport stakeholders who are not interested in the level of product - trade content - and could not significantly benefit from such type of information. While the level of product is most practical in its aggregated form the level of partner - trade direction - which applies to transport corridors, is additionally useful in its disaggregated form. Transport stakeholders requiring such level of analysis could for example be either one of the European port authorities or liner shipping companies. The situation however is different for land transport stakeholders among which the level of specialization can vary significantly. For example small/medium trucking companies tend to be more focused on specific market segments while this is not necessarily the case for freight forwarders or big trucking companies.

Furthermore total trade in terms of either imports or exports accounted for separately or aggregated is more suitable for the making of econometric estimations. This is particularly true in cases where indicators are used in multivariate analyses since they are much easier to source and are typically indicators which are not split per sector but are kept aggregated. Lastly, although total trade can be directly applicable to transport research by means of weight - in either kilograms or tons - it is the tendency of containerization which needs to be addressed in order for total trade to become more utilizable in a transportation context. The extent to which the aggregated trade approach could provide good estimates of containerized trade is investigated further in chapter seven.

From the perspective of a policy maker, aggregated trends are important and are usually coupled with the disaggregated view point. The link with policy makers is either direct or indirect. A direct application is demonstrated by the interaction between the policy maker and the transport industry in the case for example of public funds being used for port investment plans. Indirect applications extend to other policy dimensions beyond transport which link to either trade or trade and transport. This discussion extends to the spillovers between policies for which transport is a good example. This is further discussed in chapter nine.

# 5. Linear and non linear growth models using mixed modeling: An application on European Import volumes

The purpose of chapter five is the identification of appropriate growth models for trade volumes as a policy tool. It represents the complete work of the working paper of Markianidou and Weeren (2011). The methodology is based on linear and nonlinear mixed modeling. The specifications tested are the linear, the exponential, the logarithmic and the logistic model. The focus lies on the imports of Europe from the world. Two pilot cases are presented corresponding to different levels of aggregation in terms of country groups and product categories, thus emphasizing the differences between aggregate and disaggregate approaches. The implications of each specification on policy decision making is consequently discussed and a recommendation on the use of such models for policy making is made. The growth models are further employed for the purpose of trend extrapolation, to initiate a discussion on the role and responsibility of transport policies implemented today based on alternative future scenarios 20 years ahead.

The structure of the chapter is as follows. Chapter 5.1 introduces the application. The appropriateness of the mixed procedure for this research is explained in chapter 5.2. Chapter 5.3 contains a description of the growth specifications, coupled with a special note on the discussion concerning stochastic trends and economic cycles. This chapter is complemented by the growth specification's appliance in the mixed context in chapter 5.4. Chapter 5.5 explains the decisions made in selecting the pilot cases which are interpreted in a transport context. The empirical results of the pilot cases are described in chapter 5.6. Chapter 5.7 contains the expectation based projections and chapter 5.8 a summary of findings. The chapter ends with a discussion on the usefulness of the results for transport policy making in chapter 5.9 and the concluding remarks in chapter 5.10.

## 5.1 Introduction

The objective of this chapter is the identification of appropriate growth models of volume flows in order to draw inferences for freight transport policy making. The methodology utilized is based on linear and non linear mixed modeling and the specifications tested are the linear, the exponential, the logarithmic and the logistic model. An investigation is hence made regarding which growth function best describes the observed growth patterns. The assumptions made are that trade and freight flows are subject to variability due to country specific effects while growth patterns vary per product category. Additionally, external effects occurring on a global scale and in particular on the short to medium term disrupt those trends unequally between countries and product categories.

The application in this chapter follows a different approach from either the strictly structural, time series techniques or gravity models. The innovative element is the use of mixed models for countries and the application of nonlinear specifications for modeling trade volumes. In particular longitudinal data are used and both linear and nonlinear trend models of several growth specifications are applied, namely the linear, exponential, logarithmic and logistic model, estimated in a mixed model setting.

The mixed approach in particular is to be preferred because of its ability to realistically capture the variability observed in the cross section units, by in particular allowing the modeling of random effects. The cross section variability is represented by the trading profiles of European countries, in terms of trade volume and growth rate. Product variability on the other hand is addressed by applications of different growth specifications for different levels of product aggregation.

Mixed modeling applications are usually concentrated in the fields of the medical, biological and social sciences. In particular a lot is found on issues within the field of psychology and mobility patterns. In the broader literature, these types of models are often quoted under different names like hierarchical or multi-level models. Under the latter name the amount of applications is bigger but the spectrum is not necessarily broader. A large part of the literature on mixed modeling focuses on the theoretical background and software advancements. Specifically on longitudinal data analysis, which fits the type of input of this chapter, Diggle et al (2002), Verbeke and Molenberghs (2000), Singer and Willet (2003) are standard references in the field. Concerning the theory of nonlinear mixed models, Pinheiro and Bates (1990, 1995) are typically quoted. The field of nonlinear mixed models is less mature and hence there are only a limited amount of applications.

The growth models are further utilized for trade volume forecasting. By applying the trend models of the different specifications, the intention is to reflect considerations regarding the final user. The reason is that the final user, in this case transport decision makers (transport agents or policy makers), are mostly driven by expectation. Such practice, emphasizing on the final user rather than the data or the model, can be compared to the statements made by international organizations in their applications of structural modeling, in which expert opinion is used for the forecasting exercises. The OECD's INTERLINK or the IMF's GEM or the European commission's QUEST models are examples where expert opinion is used. In this sense the different growth models each in their own right reflect a different expectation and somehow substitute the use of experts in adjusting forecasting output.

## 5.2 Mixed models

The general form of the mixed model is given in figure 5.1. What it defines is that y is the vector of responses, X is the design matrix for the fixed effects, β is the vector of fixed-effects parameters, Z is the design matrix for the random effects, γ is the vector of random effects and ε is the vector of unobservable residual errors. The matrices denoted as G and R are covariance matrices.

Figure 5.1: Linear/Nonlinear Mixed model assumptions

| | |
|---|---|
| $y = X\beta + Z\gamma + \varepsilon$ | 1. Normally distributed. random effects |
| | 2. Normally distributed residual errors* |
| $\gamma \sim N(0,G)$ | 3. Independently distributed residual errors of random effects. |
| $\varepsilon \sim N(0,R)$ | 4. Linear conditional mean of the data in the fixed effects |
| | 5. Linear conditional mean of the data the random effects |
| $Cov[\gamma,\varepsilon] = 0$ | 6. Linear marginal mean of the data in the fixed-effects parameters. |

In other words, β represents parameters that are the same for all subjects and γ represents parameters that are allowed to vary over subjects. The assumptions which need to be satisfied by a linear mixed model involve the normality of both random effects γ and residuals ε with mean and variance expressed in matrix form in the following way:

$$E\begin{bmatrix}\gamma\\ \varepsilon\end{bmatrix} = \begin{bmatrix}0\\ 0\end{bmatrix} \qquad Var\begin{bmatrix}\gamma\\ \varepsilon\end{bmatrix} = \begin{bmatrix}G & 0\\ 0 & R\end{bmatrix}$$

The justification for the mixed model choice is a consequence of the data itself where: a) yearly measurements of trade on each country included in the sample are correlated and b) the geographic groups demonstrate variation between the countries in the same geographic group and between geographic groups. The variability between the countries is conformed by graphical analysis of the data and more formally through initial separate estimations of the different specifications (linear, logarithmic, exponential, logistic) per country. For this purpose, the models are estimated without random variables which results show clear variability in the parameters between the countries. Additionally a null model test where all effects are fixed against the model being estimated with mixed effects is performed. The discussion however on whether the fixed instead of the mixed model is more appropriate is quite complex and no clear cut answers are found in the literature.

According to Verbeek (2008) the fixed model is intuitively chosen when the individuals in the sample are one of a kind which is the case of countries as in the current study. However fixed effects methods completely ignore the between-country variation and focus only on the within-country variation. Discarding the former can yield standard errors that are considerably higher than those produced by methods that utilize both within- and between-item variation. On the other hand the between country variation may be contaminated by other unmeasured country characteristics which are correlated with the volume of trade. This results in biased estimates. Another practical difficulty is that with a large number of levels in a fixed effects model, like countries in this study, this leads to a huge overhead of parameters, especially since interactions need to be included in the model. Doing so wastes a lot of degrees of freedom.

Another reason is that one wants the overall model to be valid irrespective of which countries happen to be included in the study. Bearing the limitations of both approaches in mind and considering the objective of the trend modeling which includes the making of projections the approach for choosing the most suitable model is by means of econometric testing, graphical fit and model comparisons. The comparisons considered are the following:

- Compare the models split in geographic groups (model HW, model HS, model HE) with the model with the geographic groups estimated together (model HWHSHE);
- Compare the disaggregated model HWHSHE of cat 6 (HWHSHE_cat6) with the aggregated model HWHSHE of total trade (HWHSHE_TOTAL);
- Compare covariance structures autoregressive (AR(1)) and unstructured (UN);
- Compare the mixed models with the models with only fixed effects;
- Compare model quality in terms of residuals analysis;
- Compare models when the dataset changes due to the different sources10 ;
- Compare the different growth specifications for the HWHSHE models.

The anticipation from such an extensive quality control is that appropriate growth models are constructed which reflect true patterns and variability between the European countries and can therefore be used as policy tools which produce high quality trend forecasts.

## 5.3 Growth specifications

The different specifications include the linear, exponential, logarithmic and logistic functions which correspond to different growth expectations. The conceptual background for each growth model is described below:

- A linear growth is order 0 and characterizes a quantity which grows by the same amount in each time step;
- An exponential growth is order 1 and characterizes a quantity which increases at a fixed rate proportionally to itself;
- A logarithmic growth is not supported by any growth theory. It characterizes a quantity whose growth can be described as a logarithm function of some input. It is the inverse of the exponential growth and is very slow;

[10] The problem was identified when comparing databases sourced from the uncomtrade directly or from the World Integrated Trade Solution (WITS) or when sourcing data based on different flow direction i.e. imports of countries as reporters from the world and exports of the world to countries as partners.

- A logistic growth is order 2, characterizes a quantity whose initial stage of growth is approximately exponential and as saturation begins, the growth slows, and at maturity, growth stops.

The reason why these four cases are chosen is firstly due to what is observed by plotting the data. Furthermore and most importantly, because these model specifications are interpretable in economic terms which can thus also be used for the making of projections. The consideration of alternative specifications like for example a cubic polynomial would yield more flexible, fitting the data reasonably well, but would lead to nonsensical projections. The reason is that polynomial models, especially of higher order, behave really badly in an extrapolation setting, and hence cannot be used in a trend fitting application.

By fitting a dataset to a particular mathematical specification one opts to explain and understand the historic pattern on the basis of the mathematical properties inherent to the equations themselves. The choice of which model to use from this broad pallet of models is subject to the expectations of the decision maker. The fact that the linear growth pattern is very popular is because of its computational simplicity and because during times of growth it has given good estimates of future outcomes, provided the considered horizon is not that long. This is also true for the logarithmic growth which provides for more moderate estimates of future growth. In the case of the exponential growth, it is typically observed in the initial stage of growth. It is an extreme form of unbounded growth and hence it is of no use for the purpose of long term projections. Nevertheless, it's worth mentioning that given the impressive growth patterns experienced for example by the BRIC countries, projections of their growth using the exponential model in the past would have proven to be very reliable on the short term.

With the unbounded growth being the major disadvantage of all previous mentioned growth models, further considerations on other nonlinear specifications led to the consideration of fitting a logistic growth specification. The latter is a sigmoid curve described by an initial stage of growth which initially behaves almost exponential and as saturation begins, the growth slows, and at maturity, growth stops. As such this model is very well suited and regularly used for the description of growth of physical phenomena. Its most well-known applications is in explaining population growth. It is not difficult to show that the option of a logistic type of growth derives from the law of diminishing marginal utility. Metz (2010) describes apparent patterns of saturation in terms of passenger travel (daily travel demand) and discusses the possibility of saturation patterns in freight.

The analysis is based on a large database of the National Travel Survey in 2009 where he observes the presence of a plateau type of growth. Concerning freight the main argumentations used explaining saturation are amongst others: diminishing marginal utility, a mix of elements in terms of population growth, scale of sourcing from abroad, the composition of consumer goods and the high level of ownership of durables in the developed world.

More specifically, freight growth maturity is primarily discussed by McKinnon (2007) and Osenton (2004) who argue that the process of road freight driven by the concentration of economic activity cannot continue indefinitely, while pointing out that the possibility of saturation of demand for consumer durables needs to be recognized. Therefore unbounded growth models are less suitable.

A parallel discussion among economists, relevant to the discussion of saturation but within a different stream of research, relates to what constrains economic growth. This research field highlights factors like diminishing returns to capital in production, Research and Development (R&D) technology and saturation of demand. As such technical progress and the addition of new products and industries have been discussed as necessary factors sustaining economic growth (Masanao, 2001; Grossman and Helpman, 1991). Hence, one could argue that while saturation may come to play due to diminishing marginal utilities for existing products, new products can stimulate further growth. In the absence however of new products saturation may occur. In the database used in this research however one cannot distinguish between existing and new products since the latter fall under the same headings of existing products. Furthermore it is very complex to define what represents to the consumer a "new" product. It is hence unclear whether saturation patterns will be observed in the investigation.

A point of attention in this approach is the discussion on trends versus economic cycles. In this approach the growth models are tested for their fit to the import volume data of a panel of European countries. The models are then used for trend extrapolations and no consideration of business cycles is taken into account. An important discussion between macroeconomists since the 1970's has been the distinction between trends and cycles of economic activity. This discussion is prominent to this analysis given its impact on the future projections. The argument used to be that trends and cycles in economic activity are investigated as distinct economic phenomena and should be explained with different models or at a minimum, with different impulses or sources of shocks. Departures from this traditional approach integrate the study of trends and cycles.

The latter studies investigate the extent to which economic cycle fluctuations are understood as the result of one or more common unobserved stochastic trends. Shifts hence occur as a result of shocks to the stochastic trends (King, Plosser, Stock and Watson, 1987). This discussion largely continues in extensions from the univariate to the multivariate setting with a discussion on the cointegration concept and the presence of common stochastic trends.

What is important to note is that in this research when for example the logistic growth model is fitted and used for trend extrapolations no consideration of the integration of the trend with economic cycles is made. The fact that a long term trend might incorporate a logistic growth cycle is hence not being considered. This limitation in the current study constitutes a reason why it is considered important to simultaneously use all growth models for the purpose of forecasting.

## 5.4 Growth models in a mixed context

The aforementioned individual growth models to be used in the modeling application are explained in a mixed context. For each model, two cases are considered. The first estimation is made with a single random effect - the intercept - and the second estimation with two random effects - the intercept and the slope -. In the case of the exponential and the logistic growth models the estimations without random variables show that all three parameters – in the case of the exponential being the intercept, the natural parameter space and the initial slope and in the case of the logistic being the intercept, slope and point of inflection - should be classified as random effects. However, for reasons of cross model comparisons, resulting computational load and attribution of clear economic interpretation to the parameters it is decided against estimating the logistic model with three random variables.

The specifications are listed in Table 5.1. They include for each growth model the specification with one random (intercept) and two random (intercept and slope) variables. In all equations (1) until (8) $b_0$ $b_1$, $b_2$ are the fixed effect parameters, $ui_1$ , $ui_2$ are the random effect parameter assumed to be independent and identically distributed $N(0,\sigma^2 u)$ and eij are the residual errors assumed to be independent and identically distributed $N(0,\sigma^2 e)$.

Table 5.1: Mixed Model Specifications

| | | |
|---|---|---|
| Linear one random | $y_{it} = (b_0 + u_{i1}) + b_1 \cdot t + e_{it}$ | (1) |
| Linear two random | $y_{it} = (b_0 + u_{i1}) + (b_1 + u_{i2}) \cdot t + e_{it}$ | (2) |
| Logarithmic one random | $y_{it} = (b_0 + u_{i1}) + b_1 \cdot \log t + e_{it}$ | (3) |
| Logarithmic two random | $y_{it} = (b_0 + u_{i1}) + (b_1 + u_{i2}) \cdot \log t + e_{it}$ | (4) |
| Exponential one random | $y_{it} = (b_0 + u_{i1}) + b_1 \cdot \exp b_2 \cdot t + e_{it}$ | (5) |
| Exponential two random | $y_{it} = (b_0 + u_{i1}) + b_1 \cdot \exp((b_2 + u_{i2}) \cdot t) + e_{it}$ | (6) |
| Logistic one random | $y_{it} = \dfrac{(b_0 + u_{i1})}{1 + \exp\left(-\dfrac{(t - b_1)}{b_2}\right)} + e_{it}$ | (7) |
| Logistic two random | $y_{it} = \dfrac{(b_0 + u_{i1})}{1 + \exp\left(-\dfrac{(t - b_1)}{b_2 + u_{i2}}\right)} + e_{it}$ | (8) |

Where,

y : volume of imports in kg
i : country
t : year
$b_0$, $b_1$ : fixed effects
$ui_1$, $ui_2$ : random effects
$e_{it}$ : residual errors

In the linear equation (1) the trajectory for the import volume is a function of the intercept b0 - the import volume at year 1980 - which is a random variable ui1 and the slope b1 - the growth rate- while in the linear equation (2) the second random effect added is the slope represented by ui2, The same symbolism and logic applies to the logarithmic models in equations (5) and (6) with the difference that the import volume is described as a logarithm function of time. It is the inverse of the exponential growth and is very slow. In the case of the exponential equations (3) and (4) a parameterization is used which has no clear economic interpretation in terms of its b1 and b2. The parameter b0 represents the initial volume of imports. In the logistic equation (7) The specification of the one random effect mixed logistic growth model is borrowed from Pinheiro and Bates (1995) where the import volume is a function of the intercept b0 which is a random variable ui1 the slope b1 and inflection point b2. The two random effects specification in the equation (8) is borrowed from Litell et al (2006) with the difference that the second random effect ui2 is added for the slope instead of the point of inflection.

The specifications in Table 5.1 are re-estimated to account for the crisis year through the addition of dummy variables for the year 2009 (b4). In each model the dummy takes the values 0 or 1 to indicate the presence of the crisis. This approach addresses the sharp declines observed during the crisis year. In this chapter the estimations with and without the dummy variable are described.

The non linear specifications in particular, require an additional step, the setting of initial values. The way this is done is described in box 1 and box 2 in Annex I which describe the process for the models of exponential and logistic growth respectively.

## 5.5 Pilot cases and Data

The pilot cases consider different levels of aggregation in terms of product composition. The justification for using disaggregated data on the product level is that valuable information is lost due to the aggregation of product categories. This is explained in detail in chapter three.

The chosen pilot concerning the disaggregated analysis is category six, which is 81% composed of processed industrial supplies, titled “manufactured goods chiefly categorized by material” (see annex 1).

It belongs to the broader category of manufactured goods completed by category five “Chemicals and related products”, seven “Machinery and transport equipment” and eight “Miscellaneous manufactured articles”. In particular categories eight and the pilot case comprise of the category of “other manufactured goods”. The reason why it is chosen as a pilot is because it belongs to the category of manufactures, which is a sector largely relocated from Europe to countries with lower labor costs. Interestingly, category six remains a category which is still produced within Europe and hence included in the intra European trade datasets. At the same time - given structural tendencies of relocation of industries in the manufacturing sector in Europe (Rowthorn and Ramaswamy, 1997) - it is seen as representing potential volumes which due to the structural tendencies could ultimately be transported from overseas and hence become relevant to the maritime sector. An example is the imports of category six from China which currently in terms of volumes are less important when compared to intra trade volumes but the exponential growth pattern (see chapter four) shows potential for further growth.

Typically, analyses on trade utilize data in values which are widely available in extensive detail from a number of sources. For this analysis however to make sense for the transport sector the data unit desired is the one of volume. Such data are however scarce and not directly attainable on all levels of product disaggregation. The database utilized in this chapter is the result of an extensive data mining exercise performed on the digit 3 level SITC classification from the UNCOMTRADE. All data are checked for their coverage and quality thoroughly and are found suitable for their subsequent use for modeling.

An exception is the data for the year 2009 where sharp declines are observed. The declines are so severe that question-marks are raised on the reliability of the data. This is particularly the case of imports for goods of category six. It is for this reason that the data for that year have been double checked and alternative sources have been consulted in order to somehow validate the accuracy of the data. Given the lack of strong evidence against the data of the UNCOMTRADE (and the data compilation/mining performed by the author) the data are kept as originally sourced. The intention is to recheck the data of 2009 for any updates after the release of the data for 2010.

The only exception to the above is the case of the NLD which according to the World Economic Outlook (WEO) of the IMF it did not experience sharper declines than the other countries of Western Europe (see table 4.2 in chapter 4). The indicator chosen to draw inferences on data quality is the volume of import of goods for the sample countries. Given however the additional proof from that same database of an almost complete recovery the final decision taken is to keep the original data and estimate the models with the dummy for 2009 and a full recovery in 2010 for the forecasts.

In particular the estimations of the disaggregated and aggregated database include the total of 19 countries, listed in Table 5.2.

Table 5.2: Country levels

| Class Level Information | | |
|---|---|---|
| Class | Levels | Values |
| Partner | 19 | AUT BGR BLX CHE CYP CZE DEU ESP FRA GRC HUN ITA MLT NLD POL PRT ROM SVK SVN |

The results reported in this document only include estimations without missing values. However, it should be noted that not all countries have complete time series from the 1980's until 2009. For this reason, applications are made twice, the first time with the complete sample of countries and the second including only those countries with complete datasets. The procedure used (proc mixed of SAS) does not delete an entire subject when a single observation is missing and it analyzes all of the data that are present. However, while the proc mixed procedure can accommodate missing values, (which is confirmed in the current application by comparing the estimation results between the two datasets, complete and reduced) the preferred approach in this research is to present the results incorporating only the models estimated without any missing values. The total number of observations hence amounts to 464.

In the case where the geographic groups are estimated separately the countries with missing values are included but with a reduced time scale in order to estimate the models without missing values. In particular the latter case corresponds to the geographic group of the Eastern European countries for which the sample includes observations from 1996 until 2009. The main reason for excluding the countries with missing values (when estimating all countries in a single dataset) in the first case and reducing the sample size in the second case (when estimating countries per geographic group) is because the data are not missing at random which invalidates the analysis. This situation occurs when systematic factors lead to missing data. In this case the missing observations for the countries SVN, SVK, CZE, between 1980 and 1996 relate to the political conditions of that time which endured until the year 1990. The final assessment therefore is that the data are not missing at random and it is therefore best to exclude them from the analysis. The data are sourced for the European countries listed in Table 5.3.

Table 5.3: Country groups

| Flow | Groups | Countries |
|---|---|---|
| Partner/ Reporter | HW | AUT BLX CHE DEU FRA NLD |
| | HS | CYP ESP GRC ITA MLT PRT |
| | HE | BGR CSK HUN POL ROM SVN |

The criterion for creating the country groups is based on geographical considerations as defined by the United Nations classification. HW includes Western European countries while HS and HE Southern and Eastern countries respectively. Sample countries from Northern Europe are not included given the extreme diversity between the countries in their patterns of trade. The geographic division thus made less sense and it is hence decided to exclude them entirely from the analysis.

## 5.6 Growth models in practice

This chapter presents the results of the modeling exercises for both the disaggregated and aggregated datasets and for both the geographic groups separately (HW, HS, HE) and all together in one dataset (HWHSHE) with the addition of examples of country results for BLX, DEU and NLD.

For all groups the data has for the facilitation of the convergence of the models (linear and non linear) been standardized. The “range” method of SAS is in particular used. This information should be taken into account when looking at the graphs’ axis.

The intention is to estimate the models using the same specifications across the different cases. However empirical results in some cases did not allow for exact replication due to mainly computation reasons of a non invertible Hessian Matrix or non convergence.

The starting point is that ideally all models should be specified with two random effects, the slope and intercept. This is instructed by the individual proc nlin applications which give an indication of the variability between the countries with respect to both intercept and slope.

Furthermore all models should be estimated with and without a dummy variable, hence with and without the year 2009. The estimations without the dummy are performed due to the extreme values observed for the year 2009. The estimations with the dummy are particularly useful for the making of forecasts. In particular the use of a dummy adds flexibility in defining the recovery observed in 2010 since data for that year are at this moment not yet available.

Finally, the preferred covariance structure is the AR(1). It is the first-order autoregressive correlation type of the error correlation structure. The AR(1) structure is deemed appropriate since it represents a structure which has homogeneous variances and correlations that decline exponentially with distance. It means that two measurements that are right next to each other in time are going to be correlated but that as measurements get farther and farther apart they are less correlated (Kincaid, 2005). The choice of the AR(1) structure is intuitive but is complemented by a trial and error approach, by testing with other error structures, in particular the unstructured one which is the most flexible of all.

However deviations from the idealized estimation choices described above are encountered due to the numerical issues described above. The specifics are listed below:

- In the case of the exponential models the estimations are performed without the dummy variable. The reason is the reduced number of countries included in the sample, which led to convergence issues;
- In the case of the linear model only the intercept is included as random. Although an initial exploratory study involving proc nlin indicates a possible random effect in the slope the singular Hessian is obtained. The fact that the algorithm encounters a singular Hessian can be caused by numerical reasons. The random effect for the slope is hence omitted;
- The AR(1) autoregressive covariance structure is always preferred and only when problems are encountered is the unstructured covariance structure (UN) chosen.

The output is described per level of aggregation and per model. For each model the estimation results with and without the dummy are reported. The output for each contains the mixed model output for either linear or non linear models as provided by the SAS software. All estimations are performed in levels and the error analysis is found in Annex VII.  In each group the candidate models are estimated, evaluated and compared with each other. The commentary within the text includes a) parameter significance of fixed and covariance parameter estimates, b) test result regarding the suitability of the mixed approach, c) comments on the error structure chosen, d) fit statistics comparisons and e) comparisons on the grounds of Mean Absolute and Mean Squared Error. The final choice on which model(s) best represent(s) the growth pattern is made according to the econometric properties of the models and considerations of model bias and robustness in chapter 5.8.

### 5.6.1 Disaggregated

The results of the disaggregated estimations are summarized in tables 5.4 until 5.7. The mixed model output is reported including the estimations for the fixed and random variables and the fit statistics.

In the linear applications according to tables 5.4 and 5.5 fixed and covariance parameter estimates for both the linear and logarithmic models are highly significant. The exponential trend is only fitted to the geographic groups HS and HE although only the latter displays a clear exponential growth pattern. According to Table 5.6 the parameters for the HS and HE geographic groups of category six are significant. The results of the logistic estimation described in Table 5.7 also show that both fixed and random parameters are significant. The insignificant variance estimate does not have an interpretational interest to this chapter[11].

Concerning the suitability of the mixed approach (in the case of only the linear models), the covariance structure is significant based on the "null model likelihood ratio test" where the null model (one with only the fixed effects listed in the model) is rejected. In other words the linear and logarithmic models including random effects are superior to the models with only the fixed effects.

In all cases, models with the sample countries in a single dataset are the best performing models compared to the models estimated for the geographic groups separately. This is expected given the larger sample size of the former database and is also established through a comparison of fit statistics (See Annex VII). Among the linear models estimated the HE model produces the best fit from the geographic grouped models which is also the case for the logarithmic models. The best performer for the exponential and logistic models is the HS group. Such statistics are influenced by the number of observations and given that each group contained a different number of countries, results should be viewed with caution.

Finally a comparison of Mean Absolute Error (MAE) and Mean Squared Error (MSE) is performed with the aim of comparing the model specifications to each other. However, no model showed clear superiority with only very little differences between the calculated values.

[11] This is most likely due to numerical and algoritmic issues. Since this variance is estimated as one of the likelihood parameters this can sometimes happen. It however does not mean it is actually zero.

Table 5.4-a: Linear Growth - dummy: : $y_{it} = (\beta_0 + u_{i1}) + \beta_1 t + \beta_4 (year \quad 2009) + e_{it}$

$y_{it} = -7.2315 + 0.003679 \quad t - 0.1254 \quad (year \quad 2009)$

| LINEAR_HWHSHE_CAT6_ dummy | | | | | |
|---|---|---|---|---|---|
| Covariance Parameter Estimates | | | | | |
| Cov Parm | Subject | Estimate | Standard Error | Z Value | Pr > Z |
| Variance | Partner | 0.03184 | 0.01080 | 2.95 | 0.0016 |
| AR(1) | Partner | -0.9608 | 0.03975 | -24.17 | <.0001 |
| Residual | | 0.004072 | 0.000255 | 15.99 | <.0001 |
| Solution for Fixed Effects | | | | | |
| Effect | Estimate | Standard Error | DF | t Value | Pr>\|t\| |
| Intercept | -7.2315 | 0.6670 | 17 | -10.84 | <.0001 |
| Year | 0.003679 | 0.000334 | 503 | 11.02 | <.0001 |
| year2009 | -0.1254 | 0.04503 | 17 | -2.78 | 0.0127 |
| Fit Statistics | CAT6_ dummy | | | | |
| -2 Log Likelihood | -1041.3 | | | | |
| AIC (smaller is better) | -1029.3 | | | | |
| AICC (smaller is better) | -1029.1 | | | | |
| BIC (smaller is better) | -1024.6 | | | | |

Table 5.4-b: Linear Growth – no dummy $y_{it} = (\beta_0 + u_{i1}) + \beta_1 t + e_{it}$

$y_{it} = -16.4 + 0.008315 \quad t$

| LINEAR_HWHSHE_CAT6_no dummy | | | | | |
|---|---|---|---|---|---|
| Covariance Parameter Estimates | | | | | |
| Cov Parm | Subject | Estimate | Standard Error | Z Value | Pr > Z |
| UN(1,1) | Partner | 0.03556 | 0.01264 | 2.81 | 0.0025 |
| Residual | | 0.005583 | 0.000373 | 14.97 | <.0001 |
| Solution for Fixed Effects | | | | | |
| Effect | Estimate | Standard Error | DF | t Value | Pr > \|t\| |
| Intercept | -16.4060 | 0.8280 | 15 | -19.81 | <.0001 |
| Year | 0.008315 | 0.000415 | 447 | 20.06 | <.0001 |
| Fit Statistics | CAT6_ no _dummy | | | | |
| -2 Log Likelihood | -1006.9 | | | | |
| AIC (smaller is better) | -998.9 | | | | |
| AICC (smaller is better) | -998.8 | | | | |
| BIC (smaller is better) | -995.8 | | | | |

Table 5.5-a: Logarithmic growth - dummy: $y_{it} = (\beta_0 + u_{i1}) + (\beta_1 + u_{i2}) \log t + \beta_4 (year\ 2009) + e_{it}$

$$y_{it} = -0.1827 + 0.1262 \log t - 0.1831(year\ 2009)$$

| LOGARITHMIC_HWHSHE_CAT6_ dummy | | | | | |
|---|---|---|---|---|---|
| Covariance Parameter Estimates | | | | | |
| Cov Parm | Subject | Estimate | Standard Error | Z Value | Pr > Z |
| Variance | Partner | 0.01400 | 0.005018 | 2.79 | 0.0026 |
| AR(1) | Partner | -0.7822 | 0.1049 | -7.45 | <.0001 |
| Residual | | 0.003268 | 0.000220 | 14.88 | <.0001 |
| Solution for Fixed Effects | | | | | |
| Effect | Estimate | Standard Error | DF | t Value | Pr>\|t\| |
| Intercept | -0.1827 | 0.03294 | 15 | -5.55 | <.0001 |
| Lyear | 0.1262 | 0.03001 | 15 | 4.20 | 0.0008 |
| year2009 | -0.1831 | 0.01496 | 447 | -12.24 | <.0001 |
| Fit Statistics | CAT6_ dummy | | | | |
| -2 Log Likelihood | -1260.3 | | | | |
| AIC (smaller is better) | -1248.3 | | | | |
| AICC (smaller is better) | -1248.1 | | | | |
| BIC (smaller is better) | -1024.6 | | | | |

Table 5.5-b: Logarithmic growth – no dummy: $y_{it} = (\beta_0 + u_{i1}) + (\beta_1 + u_{i2}) \log t + e_{it}$

$$y_{it} = -0.1827 + 0.1262 \log t$$

| LOGARITHMIC_HWHSHE_CAT6_no dummy | | | | | |
|---|---|---|---|---|---|
| Covariance Parameter Estimates | | | | | |
| Cov Parm | Subject | Estimate | Standard Error | Z Value | Pr > Z |
| Variance | partner | 0.01952 | 0.006772 | 2.88 | 0.0020 |
| AR(1) | partner | -0.8314 | 0.08040 | -10.34 | <.0001 |
| Residual | | 0.002159 | 0.000148 | 14.63 | <.0001 |
| Solution for Fixed Effects | | | | | |
| Effect | Estimate | Standard Error | DF | t Value | Pr > \|t\| |
| Intercept | -0.1827 | 0.03686 | 15 | -4.96 | 0.0002 |
| Lyear | 0.1262 | 0.03516 | 15 | 3.59 | 0.0027 |
| Fit Statistics | CAT6_ no_dummy | | | | |
| -2 Log Likelihood | -1389.6 | | | | |
| AIC (smaller is better) | -1379.6 | | | | |
| AICC (smaller is better) | -1379.5 | | | | |
| BIC (smaller is better) | -1375.7 | | | | |

Table 5.6: Exponential growth – no dummy: $y_{it} = (\beta_0 + u_{i1}) + \beta_1 \exp(\beta_2 + u_{i2})t + e_{it}$

$y_{it} = -0.09636 + 0.07377 \exp(0.07429)t$

| Parameter Estimates HE_CAT6 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter | Estimate | Standard Error | DF | t Value | Pr > \|t\| | Alpha | Lower | Upper | Gradient |
| b1 | -0.09636 | 0.02747 | 3 | -3.51 | 0.0392 | 0.05 | -0.1838 | -0.00895 | -1.39E-6 |
| b2 | 0.07377 | 0.01783 | 3 | 4.14 | 0.0256 | 0.05 | 0.01703 | 0.1305 | -7.26E-6 |
| b3 | 0.07429 | 0.01162 | 3 | 6.40 | 0.0077 | 0.05 | 0.03733 | 0.1113 | -2.16E-6 |
| s2u1 | 0.000233 | 0.000344 | 3 | 0.68 | 0.5470 | 0.05 | -0.00086 | 0.001327 | 0.000018 |
| s2u2 | 0.000391 | 0.000257 | 3 | 1.52 | 0.2262 | 0.05 | -0.00043 | 0.001210 | -0.0003 |
| s2e | 0.004460 | 0.000542 | 3 | 8.22 | 0.0038 | 0.05 | 0.002733 | 0.006186 | 2.284E-6 |

$y_{it} = -0.4599 + 0.4854 \exp(0.01364)t$

| Parameter Estimates HS_CAT6 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| b1 | -0.4599 | 0.09649 | 5 | -4.77 | 0.0050 | 0.05 | -0.7079 | -0.2119 | 3.033E-9 |
| b2 | 0.4854 | 0.09182 | 5 | 5.29 | 0.0032 | 0.05 | 0.2494 | 0.7215 | -137E-12 |
| b3 | 0.01364 | 0.005730 | 5 | 2.38 | 0.0631 | 0.05 | -0.00109 | 0.02837 | -5.94E-9 |
| s2u1 | 0.002962 | 0.001645 | 5 | 1.80 | 0.1315 | 0.05 | -0.00127 | 0.007190 | 2.769E-6 |
| s2u2 | 0.000206 | 0.000120 | 5 | 1.71 | 0.1479 | 0.05 | -0.00010 | 0.000516 | 0.000058 |
| s2e | 0.000957 | 0.000098 | 5 | 9.72 | 0.0002 | 0.05 | 0.000704 | 0.001210 | 0.000019 |

| Fit Statistics | HE | HS |
|---|---|---|
| -2 Log Likelihood | -346.7 | -765.5 |
| AIC (smaller is better) | -334.7 | -753.5 |
| AICC (smaller is better) | -334.1 | -753.1 |
| *BIC (smaller is better)* | *-337.1* | *-753.9* |

Table 5.7-a: Logistic growth - dummy: $y_{it} = \dfrac{(\beta_0 + u_{i1})}{1+\exp-\left(\dfrac{(t-\beta_1-\beta_4 year2009)}{\beta_2+u_{i2}}\right)} + e_{it}$

$$y_{it} = \frac{0.4379}{1+\exp-\left(\dfrac{(t-1999.59-32.8568)}{10.2672}\right)}$$

| LOGISTIC_HWHSHE_CAT6_ dummy | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter Estimates | | | | | | | | | |
| Parameter | Estimate | Standard Error | DF | t Value | Pr > \|t\| | Alpha | Lower | Upper | Gradient |
| b1 | 0.4379 | 0.1157 | 14 | 3.78 | 0.0020 | 0.05 | 0.1897 | 0.6861 | 2.27E-10 |
| b2 | 1999.59 | 1.3577 | 14 | 1472.73 | <.0001 | 0.05 | 1996.68 | 2002.50 | 1.427E-9 |
| b3 | 10.2672 | 1.4780 | 14 | 6.95 | <.0001 | 0.05 | 7.0973 | 13.4372 | -72E-14 |
| b4 | 32.8568 | 2.1282 | 14 | 15.44 | <.0001 | 0.05 | 28.2923 | 37.4213 | 1.47E-11 |
| S2u1 | 0.2047 | 0.07449 | 14 | 2.75 | 0.0157 | 0.05 | 0.04493 | 0.3645 | 2.026E-9 |
| C12 | 22.6656 | 9.4274 | 14 | 2.40 | 0.0306 | 0.05 | 2.4459 | 42.8852 | -182E-12 |
| S2u2 | 1.1700 | 0.6712 | 14 | 1.74 | 0.1032 | 0.05 | -0.2695 | 2.6095 | 2.41E-10 |
| s2e | 0.001524 | 0.000102 | 14 | 14.98 | <.0001 | 0.05 | 0.001306 | 0.001742 | 7.753E-6 |
| Fit Statistics | CAT6_ dummy | | | | | | | | |
| -2 Log Likelihood | -1613 | | | | | | | | |
| AIC (smaller is better) | -1597 | | | | | | | | |
| AICC (smaller is better) | -1596 | | | | | | | | |
| BIC (smaller is better) | -1591 | | | | | | | | |

Table 5.7-b: Logistic growth – no dummy: $y_{it} = \dfrac{(\beta_0 + u_{i1})}{1+\exp-\left(\dfrac{(t-\beta_1)}{\beta_2+u_{i2}}\right)} + e_{it}$

$$y_{it} = \frac{0.4292}{1+\exp-\left(\dfrac{(t-1999.12)}{10.1786}\right)}$$

| LOGISTIC_HWHSHE_CAT6_no dummy | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter Estimates | | | | | | | | | |
| Parameter | Estimate | Standard Error | DF | t Value | Pr > \|t\| | Alpha | Lower | Upper | Gradient |
| b1 | 0.4292 | 0.1131 | 14 | 3.79 | 0.0020 | 0.05 | 0.1865 | 0.6718 | 1.738E-6 |
| b2 | 1999.12 | 1.1221 | 14 | 1781.60 | <.0001 | 0.05 | 1996.71 | 2001.52 | -0.00002 |
| b3 | 10.1747 | 1.5163 | 14 | 6.71 | <.0001 | 0.05 | 6.9226 | 13.4267 | -0.00003 |
| s2u1 | 0.1984 | 0.07146 | 14 | 2.78 | 0.0149 | 0.05 | 0.04512 | 0.3516 | -4.16E-6 |
| c12 | 1.1786 | 0.6853 | 14 | 1.72 | 0.1075 | 0.05 | -0.2912 | 2.6485 | -0.00007 |
| s2u2 | 25.7867 | 10.5419 | 14 | 2.45 | 0.0283 | 0.05 | 3.1765 | 48.3969 | -0.00186 |
| s2e | 0.001364 | 0.000093 | 14 | 14.70 | <.0001 | 0.05 | 0.001165 | 0.001563 | -0.00002 |
| Fit Statistics | CAT6_no_ dummy | | | | | | | | |
| -2 Log Likelihood | -1601 | | | | | | | | |
| AIC (smaller is better) | -1587 | | | | | | | | |
| AICC (smaller is better) | -1587 | | | | | | | | |
| BIC (smaller is better) | -1582 | | | | | | | | |

### 5.6.2 Aggregated

The results of the aggregated estimations are summarized in tables 5.8 until 5.11. The mixed model output is reported including the estimations for the fixed and random variables and the fit statistics. In general equivalent results as for the disaggregated cases are produced.

In the linear applications according to tables 5.8 and 5.9, fixed and covariance parameter estimates for both the linear and logarithmic models are highly significant. The nonlinear exponential trend described in Table 5.10 is only fitted to the geographic groups HE and HS. The parameters for the geographic groups are not significant. The results of the logistic estimation described in Table 5.11 show that both fixed and random parameters are significant. The insignificant variance estimate does not have an interpretational interest to this chapter[12].

Concerning the suitability of the mixed approach (in the case of only the linear models), the covariance structure is significant based on the "null model likelihood ratio test". In other words as for the disaggregated models the linear and logarithmic models including random effects are superior to the models with only the fixed effects.

In all cases, models with the sample countries in a single dataset are the best performing models compared to the models estimated for the geographic groups separately. Same reasons of sample size confirmed by fit statistic are also valid in the aggregated case. Among the linear models estimated the HW model produces the best fit among the geographic grouped models. Among the logarithmic the best fit is achieved by the HE countries. Finally the HS group produces the best fit from the logistic growth models. Such statistics are influenced by the number of observations and given that each group contained a different number of countries, results should be viewed with caution. Finally the comparison of Mean Absolute Error (MAE) and Mean Squared Error (MSE) positions all model specifications on an equal performance level.

[12] See comment 8.

Table 5.8-a: Linear growth - dummy: $y_{it} = (\beta_0 + u_{i1}) + \beta_1 t + \beta_4 (year\ 2009) + e_{it}$

$y_{it} = -12.8033 + 0.006515\, t - 0.07852\, (year\ 2009)$

| LINEAR_HWHSHE_TOTAL_dummy | | | | | |
|---|---|---|---|---|---|
| Covariance Parameter Estimates | | | | | |
| Cov Parm | Subject | Estimate | Standard Error | Z Value | Pr > Z |
| UN(1,1) | Reporter | 0.04908 | 0.01597 | 3.07 | 0.0011 |
| Residual | | 0.003776 | 0.000238 | 15.86 | <.0001 |
| Solution for Fixed Effects | | | | | |
| Effect | Estimate | Standard Error | DF | t Value | Pr > \|t\| |
| Intercept | -12.8033 | 0.6849 | 18 | -18.69 | <.0001 |
| Year | 0.006515 | 0.000342 | 501 | 19.03 | <.0001 |
| year2009 | -0.07852 | 0.01513 | 501 | -5.19 | <.0001 |
| Fit Statistics | TOTAL_ dummy | | | | |
| -2 Log Likelihood | -1319.5 | | | | |
| AIC (smaller is better) | -1309.5 | | | | |
| AICC (smaller is better) | -1309.4 | | | | |
| BIC (smaller is better) | -1304.8 | | | | |

Table 5.8-b: Linear growth – no dummy: $y_{it} = (\beta_0 + u_{i1}) + \beta_1 t + e_{it}$

$y_{it} = -13.2969 + 0.006785\, t$

| LINEAR_HWHSHE_TOTAL_no dummy | | | | | |
|---|---|---|---|---|---|
| Covariance Parameter Estimates | | | | | |
| Cov Parm | Subject | Estimate | Standard Error | Z Value | Pr > Z |
| UN(1,1) | reporter | 0.05184 | 0.01898 | 2.73 | 0.0032 |
| Residual | | 0.004135 | 0.000285 | 14.49 | <.0001 |
| Solution for Fixed Effects | | | | | |
| Effect | Estimate | Standard Error | DF | t Value | Pr > \|t\| |
| Intercept | -13.2969 | 0.7371 | 14 | -18.04 | <.0001 |
| Year | 0.006785 | 0.000368 | 419 | 18.41 | <.0001 |
| Fit Statistics | TOTAL_ no_dummy | | | | |
| -2 Log Likelihood | -1064.5 | | | | |
| AIC (smaller is better) | -1056.5 | | | | |
| AICC (smaller is better) | -1056.4 | | | | |
| BIC (smaller is better) | -1053.7 | | | | |

Table 5.9-a: Logarithmic growth – dummy: $y_{it} = (\beta_0 + u_{i1}) + (\beta_1 + u_{i2}) \log t + \beta_4 (year\ 2009) + e_{it}$

$y_{it} = -0.1358 + 0.1067 \log t - 0.04615 (year\ 2009)$

| LOGARITHMIC_HWHSHE_TOTAL_ dummy | | | | | |
|---|---|---|---|---|---|
| Covariance Parameter Estimates | | | | | |
| Cov Parm | Subject | Estimate | Standard Error | Z Value | Pr > Z |
| UN(1,1) | Reporter | 0.02358 | 0.008428 | 2.80 | 0.0026 |
| UN(2,1) | Reporter | -0.00743 | 0.003864 | -1.92 | 0.0545 |
| UN(2,2) | Reporter | 0.008196 | 0.002744 | 2.99 | 0.0014 |
| Residual | | 0.001625 | 0.000104 | 15.59 | <.0001 |
| Solution for Fixed Effects | | | | | |
| Effect | Estimate | Standard Error | DF | t Value | Pr > \|t\| |
| Intercept | -0.1358 | 0.03307 | 18 | -4.11 | 0.0007 |
| Lyear | 0.1067 | 0.02516 | 18 | 4.24 | 0.0005 |
| year2009 | -0.04615 | 0.01096 | 447 | -4.21 | <.0001 |
| Fit Statistics | TOTAL_ dummy | | | | |
| -2 Log Likelihood | -1412.2 | | | | |
| AIC (smaller is better) | -1398.2 | | | | |
| AICC (smaller is better) | -1397.9 | | | | |
| BIC (smaller is better) | -1393.2 | | | | |

Table 5.9-b: Logarithmic growth – no dummy: $y_{it} = (\beta_0 + u_{i1}) + (\beta_1 + u_{i2}) \log t + e_{it}$

$y_{it} = -0.05445 + 0.1017 \log t$

| LOGARITHMIC_HWHSHE_TOTAL_no dummy | | | | | |
|---|---|---|---|---|---|
| Covariance Parameter Estimates | | | | | |
| Cov Parm | Subject | Estimate | Standard Error | Z Value | Pr > Z |
| Variance | Reporter | 0.01641 | 0.005145 | 3.19 | 0.0007 |
| AR(1) | Reporter | -0.5306 | 0.1906 | -2.78 | 0.0054 |
| Residual | | 0.001668 | 0.000117 | 14.20 | <.0001 |
| Solution for Fixed Effects | | | | | |
| Effect | Estimate | Standard Error | DF | t Value | Pr > \|t\| |
| Intercept | -0.05445 | 0.03476 | 14 | -1.57 | 0.1396 |
| lyear | 0.1017 | 0.03328 | 14 | 3.05 | 0.0086 |
| Fit Statistics | TOTAL_no_dummy | | | | |
| -2 Log Likelihood | -1400.9 | | | | |
| AIC (smaller is better) | -1390.9 | | | | |
| AICC (smaller is better) | -1390.8 | | | | |
| BIC (smaller is better) | -1387.4 | | | | |

Table 5.10: Exponential Growth output – no dummy: $y_{it} = (\beta_0 + u_{i1}) + \beta_1 \exp(\beta_2 + u_{i2})t + e_{it}$

$y_{it} = 0.04452 + 0.000038 \exp(0.2332)t$

| *Parameter Estimates HE_TOTAL* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter | Estimate | Standard Error | DF | t Value | Pr > \|t\| | Alpha | Lower | Upper | *Gradient* |
| b1 | 0.04452 | 0.01098 | 4 | 4.06 | 0.0154 | 0.05 | 0.01404 | 0.07500 | *-0.00036* |
| b2 | 0.000038 | 0.000156 | 4 | 0.24 | 0.8192 | 0.05 | -0.00039 | 0.000470 | *-9.86458* |
| b3 | 0.2332 | 0.1431 | 4 | 1.63 | 0.1787 | 0.05 | -0.1642 | 0.6306 | *-0.00882* |
| s2u1 | 0.000554 | 0.000324 | 4 | 1.71 | 0.1623 | 0.05 | -0.00035 | 0.001454 | *-0.00074* |
| s2u2 | 0.000225 | 0.000180 | 4 | 1.25 | 0.2797 | 0.05 | -0.00027 | 0.000724 | *-0.28108* |
| *s2e* | *0.000047* | *8.267E-6* | *4* | *5.70* | *0.0047* | *0.05* | *0.000024* | *0.000070* | *-0.37915* |

$y_{it} = -0.01259 + 0.009902 \exp(0.09180)t$

| Parameter Estimates HS_TOTAL | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter | Estimate | Standard Error | DF | t Value | Pr > \|t\| | Alpha | Lower | Upper | *Gradient* |
| b1 | -0.01259 | 0.003989 | 2 | -3.16 | 0.0875 | 0.05 | -0.02975 | 0.004575 | -0.00001 |
| b2 | 0.009902 | 0.001884 | 2 | 5.25 | 0.0344 | 0.05 | 0.001794 | 0.01801 | -0.00016 |
| b3 | 0.09180 | 0.01189 | 2 | 7.72 | 0.0164 | 0.05 | 0.04062 | 0.1430 | 8.249E-7 |
| s2u1 | 0.000017 | 0.000017 | 2 | 0.97 | 0.4363 | 0.05 | -0.00006 | 0.000091 | -0.392 |
| s2u2 | 0.000402 | 0.000289 | 2 | 1.39 | 0.2994 | 0.05 | -0.00084 | 0.001647 | 0.000232 |
| *s2e* | *0.000111* | *0.000015* | *2* | *7.32* | *0.0182* | *0.05* | *0.000046* | *0.000176* | *-0.01772* |

| Fit Statistics | HE | HS |
|---|---|---|
| -2 Log Likelihood | -776.8 | -701.3 |
| AIC (smaller is better) | -764.8 | -689.3 |
| AICC (smaller is better) | -764.0 | -688.5 |
| *BIC (smaller is better)* | *-768.5* | *-693.0* |

Table 5.11-a: Logistic Growth Output - dummy: $y_{it} = \dfrac{(\beta_0 + u_{i1})}{1+\exp-\left(\dfrac{(t-\beta_1-\beta_4 year\,2009)}{\beta_2+u_{i2}}\right)} + e_{it}$

$$y_{it} = \frac{0.4734}{1+\exp-\left(\dfrac{(t-1994.76-10.9782)}{16.9144}\right)}$$

| LOGISTIC_HWHSHE_TOTAL dummy | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter Estimates | | | | | | | | | |
| Parameter | Estimate | Standard Error | DF | t Value | Pr > \|t\| | Alpha | Lower | Upper | Gradient |
| b1 | 0.4734 | 0.1198 | 13 | 3.95 | 0.0017 | 0.05 | 0.2145 | 0.7322 | -712E-12 |
| b2 | 1994.76 | 0.7404 | 13 | 2694.22 | <.0001 | 0.05 | 1993.16 | 1996.36 | -1.5E-9 |
| b3 | 16.9144 | 2.9073 | 13 | 5.82 | <.0001 | 0.05 | 10.6337 | 23.1952 | 1.27E-10 |
| b4 | 10.9782 | 0.8784 | 13 | 12.50 | <.0001 | 0.05 | 9.0806 | 12.8759 | -617E-13 |
| s2u1 | 0.2139 | 0.07853 | 13 | 2.72 | 0.0174 | 0.05 | 0.04426 | 0.3836 | 1.599E-9 |
| c12 | 89.4892 | 35.4977 | 13 | 2.52 | 0.0256 | 0.05 | 12.8011 | 166.18 | -658E-13 |
| s2u2 | 2.1565 | 1.3898 | 13 | 1.55 | 0.1448 | 0.05 | -0.8461 | 5.1590 | -137E-13 |
| s2e | 0.001152 | 0.000079 | 13 | 14.53 | <.0001 | 0.05 | 0.000981 | 0.001324 | -4.02E-6 |
| Fit Statistics | TOTAL_ dummy | | | | | | | | |
| -2 Log Likelihood | -1623 | | | | | | | | |
| AIC (smaller is better) | -1607 | | | | | | | | |
| AICC (smaller is better) | -1606 | | | | | | | | |
| BIC (smaller is better) | -1601 | | | | | | | | |

Table 5.11-b: Logistic Growth - no dummy: $y_{it} = \dfrac{(\beta_0 + u_{i1})}{1+\exp-\left(\dfrac{(t-\beta_1)}{\beta_2+u_{i2}}\right)} + e_{it}$

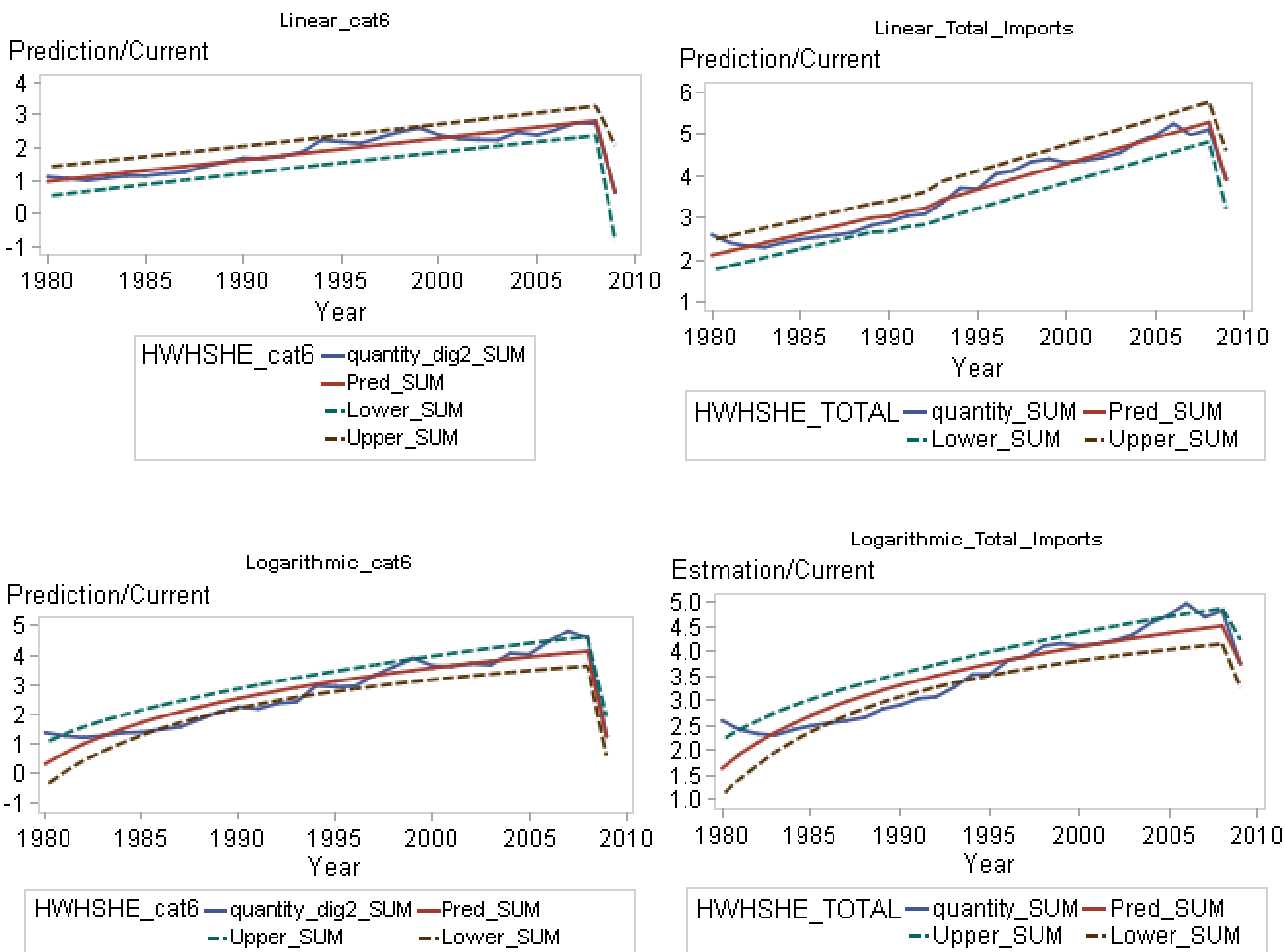
$$y_{it} = \frac{0.4813}{1+\exp-\left(\dfrac{(t-1995.28)}{16.8761}\right)}$$

| LOGISTIC_HWHSHE_CAT6_no dummy | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter Estimates | | | | | | | | | |
| Parameter | Estimate | Standard Error | DF | t Value | Pr > \|t\| | Alpha | Lower | Upper | Gradient |
| b1 | 0.4813 | 0.1221 | 13 | 3.94 | 0.0017 | 0.05 | 0.2175 | 0.7451 | -3.71E-9 |
| b2 | 1995.28 | 1.0479 | 13 | 1904.09 | <.0001 | 0.05 | 1993.02 | 1997.55 | -1.19E-9 |
| b3 | 16.8761 | 2.8256 | 13 | 5.97 | <.0001 | 0.05 | 10.7716 | 22.9805 | 6.14E-10 |
| s2u1 | 0.2207 | 0.08135 | 13 | 2.71 | 0.0178 | 0.05 | 0.04494 | 0.3964 | 1.423E-9 |
| c12 | 85.6326 | 34.3491 | 13 | 2.49 | 0.0269 | 0.05 | 11.4259 | 159.84 | -569E-12 |
| s2u2 | 2.1987 | 1.3795 | 13 | 1.59 | 0.1350 | 0.05 | -0.7815 | 5.1789 | 1.484E-9 |
| s2e | 0.000973 | 0.000068 | 13 | 14.26 | <.0001 | 0.05 | 0.000826 | 0.001121 | -0.00002 |
| Fit Statistics | TOTAL_ no_dummy | | | | | | | | |
| -2 Log Likelihood | -1633 | | | | | | | | |
| AIC (smaller is better) | -1619 | | | | | | | | |
| AICC (smaller is better) | -1619 | | | | | | | | |
| BIC (smaller is better) | -1614 | | | | | | | | |

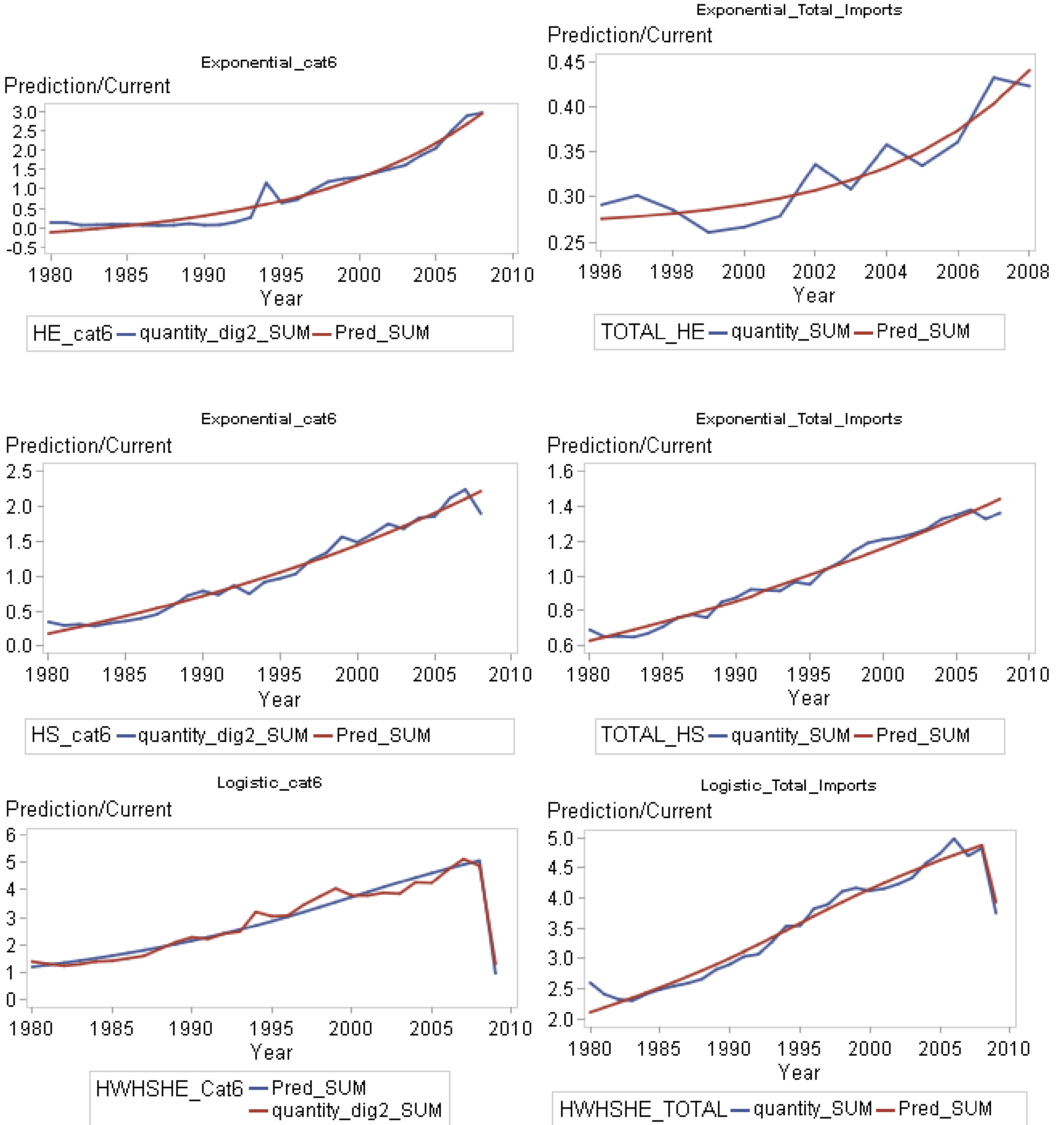
### 5.6.3 Graphical assessment of model fit

Using an exclusively graphical approach towards narrowing down the models which fit the data best, inevitably involves some degree of arbitrariness. The fit of the estimated models with the countries in one single dataset aggregated are illustrated in Graph 5.1. Evidently more than one specification fits the data well.

Graph 5.1: Model Fit - Category 6 Import & Total Imports



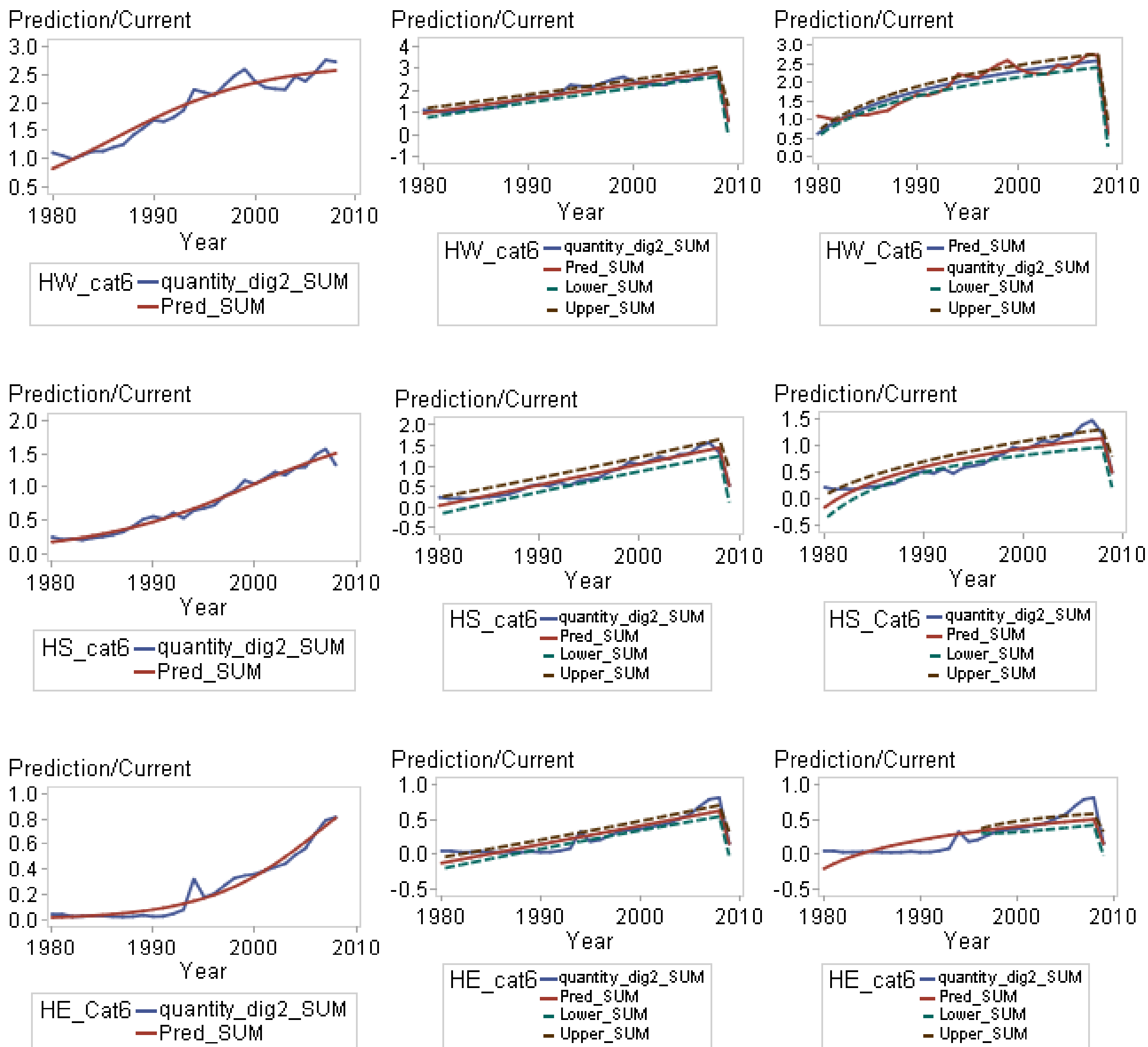
Graph 5.1 (continued): Model Fit - Category 6 Imports & Total Imports




The graphical fit for each geographic group and a sample of countries, in particular BLX, DEU and NLD is illustrated in graphs 5.2 and 5.4 for category six and 5.3 and 5.5 for total trade respectively. In the majority of cases more than one specification fits the data well as shown in Graph 5.1 too.

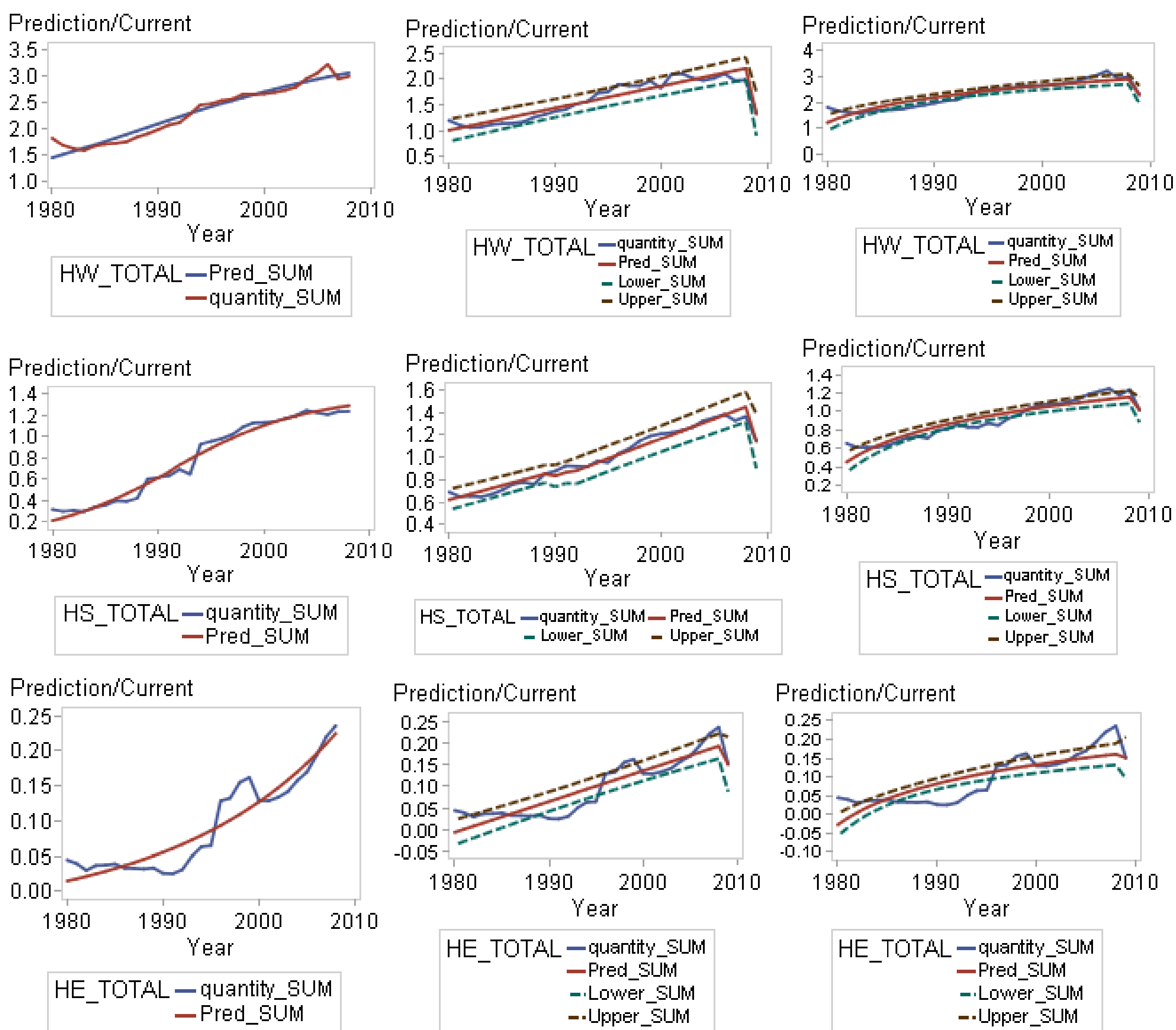
Graph 5.2: Model Fit per geographic group - Category 6 Imports

**Logistic** **Linear** **Logarithmic**



Graph 5.3: Model Fit per geographic group - Total Imports

**Logistic** **Linear** **Logarithmic**




What is observed is that the logistic growth function provides for a reasonable fit to both hinterland groups and countries. The reason for its graphical performance is due to the initial phase that resembles exponential growth and succeeding slowdown phase, that is almost linear, a pattern observed in many countries in Western Europe. The model is however not yet saturating. The presence of currently saturated flows is therefore rejected for both aggregated and disaggregated applications.

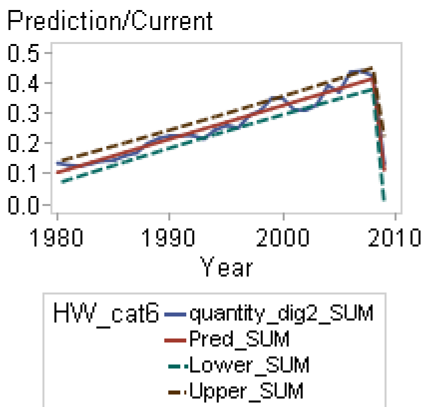
Besides the logistic growth model however the linear specification, initially intended as a benchmarking tool, performs reasonably well.

The logarithmic model on the contrary does not perform very well. The exponential model clearly also performs very well especially in the applications for Eastern European countries.

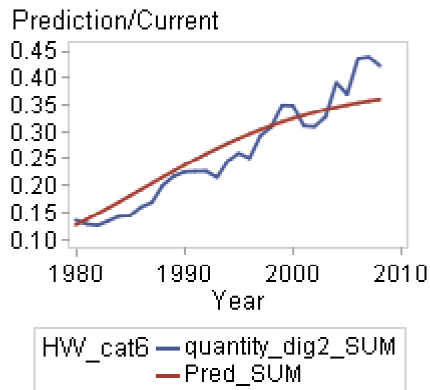
Graph 5.4: Model Fit per country - Category 6 imports

**Fit_BLX**

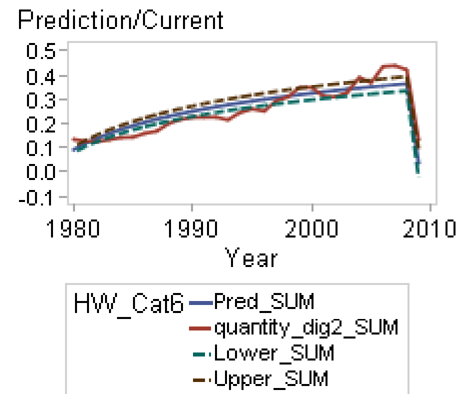
Linear




Logistic/exponential

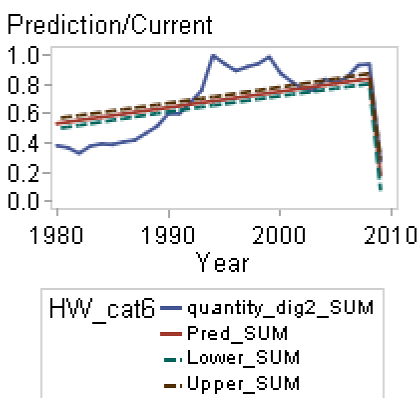



Logarithmic

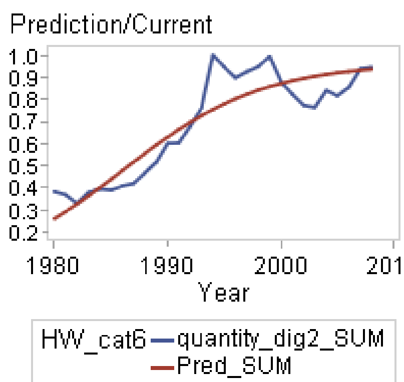



**Fit_DEU**

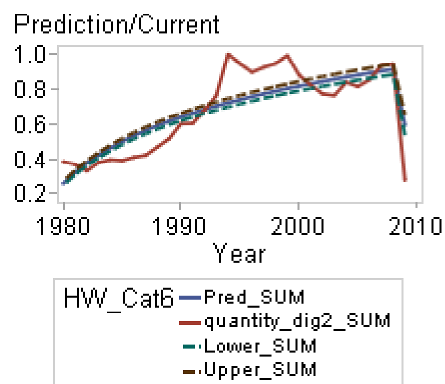
Linear




Logistic/exponential

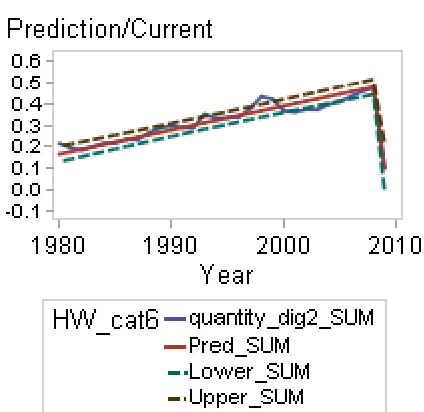



Logarithmic

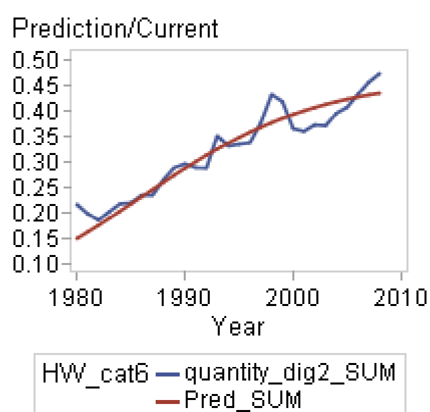



**Fit_NLD**

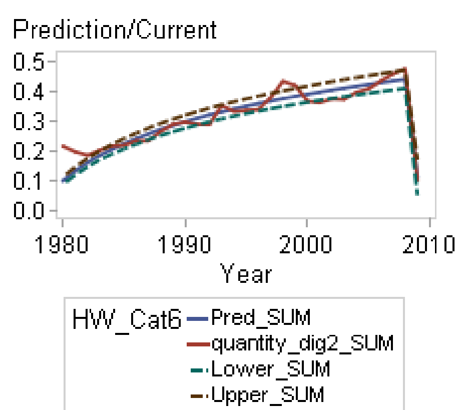
Linear




Logistic/exponential



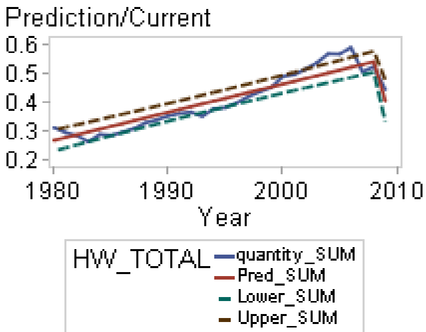

Logarithmic



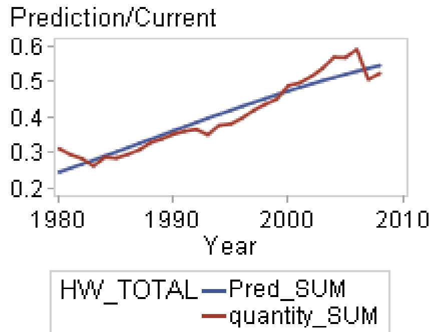
Graph 5.5: Model Fit per country - Total Imports

**Fit_BE**

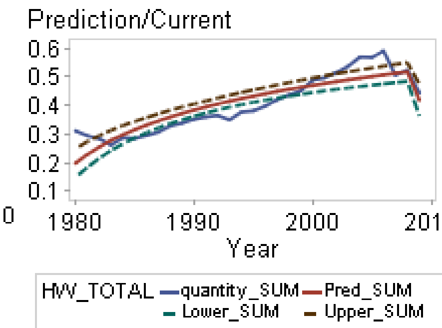
Linear




Logistic/exponential

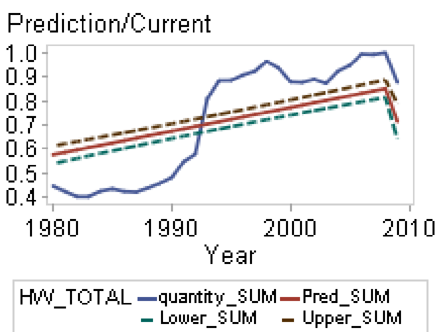



Logarithmic

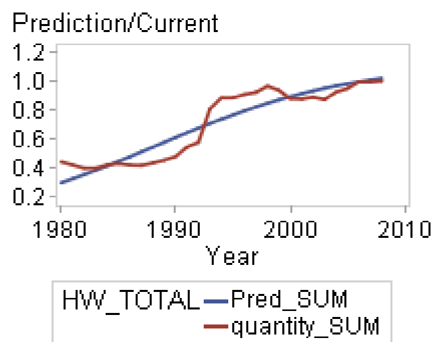



**Fit_DEU**

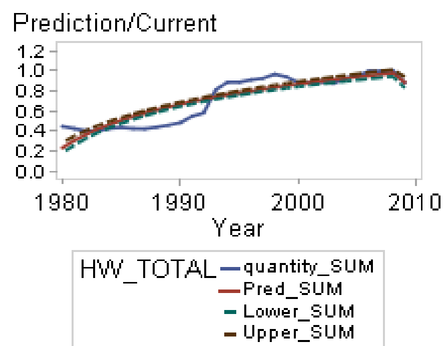
Linear




Logistic/exponential

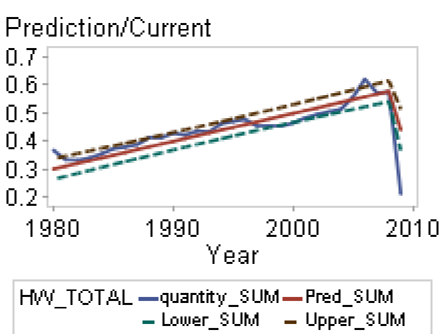



Logarithmic

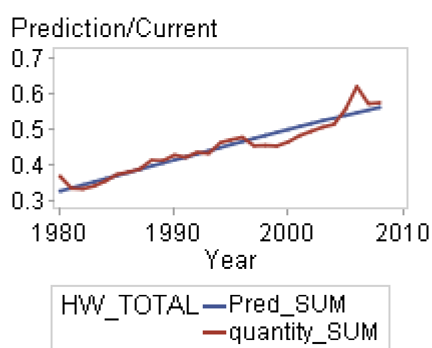



**Fit_NLD**

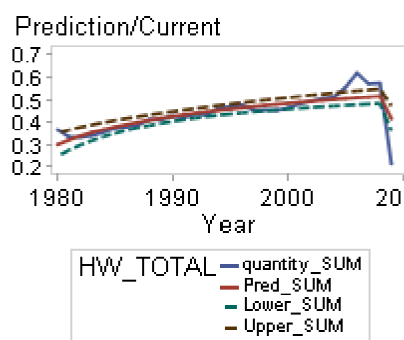
Linear




Logistic/exponential




Logarithmic




An exception to the latter commentary on saturated flows is the case of the DEU, where the pattern appears to follow a complete S shaped curve. The growth pattern of DEU is historically explained by the unification of Eastern and Western Germany in 1990 and the 2003 “Agenda 2010” measures which intended to make Germany a more competitive economy. The overall pattern of growth is often explained by the German economic model of an export driven economy which stimulates its competitiveness by restricting wage growth and domestic demand as quoted and systematically indicated by the press (Financial times, 2011; 2010; 2008; 2005).

## 5.7 Trend extrapolation

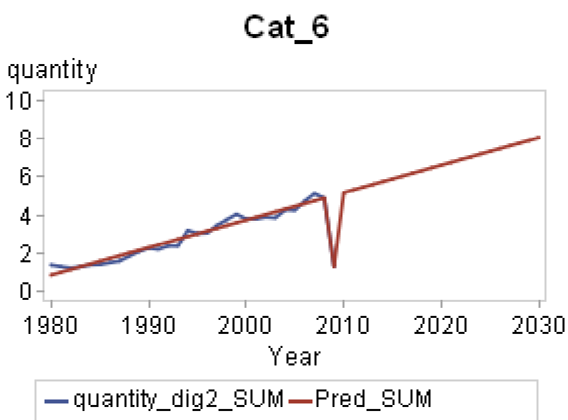
The trend models are extended in their use for the making of future projections. The applications in particular go beyond the discussion of best model fit. The main reason is that models producing a very good fit are not necessarily the best forecasting models. The predictive power of models is thus seen independently to model fit.

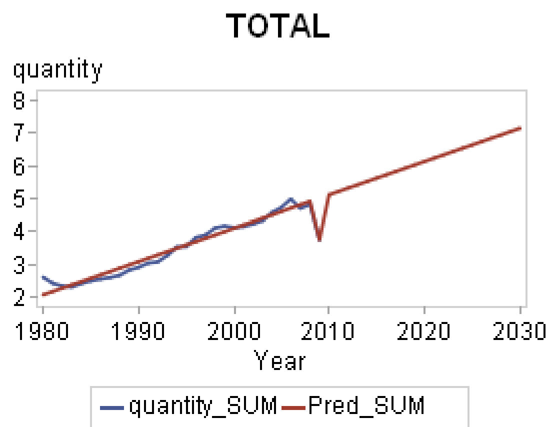
The spectrum of scenarios includes three options. The first scenario represents the full recovery of the global economies after the crisis leading to a recovery of the growth pattern for trade in 2010. Under this assumption the underlying dynamics forming the global economy are based on sustainable foundations which have additionally not been fundamentally altered by the global economic crisis. The second scenario represents the case of a pertaining crisis effect, by specifying the dummy as an increasing linear function of time after 2009. The third scenario represents the case of a pertaining crisis effect by imposing a predefined number of time lags before full recovery. The final choice is to apply scenario 1 only, given the information acquired from the IMF's World Economic Outlook (WEO) of an almost complete recovery of the flows for 2010 (see Table 4.2). Nevertheless, it should be noted that while the first scenario represents according to early data on 2010 the most realistic one the assumption of sustainable foundations of the growth patterns is uncertain.

The projections use trend extrapolations based on the growth models estimated in chapter 5.4 for both total imports and imports of category six. The data are rescaled according to the method range as mentioned in chapter 5.6. The models include the year 2009 as a dummy. Forecasts are made until the year 2030. Illustrations include the linear, logarithmic and logistic models for the models estimated with all countries in a single dataset. The exponential model is not used for forecasting since it is an extreme case of an unbounded growth model and is not considered suitable for forecasts in such long term horizon of 21 years.

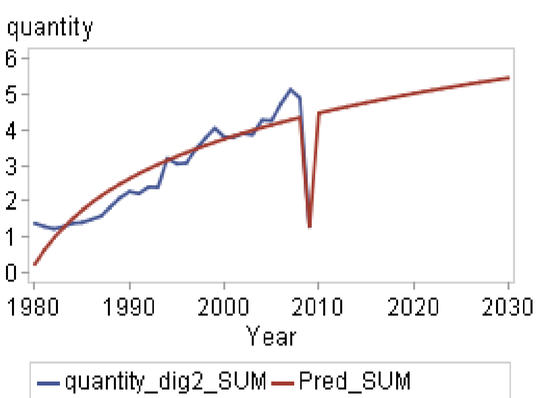
Graph 5.6: Trend Extrapolation – Category_6 Imports & Total Imports

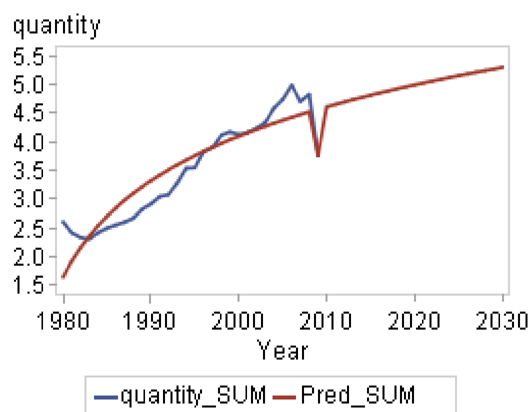
**Linear – HWHSHE (Western, Southern, Eastern country groups)**



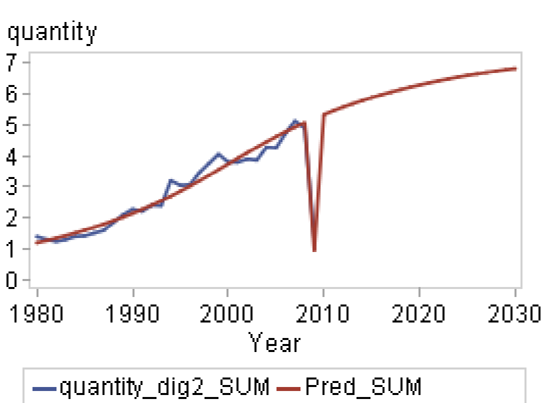



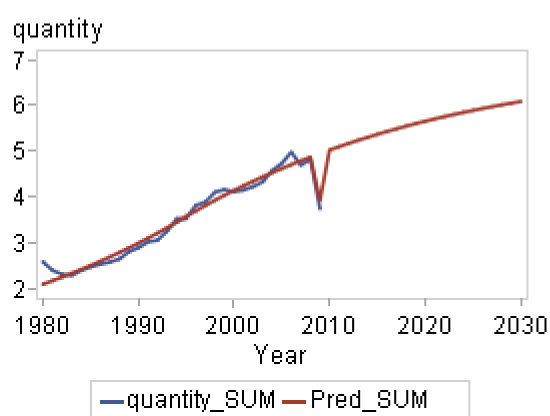

**Logarithmic - HWHSHE (Western, Southern, Eastern country groups)**




**Logistic - HWHSHE (Western, Southern, Eastern country groups)**



The findings from the forecasts of total trade with the one year as intervention point are summarized in Table 5.12. The growths are calculated with 2008 as the basis with 2020 and 2030 being the forecast target.

Table 5.12: Forecasts

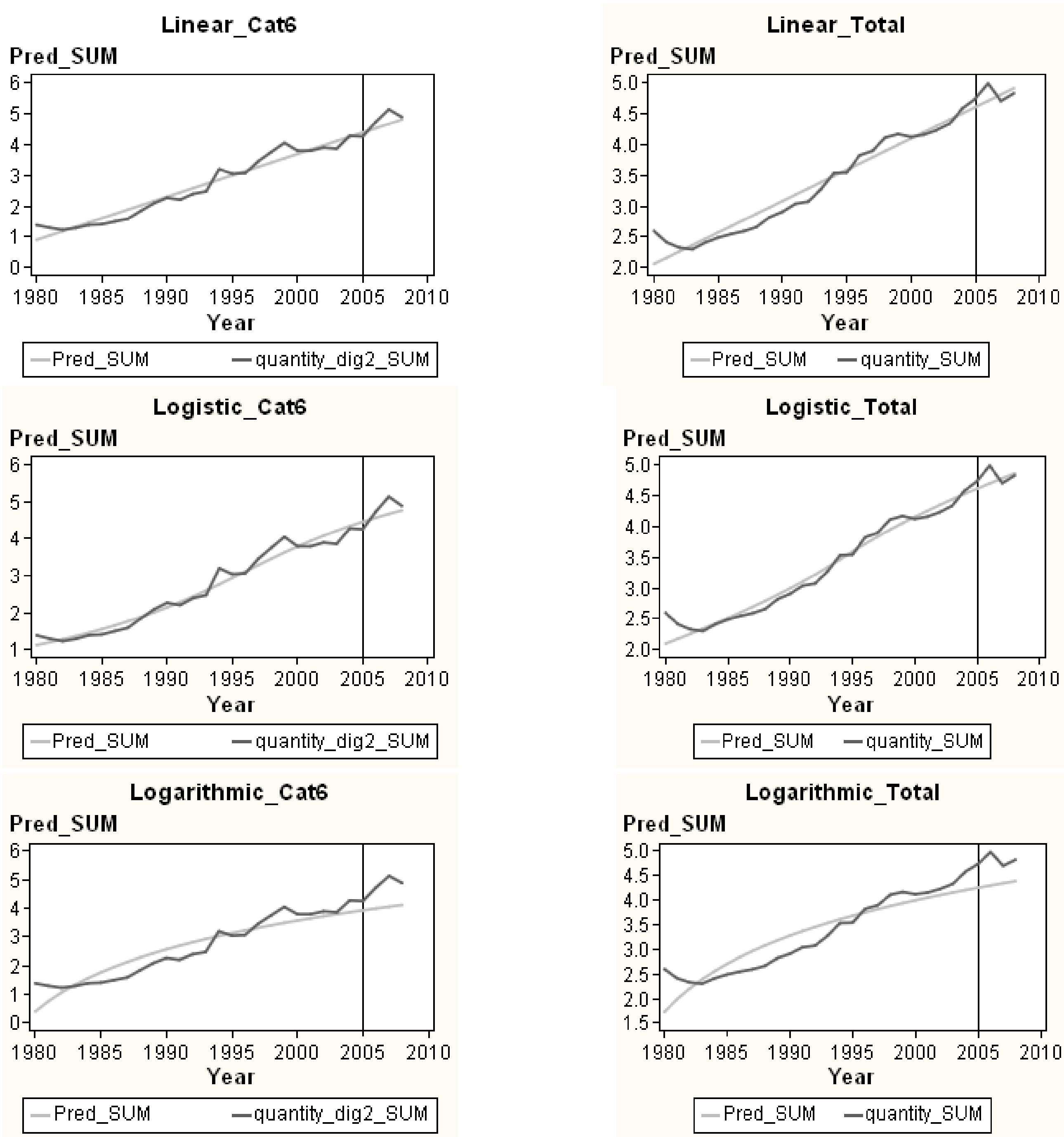
| Aggregation Level | Growth Model | Market confidence | Forecasts_TOTAL (**% growth** basis year=2008) | |
|---|---|---|---|---|
| | | | **2020** | **2030** |
| Total Trade HWHSHE | Linear | Median-high | 25% | 46% |
| | Logarithmic | Median-low | 11% | 19% |
| | Logistic | Low | 16% | 25% |

| Aggregation Level | Growth Model | Market confidence | Forecasts_CAT_6 (**% growth** basis year=2008) | |
|---|---|---|---|---|
| | | | **2020** | **2030** |
| Total Trade HWHSHE | Linear | Median-high | 35% | 65% |
| | Logarithmic | Median-low | 16% | 26% |
| | Logistic | Low | 24% | 34% |

The forecasts assume no structural effects resulting from the crisis year of 2009 which reflects the scenario of recovery in the year 2010. By definition the linear and logarithmic unbounded growth models produce positive growth forecasts. Additionally the forecasts from the logistic growth model give no indication of import saturation on the total level of either total import flows or the import flows of category six. On the contrary, when using trend extrapolation having fitted a logistic growth function, imports continue to grow for at least another 20 years.

The trend forecasts are evaluated by performing in-sample forecasts. The results are illustrated in graph 5.7. For this purpose the models are re-estimated until the year 2005 and forecasts are made until the year 2008, excluding hence the crisis year of 2009. According to the graphical plots, except for the logarithmic model the linear and logistic models perform well.

Graph 5.7: Forecasts Evaluation (in sample forecasts 2006-2008) – Category 6 Imports & Total imports




The graphical fit is complemented by the calculation of the Theil forecasting accuracy statistics, U1 and U2 for in sample total forecasts and forecasts of category six. The results are documented in table 5.13.

Table 5.13: Theil Forecasting Accuracy Statistics

| TOTAL IMPORTS | | | |
|---|---|---|---|
| Forecast Evaluation Statistics | Linear | Logarithmic | Logistic |
| Theil's U1 | 0.01 | 0.04 | 0.02 |
| Theil's U2 | 0.71 | 2.05 | 0.74 |

| CAT_6 IMPORTS | | | |
|---|---|---|---|
| Forecast Evaluation Statistics | Linear | Logarithmic | Logistic |
| Theil's U1 | 0.03 | 0.07 | 0.03 |
| Theil's U2 | 0.74 | 1.77 | 0.87 |

The U1 statistic is bounded between 0 and 1 and values closer to 0 indicate greater forecasting accuracy. The U2 statistic takes the value 1 under the naïve forecasting method. Values less than 1 indicate greater forecasting accuracy than the naïve forecasts and vice versa. The results confirm the graphical inspection showing the both the linear and logistic growth models perform very well while the same is not true for the logarithmic growth model. As shown in table 5.13 the U2 values for both total imports and imports of category six are greater than 1.

It should however be noted that trend forecasts are not suitable for long term forecasts since structural changes have no baring on the forecasts. It is for this reason that alternative growth specifications are applied which in reality represent different scenarios. To capture structural changes, structural modeling typically constructed with simultaneous equation systems is a more suitable approach. As explained in chapter three, structural approaches are resource intensive and given the purpose of this research they have not been chosen as the preferred approach. The reduction of the structural approaches to for example the inclusion of an independent variable to the current approach is not considered. The reason is the absence of predicted values of the independent variable. Given hence the lack of such input no improvement of the current forecasts is expected. Nevertheless, in recognition to the limitations of the trend models dynamic time series approaches are further employed in chapter six.

## 5.8 Summary of findings and Comparisons

The growth model findings are explained by means of comparison through a summary of main findings for total trade which are contrasted by the main findings for the trade of category six. In this way the overall conclusions are described while highlighting the advantages and disadvantages of the two approaches, disaggregated and aggregated.

The findings for total trade are split in the following blocks:

**Methodological choice**

- Mixed models are superior to the fixed models because they account for between-country variation;
- The specifications with two random effects are in general superior to the ones with only one random effect. The variability hence lies in both volume and growth rate between the European countries;
- The fixed effect and random effect parameters are significant in all the model applications. Especially for the random effects this is to be expected given the differences across European countries in terms of their volume and the growth of imports;

**Model Fit**

- The model best describing the trend for the single database is inconclusive with the linear, the logistic and the logarithmic specification showing no clear econometric superiority;
- Based on graphical inspection, the best fit is achieved by the linear and the logistic specification;
- The logistic model performs well. There is however at present, no indication of saturation;
- No indication of future import saturation on the aggregated European country level exists, for at least another 20 years. Nevertheless, the more disaggregated the analysis is, the more likely it becomes that saturated patterns of growth may be found like in the case of DEU;
- The linear model is a model worthy of consideration and can be used as a benchmarking tool;

**Country sample grouping Fit**

- When estimating the models under the different specifications with the countries in one dataset the resulting models are always superior to the models of the geographic groups HW, HS, HE estimated separately on the grounds of fit statistics due to the increased number of observations in the former case;

- The growth pattern for the HE countries is graphically best described by the exponential model. The growth patterns for the HW and HS countries are econometrically inconclusive though graphics suggest it is best described by in this case too the logistic growth model for the HS countries and the linear growth model for the HW countries;

**Error analysis**

- The error analysis showed that in the majority of the models the errors are homoscedastic and normally distributed;
- Serial correlation is addressed by defining the correlation structure. Typically the AR(1) is preferred but the most appropriate structure is chosen on the basis of trial and error and comparison of the AIC and BIC values. The alternative structure tested is the unstructured which is also the most flexible one. Serial correlation does not bias the estimators. Furthermore it does not influence the projections since the trend extrapolations are independent of time. For this reason a full correlation elimination approach is not further pursued.

The main findings when compared to the disaggregated approach:

**Aggregated versus disaggregated trade**

- In the estimation of the model of category six for the equivalent applications as for total trade the model best describing the trend is also inconclusive. None of the logistic, the logarithmic or the linear specification show clear econometric superiority. Hence in the case of category six, the disaggregated approach did not provide for clearer indications of best fit. Such cases could be possible when disaggregating category six further in its sub-products;
- The growth pattern for the HS and HE countries is best described by the exponential model. The growth pattern for the HW countries is inconclusive as in the case of the total trade model. Nevertheless, the logistic growth model performs best based on graphical inspection;
- No indication of current or future saturation of import flows on the aggregated level is established;

**Forecasting**

- Ex post forecasting accuracy evaluation methods show that the linear and logistic growth models perform best.

Given the limitations in attributing clear superiority to just one growth specification it is more appropriate to focus on the illustration of advantages and disadvantages from the use of either one of the specifications estimated. This discussion is important for the final model choice when the purpose is forecasting. The commentary involves model reliability in terms of model bias and robustness.

Advantages:

- The linear models – linear and logarithmic- are robust. This means that they are insensitive to small departures from the idealized assumptions. This is proven through the testing with the different covariance structures. Additionally, the testing with the different datasets resulting from the different sources confirmed the stability of the estimators;
- The nonlinear models - exponential and logistic - fit the data best. This means that the difference between this estimator's expected value and the true value of the parameter being estimated is small leading to unbiased estimators;

Disadvantages:

- The linear models have the poorest fit. This means that they do not predict well the current trend leading to biased estimators;
- Both linear and nonlinear models are subject to robustness issues in the presence of outliers. This means that by changing one point the reliability of the models is questioned. This could lead to misleading results in the case of outliers present in for example the third phase of the logistic growth model.

The aforementioned econometric findings and the discussion on graphical fit are exclusively based on the empirical output. The choice however on the most appropriate growth model for the making of trend extrapolations goes beyond model fit. As mentioned in chapter 5.7, the model which best fits the historical values does not necessarily produce the most reliable forecasts. A combination of goodness of fit and forecasting accuracy is thus necessary. International organizations go a step further and use expert opinion before publishing their forecasts. In this application too it is believed that expert opinion plays a crucial role. While the discussion of experts typically concerns the input parameters of a structural model in the current application experts' discussion would evolve around the most suitable growth pattern. For this reason, empirical output now has to be translated into insights for transport research.

## 5.9 Discussion on mixed growth model suitability and impact on the transport sector

The understanding of the pattern of growth and the variability of this pattern between the countries represents high added value knowledge to transport stakeholders.

Since not being able to definitively single out a particular specification, one should treat the different specifications as different scenarios of future behavior. The suggested approach in today's extraordinary times of high uncertainty is to use all growth models and draft strategies on the basis of expectation assumptions. What is hence recommended is the reliance on all specifications for the provision of a spectrum of possible future outcomes in this case possible volumes of goods.

Each specification in particular has different implications on policy decisions and in particular on investment decisions and on concerns about sustainability. In fact, while the challenges defined in the White paper for Transport remain, adjustments in funding priorities and the implementation mix of short and long term solutions might differ per growth expectation.

For example the logistic growth specification when used for forecasting presupposes asymptotically zero growth. Hence, on the basis of the belief of diminishing marginal utility and no new products entering the market it would indicate that growth asymptotically comes to a halt. This can be a very informative scenario in instances where a natural limit to growth is assumed. On the other hand a linear or exponential growth based forecast puts pressure on investment decisions and at the same time inflates concerns about sustainability. Transport infrastructure and current supply chain systems would thus need to appropriately and rapidly tackle, what could be called a growing green demand, without compromising economic growth and the successful adherence to the 2020/2030/2050 emission targets. Assuming logarithmic growth even though not supported by any growth theory it represents a scenario of slow growth. As such, necessary policy implementations would not be exposed to the pressure and risk assumed by the linear or particularly an exponential pattern of growth.

A similar reasoning applies to the transport sector. The expectations hence of future growth are instructive for decisions on future investments, be it infrastructure or operational. Furthermore decisions regarding Mergers and Acquisitions (M&As) are heavily influenced by input on future overall growth or input on growth of a specific segment or route (OD). Given the costs involved and/or the time lag between the decision and the actual completion of the investment plan it becomes evident that the information on the range of future outcomes can significantly contribute to strategic decision making processes.

Such outcomes are suitable for the medium and short term, the latter considered as covering between one and two years. The use of trend extrapolations for the long term, are not considered a suitable approach. The reason is that in the long term the likelihood of structural changes to take place is higher and can therefore completely distort observed trends. An example is the case of DEU. In this case as pointed out by Rothengatter (2011) the structural break of the unification in the 1990's would have been impossible to predict with the use of trend models. Another example is the current sovereign debt crisis and its potential structural impact on European economies directly and the rest of the world. It is at the moment evident that the economies with not only liquidity but also solvency issues will go through substantial re-structuring in the coming years. At the same time the austerity measures implemented across Europe will at least for the short term but it is expected also for the medium term impact the European economies. These limitations are discussed in chapter six.

# 6. Dynamic projections of European import volumes

In chapter six the focus lies on suggestions of appropriate forecasting models for predicting freight flows. The choice is dynamic modeling and in particular panel VAR models, a combination of the Vector Autoregressive and the panel applications and ARIMA/ARIMAX models for single series forecasts. These techniques belong to the family of dynamic linear models which assume that future importing quantities of the sample countries depend on their importation of the previous years. Such models have often proven to outperform structural models in forecasting (Verbeek, 2008) while at the same time they do not need to be void of theoretical underpinnings. The projections of future freight growth in the dynamic context are important due to the implications they bare on policy considerations relating for example to port competitiveness, road congestion and infrastructure investment decisions among others.

The structure of the chapter is as follows. Chapter 6.1 describes the indicators under consideration and the final choices made to serve as input variables. The rest of the chapter is split in two major blocks according to the techniques used: chapter 6.2 describes the panel VAR application and chapter 6.3 the single country ARIMA/ARIMAX applications. Each chapter is sub-divided in chapters describing the specifications, data and the applications made. The chapter ends with a summary of finding in 6.4 and a discussion on the suitability of dynamic models for the transport sector in 6.5.

## 6.1 Choice of Indicators

In this part of the analysis input variables are used. For this purpose indicators are identified. By adding the dynamic element together with the use of input variables it is anticipated that more reliable forecasts can be derived. The choice of indicators is based on the challenges facing Europe, split in three pillars, economic growth, demographics and technology. The choices documented in Table 6.1 list topics which have been often discussed in the press[13] and in recent reports of the International Monetary Fund (IMF)[14] and of the United Nations (UN)[15].

[13] The Economist, Financial Times
[14] Global Financial Stability report, 2010
[15] World Economic and Social Survey, 2010

Table 6.1: Triggers of change

| Pillars | Indicators | |
|---|---|---|
| | **Change triggers** | **Quantification options** |
| Economic Growth | Rethinking drivers of fiscal/monetary policies | GDP, Green GDP, Employment Industrial production, Domestic Demand, … |
| | Balancing sovereign and bank balance sheets | Sovereign/bank debt |
| | Shifting to service driven economies | Ratio of growth of trade in services to growth in goods trade |
| Demographics | Growing population | Total population |
| | Ageing population | Population age 65 and above |
| Technology | Implementing innovative and economically viable technologies | Emissions inventory |

The pillar of economic growth includes the drivers of monetary and fiscal policies which are in the recent years heavily discussed within Europe. They are in particular often expressed by comparing the economic systems of countries, like for example the differences between the Anglo-Saxon and German economic system. Another topic under scrutiny is the adjustments of large deficits and surpluses and the strengthening of the banking sector. Especially during the crisis years the weaknesses of the global financial system have become painfully evident. New "buzzwords" like public debt, credit ratings, bond yields and so forth have been added and linked to the one of globalization. The impact of the crisis on a global scale is inevitable and its spread to a number of sectors as well. An example is the impact the crisis has on the pace of growth of the Chinese economy. Sector wise the impact on the trade volumes of European countries has been quite visible which has on its own affected freight transport flows.

Economies shifting to services driven GDP growth is another topic often quoted as a distinctive factor directly impacting trade balances. Such phenomenon is already observable in western economies. It can be understood through what is known in economics as the income–consumption curve for different goods and the Engel curves. What is relevant to this study is that according to economic theory, as income increases the demand for inferior goods decreases unlike normal or veblen goods. It is therefore important in this particular research to make a distinction of the different impact such consumption behavior has, on volumes and values of imports.

One of the challenges with respect to demographics is the actual population size and the ageing population in the western economies. This is a topic of high priority and is regularly investigated by the United Nations in their population targeted yearly reports[16]. The direct and indirect impact of demographics on trade volumes and trade composition inevitably impact the transport sector as well.

[16] See Population Division of the UN for recent reports, URL: http://www.un.org/esa/population/unpop.htm

Finally, technology faces the challenge of its role as a facilitator to growth under the assumption of a finite world. The boundaries set by resources availability are pushed with the help of technology thus stimulating further growth and extending boundaries. More stringent boundaries enforced by global warming concerns are putting ever more pressure on technological solutions. Meanwhile, it has become clear that current technology while evolutionary is subject to economic constraints in its direct applicability and can thus not solely achieve the 20% emission reduction by 2020 and the 80-95% (below 1990 levels) by 2050, set by the DG CLIMA of the European Union. Operational solutions driven by efficiency maximization have thus also been engaged. The successful implementation of technological and operational solutions in meeting the European and Global emission targets and the costs such actions imply or sanctions being imposed in case of no adherence would inevitably have an impact on trade patterns.

All aforementioned considerations on triggers of change are not directly quantifiable. At the same time, it is evident that these dynamics are very complex and cannot be simply captured in a single equation. This is evident in structural approaches and the methodologies employed as described in chapter two. In particular within those models, disposable income, relative prices of imports/exports and composite indicators like price competitiveness among others are commonly used across the structural models of the international organizations. In particular unit prices were calculated but were finally not incorporated in this research due to the unsatisfactory quality of the obtained database. Disposable income was also considered partially by the use of household final consumption expenditure, which however proved to be incomplete for the sample of countries used in this research. However, as mentioned in chapter two it is not the intention of this research to suggest a macro-economic model. The objective is to create practical tools based on time series and selected indicators. Nevertheless the indicators identified in table 6.1 are necessary for the interpretation of the results of the current applications.

The final decision made, is that the indicators used in the current study are to be chosen on the basis of two characteristics: a) their identification as quantifiable change triggers and b) resources availability in terms of data availability and timing of this research. As such Domestic Demand and GDP have been chosen as leading indicators. That is not to say that other indicators may not have a superior explanatory power. In order to draw conclusions on the best performing indicator a number of other indicators should have been tested as noted by Rothengatter (2011) but this is not the core objective of this research and for this reason no extensive testing of indicators was pursued. Moreover, the use of domestic demand was further supported by the decision to apply Vector Error Correction models for which establishing cointegration is a necessary step in the analysis. Given the limited time series for such an analysis the decision taken was to rely on the existing literature establishing cointegration between domestic demand and import volumes. This is further explained in chapter 6.3.

## 6.2 Panel VAR models

Dynamic panel applications for forecasting are not as common as single time series. A review of applications is made by Baltagi (2008) where a brief survey of forecasting with panel data is given. Applications of panel forecasting are found in the context of emission projections (Schmalensee et al., 1998), GDP projections (Hoogstrate et al. 2000) and marketing and sales projections (Frees, 2004). The majority however of the applications on dynamic panel data are found in the econometrics literature (Ahn and Shmidt, 2004; Blundel and Bond, 1998; Arrelano and Bover, 1995; Arrelano and Bond, 1991), which represent standard references in the field. Forecasting with dynamic panel models have been addressed within the macroeconomics field. Authors include Ballabriga (1995) who utilizes a structural Bayesian Vector Autoregressive and Canova (2003) who provides an alternative Bayesian model which relaxes the restrictions of no time variation and no interdependencies in the parameters among others. Furthermore, to the knowledge of the author dynamic panel data has yet not been applied for the making of trade flow forecasts.

Two of the main problems dealt within the literature are unit roots and cointegration. A survey on these topics is given by Baltagi and Kao (2000). Several unit root tests have been proposed for cointegration in panels, by for instance Pedroni's (1999). Several static panel applications are found in the economics literature in the fields of energy, exchange rates, employment and others while less applications are found in dynamic panel applications (Apergis and Payne, 2011 ;Groen and Kleibergen, 2001 Chaudhuri and Sheen, 2006). Nevertheless, to the knowledge of the author no applications on trade projections in either static or dynamic applications are available.

### 6.2.1 Data and Model Specification

The data considered include imports of 19 European countries for the years 1980 until 2009. In particular the imports of total trade are considered in the unit of volume measured in kilograms as in the previous application in chapter six. These data are hence similarly sourced by the UNCOMTRADE database and in order to obtain the measurement of kilograms, data on a three digit level are sourced (a classification defining the level of detail of product categories). This is the minimum level of disaggregation for which data in volume are available. The data of domestic demand are sourced by the World Development indicators (WDI) of the World Bank. In particular, domestic demand derives from the sum of gross capital formation, gross national expenditure and household final consumption in real terms (2000 constant US dollars). GDP data is also sourced from the WDI in real terms (2000 constant US dollars).

The model is estimated using the General Method of Moments (GMM), a dynamic panel estimator method, which allows for autoregressive processes.

The reason for using GMM instead of the Ordinary Least Squares (OLS) method is that when estimating a linear dynamic model with a lagged dependent variable with OLS, it results in biased and inconsistent estimates (Verbeek, 2001). To solve this problem first differences are taken and equation (6.2.1) is then estimated with an instrumental variables approach. Individual effects are eliminated in the process.

$$y_{it} - y_{it-1} = \gamma(y_{i.t-1} - y_{i.t-2}) + (\varepsilon_{it} - \varepsilon_{it-1}) \qquad (6.2.1)$$

The general principal of this approach is that on the basis of the available data, instrumental variables are defined and moment conditions are established in order to derive the GMM estimator. Instrumental variables should be uncorrelated with the models errors but correlated with the endogenous variables. Consistency of the instrumental variable estimator is guaranteed by the assumption that $\varepsilon_{it}$ has no autocorrelation. The instrument in equation (1) is $y_{i,t-2}$ which is correlated with $y_{i,t-2}$ but not with $e_{i,t-1,}$ as shown in Anderson and Hsiao (1981). The list of instruments can be extended by exploiting additional moment conditions which increase efficiency of the estimator (Arellano and Bond 1991). The general form of a dynamic model with an exogenous variable is given in equation (6.2.2).

$$y_{it} = x_{it}\beta + \gamma y_{i.t-1} + a_i + \delta_t + \varepsilon_{it}, \qquad t = 2,...,T. \qquad (6.2.2)$$

Where $y_{it}$ is the dependent variable, $x_{it}$ the exogenous variable, $y_{i.t-1}$ the lagged dependent variable and $a_i$, $\delta_t$, $\varepsilon_{it}$ the ith individual effect constant over time, the tme specific effect and the remaining error component assumed to be IID $(0.\sigma_\varepsilon^2)$ respectively. The exogenous variable $x_{it}$ can be defined as strictly exogenous, or predetermined which influences the construction of additional instruments. In particular the classification as strictly exogenous means that $x_{it}$ is not correlated with the error term while the classification as predetermined means that future realizations of $x_{it}$ can be correlated with the error term but its present and past realizations are not.

The main reason why the dynamic panel approach has been chosen for this application is due to its ability to model mean and individual dynamics. As such it is believed to realistically reflect the importance of the individual importing pattern of European countries. Furthermore, given yearly observations of importing volumes, the resulting limited sample in either time series or cross sections can be overcome by the use of two dimension panels. Further reasons supporting the use of panel data in terms of accuracy and efficiency of the estimators, complemented by the limitations can be found in Hsiao (2007) and Arrelano (2006).

The choice of GMM (often called difference GMM) is supported by its suitability in dynamic panel modeling, as explained above and the extensive empirical applications found in the literature.

It should be noted that the available research with an average sample size for both T time observation and N countries is limited, while typically the bulk of the literature focuses on small T large N samples. In these cases according to Judson and Owen (1999), in macro panels when the data covers a large number of countries observed over a moderate period of time the GMM estimator ranked second best after the corrected fixed effects estimator. However according to Blundel and Bond (1998) weak instruments could cause large finite-sample biases when using the first-differenced GMM procedure to estimate autoregressive models for moderately persistent series from moderately short panels. The proposed solution to reduce those biases was by incorporating more informative moment conditions that are valid under quite reasonable stationarity restrictions on the initial conditions process. Essentially this results in the use of lagged first-differences as instruments for equations in levels, in addition to the usual lagged levels as instruments for equations in first-differences (Arellano and Bover, 1995). For these reasons both GMM and system GMM estimators were used.

The dynamic model estimated in this research is described in equation (6.2.3)

$$\Delta IMP_{it} = a\Delta IMP_{i(t-1)} + \Delta DD\beta + year2009 + \beta_i + \delta_t + u_{it} \qquad (6.2.3)$$

The essential feature of the model is the dynamic effect of domestic demand on import volumes for which the speed of adjustment is governed by the coefficient of the lagged import volumes. The $\beta_i$ is the country specific effect and the $\delta_t$ is the time specific effect and $u_{it}$ a disturbance term. The error component $\varepsilon_{it}$ ($\varepsilon_{it} = \beta_i + \delta_t + u_{it}$) is assumed to be serially uncorrelated with zero mean and independently distributed across countries. Year 2009 is a dummy variable taking the value of one for the crisis year and zero for all other years. $IMP_{i(t-1)}$ is the lag of $IMP_{it}$ and DD is the domestic demand. The tests performed are the Sargan Hansen test of over-identification and the AR-test for serial correlation. For both GMM and SGMM the range of specifications are summarized in Table 6.2.1.

Table 6.2.1: Dynamic model specifications

| **Model specification** | **Variables** |
|---|---|
| I | ▪Quantity differenced & lagged;<br>▪Domestic demand differenced; |
| II | ▪Quantity differenced;<br>▪Domestic demand lagged and differenced; |
| III | ▪Quantity logged, differenced and lagged;<br>▪Domestic demand logged & differenced; |
| IV | ▪Quantity logged, differenced and lagged;<br>▪Domestic demand logged, differenced & lagged; |

Specifications II and IV were immediately rejected due to the resulting cointegration between domestic demand and its lag. Such specifications would require the use of modeling techniques which go beyond the scope of this research. Hence, only specifications I and III were further pursued.

### 6.2.2 Panel VAR application

The best performing model in terms of parameter significance is model I with the quantity of imports in levels differenced and lagged, the domestic demand and a dummy for year 2009, the crisis year. Additionally the same model is estimated without the dummy and hence without the year 2009. The results are summarized below in tables 6.2.2 and 6.2.3 respectively.

Table 6.2.2: Dynamic VAR estimation results - dummy

| Parameter Estimates | | | | | |
|---|---|---|---|---|---|
| **Variable** | **DF** | **Estimate** | **Standard Error** | **t Value** | **Pr > \|t\|** |
| **dif_quantity_1** | 1 | 0.015715 | 0.00337 | 4.66 | <.0001 |
| **dif_domestic_demand** | 1 | -1.06184 | 0.1513 | -7.02 | <.0001 |
| **year2009** | 1 | -0.1509 | 0.0163 | -9.26 | <.0001 |

Table 6.2.3: Dynamic VAR estimation results - no dummy

| Parameter Estimates | | | | | |
|---|---|---|---|---|---|
| **Variable** | **DF** | **Estimate** | **Standard Error** | **t Value** | **Pr > \|t\|** |
| **dif_quantity_1** | 1 | 0.010411 | 0.00184 | 5.67 | <.0001 |
| **dif_domestic_demand** | 1 | -0.86223 | 0.1471 | -5.86 | <.0001 |

The parameter estimates are all significant and the Sargan test[17] shows that the instruments are truly exogenous (residuals are uncorrelated with the exogenous variables), formally suggesting not to reject the over-identifying restrictions. However these results should be viewed with caution since in small samples, as in this case of 81 degrees of freedom, the Sargan test may be weak. No differences are noted between the estimations with the instruments as either correlated or exogenous. The applications with the instruments inserting the model as correlated are preferred given the uncertainty in considering them uncorrelated with the error term. The ARtest estimated, shows that in both models, with the year 2009 and without, the AR(1) and AR(2) parameters for the residuals are insignificant. Hence no remaining autocorrelation is detected.

Applying a dynamic panel to make forecasts of the importing quantities adds the dimension of the individual to the dimension of time. The model hence captures both the mean and the variability between the individual countries.

[17] The Sargan test is a specification test with a null hypothesis of “the instruments as a group are exogenous”. Therefore, the higher the p-value of the Sargan statistic the better

Before however using the current model for the making of forecasts an additional step establishing the presence of the variability between the countries is taken. For this purpose the Wallace and Hussain Variance Components model is estimated. The model however indicates no significant random effects (see Table 6.2.4). The interpretation of such outcome is that the volume of imports as explained by the lag of import volumes and domestic demand are similar across countries and time. The consequence of insignificant variance between the countries is that the use of the model for forecasts would be limited to mean projections. Hence the two dimensional advantage of forecasting with panel models is given the current specification not supported. Mean forecasts on the other hand cannot be as informative as single country applied models.

Table 6.2.4: Wallace and Hussain Variance Components model

| Variance Component Estimates | |
|---|---|
| **Variance Component for Cross Sections** | 0 |
| **Variance Component for Time Series** | 0.000031 |
| **Variance Component for Error** | 0.000836 |

Simple alternative model specifications tested with different indicators like GDP as an explanatory variable, produced similar results with significant GMM estimators but insignificant variance estimates. More complex model specifications might be needed in order to fully exploit the potential of the dynamic panel modeling techniques.

An additional point of attention in applying such models is the presence of interdependencies between the countries. The assumption of no influence of such dynamics within the context of trading activities between countries is not a realistic assumption and hence results should be viewed with caution. Techniques which overcome such limitations go beyond the scope of this application and are typically quite complex, (i.e. state space models). Given the intention of providing transport stakeholders with ready-to-use tools the decision made is to estimate simpler single country ARIMA/ARIMAX models for the making of dynamic forecasting exercises.

## 6.3 Dynamic models with individual series

Dynamic models for the individual series are tested in this chapter with the purpose of identifying reliable forecasting models for each of the countries. As such the variability between the countries is addressed in more detail and with more flexibility, compared to the panel approach. Country specific dynamics are hence the target in this application. The main limitation of the current approach is the limited time series available of 28 yearly observations, an advantage of the dynamic panel approach. Sourcing long enough annual series of about 100 observations, which would allow for more confidence in the fit and forecasting accuracy of the models, is not attainable. Nonetheless, the intention of this chapter is to address the current needs of transport stakeholders given the available resources.

### 6.3.1 ARIMA models: Specifications and Data

The models are estimated as single series for the countries separately and various specifications are tested. The model specifications are summarized in Table 6.3.1.

The core specification (model I in Table 6.3.1) is the same as the one applied in the panel setting with dependent variable the logarithm of import quantity (log_quantity) and input variables the lag of the logarithm of import quantity (lag_log_quantity) and the logarithm of domestic demand (log_domestic_demand).

Model 0, applies univariate autoregressive time series equations of order one. Model II is similar to the core specification with only difference that the input variable log_domestic_demand enters the model as a lagged input. Model III is the same as the core but with untransformed data. Finally model IV is the same as the core with the difference that instead of domestic demand as input variable, GDP is used. The reason why GDP is tested is due to the poor performance of the indicator of domestic demand in some country cases. An additional model was tested, adding oil prices to the core specification. It is however not reported in this chapter since it failed to improve both the parameter estimation results and the forecasting accuracy of the aforementioned models. The latter in particular was originally anticipated that it could capture some of the yearly volatility. This approach was however quickly abandoned since such assumption would only have been worthy of testing if shorter time intervals of the current dataset were to be available.

Table 6.3.1: ARIMA specifications

| Model | Specification | Dependent Variable | Regressors |
|---|---|---|---|
| 0 | $\Delta \log y_t = \beta_0 + \beta_1 \Delta \log y_{t-1} + \varepsilon_t$ | Log quanity | lag_logquantity |
| I | $\Delta \log y_t = \beta_0 + \beta_1 \Delta \log y_{t-1} + \beta_2 \log x_t + \varepsilon_t$ | Log quanity | lag_logquantity, logdomestic_demand |
| II | $\Delta \log y_t = \beta_0 + \beta_1 \Delta \log y_{t-1} + \beta_2 \log x_{t-1} + \varepsilon_t$ | Log quanity | lag_logquantity, laglogdomestic_demand |
| III | $\Delta y_t = \beta_0 + \beta_1 \Delta y_{t-1} + \beta_2 x_t + \varepsilon_t$ | Quantity | lag_quantity, domestic_demand |
| IV | $\Delta \log y_t = \beta_0 + \beta_1 \Delta \log y_{t-1} + \beta_2 \log x_t + \varepsilon_t$ | Log quanity | lag_logquantity, logGDP |

Finally, Error Correction Models (ECMs) via the Engle-Granger 2-step method are additionally tested. These applications bear in mind the limitations in applying ECM models for single series of only 28 observations. The reason why they are included in this analysis is because they describe the behaviour of two variables in the short term consistent with a long-run cointegrating relationship. The ECM model is described in equation 6.3.1. More details on how it is derived can be found in the majority of econometric textbooks[18].

$$\Delta \log y_t = \beta_1 \Delta \log x_t + \delta(\log y_{t-1} - \alpha_0 - \alpha_1 \log x_{t-1}) + \varepsilon_t \qquad (6.3.1)$$

With long run equilibrium relation

$$\log y_t = \alpha_0 + \alpha_1 \log x_t$$

Where δ is the adjustment to the equilibrium speed, $x_t$ is domestic demand and $y_{t-1}$ is the lag of the quantity of imports.

Before applying the model, the presence of cointegration between the variables of domestic demand and the volume of imports needs to be established. It should be noted that working on a limited sample of 28 observations, in practice means that the Augmented Dickey Fuller and Granger causality tests are not reliable and establishing cointegration is trivial. Nevertheless, from a theoretic point of view it is plausible that the growth of domestic demand is cointegrated with the growth of import volumes. Additionally, there is a WTO study of longer time series on a quarterly basis linking the growth of domestic demand and a volume indice of goods and services for the aggregated dataset of the OECD-25 countries wherein cointegration is established. The analysis is based on the Augemented Dickey Fuller and Johansen cointegration tests. Given the aforementioned reasons, the decision to apply a VEC model is therefore justified.

The specifications are estimated until the year 2008 and additionally with a dummy for the year 2009 in the same way as applied for the trend models and the panel VAR models.

[18] See for example Verbeek (2008), "A Guide to Modern Econometrics" , or Green (2002), "Econometric Analysis".

However not all countries have reported on domestic demand in 2009, while due to the integrated character (I =1 in the arima model) sensible forecasts necessitate data for 2010. In particular data for 2010 would adequately reflect the recovery of the economies from the crisis year of 2009. Given the lack of data for the year 2010 an assumption of full recovery is made in the same way as in chapter five. Such assumption appears to be a realistic one. It is supported by an investigation of alternative sources for which data does exist including the IMF data presented in chapter four, but also the Economist and data published by the OECD among other especially on the level of aggregates. A synthesis of sources relevant to the recovery which took place in 2010 is compiled by Paelinck (2011). For these reasons the decision was to only present and compare the models without the year 2009.

Concerning data transformations, all the variables in Table 6.3.1 are differenced. The transformation of a logarithmic form, which is integrated of the order one is interpreted as growth rates which is a useful and easy to communicate indicator. The data for domestic demand and GDP are sourced by the WDI and measured in constant values. The models are run for the majority of the sample countries which are summarized in Table 6.3.2. Reasons for excluding some of the countries relate to data availability of either the dependent variable or input variables.

Technical notes supporting, complementing and summarizing the above are described in the following points:

- The dependent variable Log quantity of imports for all countries is non stationary and hence first differences are taken for all countries
- After taking first differences of the dependent variable (log_qunatity) all country series are stationary but only CYP and GRC are autocorrelated, thus justifying the fitting of an ARIMA AR(1) model. The AR(1) model appears to be the most appropriate according to the ACF, PACF plots and is applied for both countries CYP and GRC.
- Besides the univariate models for the specific country cases, for all countries models with input variables are fitted. These models are called ARIMAX and are simply ARIMA's with input variables often quoted in the literature as dynamic regressions (Pankratz, 1991) among others.
- The input variables are transformed in logs and first differences are taken. The decision to difference the input series of log_domestic_demand and log_GDP is taken after performing the Dickey Fuller test which showed that taking first differences is necessary in order to obtain stationary series.
- Before applying the Engle-Granger approach the Granger causality test is performed in order to determine whether the time series of domestic demand are useful in forecasting import quantities. The null hypothesis that domestic demand does not Granger-cause quantity was rejected. However it should be noted that the test is said to be unreliable for small samples. Yet in this case but also in similar cases one cannot exclusively rely on tests for drawing inferences. Hence, given the theoretical support and results of previous studies the final conclusion drawn is that causality between the two variables exists and as a result a VEC model is a plausible approach.

It should be noted that time series techniques are data and not theory driven models. As such ideally a large number of observations is needed. However, reality and empirical research especially in economics shows that adequate numbers of observations are simply not always attainable. Feasible solutions thus need to be sought. At the same time however time series need not be void of economic content. By considering several series simultaneously, forecasts may improve while adding, economic theory considerations (Verbeek, 2008). It is for these reasons that the chosen applications of both VEC and ARIMAX have been based on theoretical underpinning through the use of input variables which have proven their explanatory power in the existing literature (OECD, 2005).

### 6.3.2 ARIMA, ARIMAX applications

The process followed for the identification of the most appropriate ARIMA for each country includes tests for stationarity, unit roots, ACF, PACF plots, a series of formal diagnostic checks and estimation results. All models are estimated separately and the results for all countries are summarized in chapter 6.3.2.1. The results presented in detail include the countries of BLX, DEU and NLD and are found in chapters 6.3.2.2 - 6.3.2.3.

#### 6.3.2.1 Evaluation

The evaluation of the best performing model is primarily based on in sample forecasts and the calculation of the Root Mean Squared Error (RMSE). Further considerations taken into account for the evaluation of the models are the presence of collinearity and the autocorrelation of the residuals.

The results for all the countries per model are summarized in Table 6.3.2 wherein the RMSE is reported. It should be noted that the RMSE can only be compared between models whose errors are measured in the same units and hence only model I, model II and model IV can be compared with each other. The weaknesses of the RMSE pointed out by Keck (2006) includes the following two main points: a) that since the error increases with the square of its size, models with few large errors may appear inferior to those with a larger number of small errors and b) the weight of the ex post forecasts are given the same weight while it might be more appropriate to assign a higher weight to more recent forecasts. For the specific country cases explained in detail the RMSE is complemented by Theil's U statistic.

According to Table 6.3.2 the models which perform best are the core model (Model I) and the model which instead of domestic demand GDP is used (Model IV). Their differences in most cases are traced in the third or fourth digit and are hence minor.

Table 6.3.2: Root Mean Squared Errors

| **Sample Countries** | **Model_0** | **Model I** | **Model II** | **Model III** | ***Model IV*** |
|---|---|---|---|---|---|
| **AUT** | | 0.34 | 0.34 | 0.03 | *0.28* |
| **BGR** | | 0.67 | 0.95 | 0.01 | *0.69* |
| **BLX** | | 0.24 | 0.32 | 0.10 | *0.25* |
| **CHE** | | 0.12 | 0.15 | 0.01 | *0.12* |
| **CSK** | *Excluded due to missing data* | | | | |
| **CYP** | 0.75 | 0.50 | 0.78 | | *0.52* |
| **DEU** | | 0.36 | 0.54 | 0.24 | *0.38* |
| **ESP** | | 0.38 | 0.53 | 0.12 | *0.38* |
| **FRA** | | 0.14 | 0.19 | 0.08 | *0.14* |
| **GRC** | 0.52 | 0.41 | 0.54 | 0.02 | *0.41* |
| **HUN** | | 0.84 | 1.28 | 0.03 | *0.84* |
| **ITA** | | 0.13 | 0.20 | 0.06 | *0.13* |
| **NLD** | | 0.16 | 0.19 | 0.07 | *0.16* |
| **POL** | *Excluded due to incomplete series of domestic demand* | | | | |
| **PRT** | | 0.39 | 0.58 | 0.03 | *0.39* |
| ***ROM*** | *Excluded due to incomplete series of domestic demand* | | | | |

The final choice however of the best forecasting model is complemented by the graphical fit of those models which is useful for comparing between models for which RMSE is not applicable. What is often times observed is that the best graphical fit does not correspond to the lowest RMSE.

An alternative model specification tested with the addition of the oil price[19] as input variable is not included in the table since it failed in improving the performance of the core specification.

In the subchapters to follow specific country case studies are described in detail. For each country a description of the series is given followed by the estimation results obtained and the graphical illustrations of in sample and out of sample forecasts.

[19] The oil price is sourced by the Energy Information Association (EIA) in constant prices.

### 6.3.2.2 The case of Belgium and Luxemburg aggregated (BLX)

The series for BLX in levels are non-stationary and the white noise hypothesis is rejected very strongly. By differencing the series the autocorrelations decrease rapidly which indicates that the series are stationary. This is formally confirmed by the dickey fuller test. The check for white noise indicates that the change in import volumes is not autocorrelated. There is hence no need to fit a univariate autoregressive model. Furthermore the diagnostic check results indicated an ARMA (0,0) confirming the previous observations.

The models estimated are described in tables 6.3.3. Specifications I and IV are the best performing models according to the fit statistics (see table 6.3.3-b).

However, as shown by the large p values, models I and IV produce insignificant lag estimates (AR1,1). The same is true for the untransformed model, specification III and model II for which models all parameters are insignificant.

The signs are as expected with a positive domestic demand and GDP (NUM1) coefficient.

Concenring in particular model IV, the lag of log_domestic demand is correlated with the mean. However, as long as this relationship continues in the future it does not compromise the quality of the forecast.

Table 6.3.3-a: Model specifications – BLX

| Model | Parameter | Estimate | Maximum Likelihood Estimation<br>Standard Error | t Value | Approx Pr > \|t\| | Lag | Variable | Shift |
|---|---|---|---|---|---|---|---|---|
| Model I | MU (MEAN) | -0.0062957 | 0.01347 | -0.47 | 0.6402 | 0 | Logquantity | 0 |
| | AR1,1 | -0.20945 | 0.19721 | -1.06 | 0.2882 | 1 | Logquantity | 0 |
| | NUM1 | 1.30776 | 0.56534 | 2.31 | 0.0207 | 0 | logdomestic_demand | 0 |
| Model II | MU (MEAN) | 0.0093289 | 0.01395 | 0.67 | 0.5036 | 0 | Logquantity | 0 |
| | AR1,1 | -0.21126 | 0.19980 | -1.06 | 0.2903 | 1 | Logquantity | 0 |
| | NUM1 | 0.64558 | 0.58377 | 1.11 | 0.2688 | 0 | Logdomestic_demand | 1 |
| Model III | MU (MEAN) | 0.0021820 | 0.0068405 | 0.32 | 0.7497 | 0 | Quantity | 0 |
| | AR1,1 | -0.16577 | 0.19883 | -0.83 | 0.4044 | 1 | Quantity | 0 |
| | NUM1 | 2.62974 | 2.70646 | 0.97 | 0.3312 | 0 | domestic_demand | 0 |
| Model IV | MU (MEAN) | -0.02185 | 0.01648 | -1.33 | 0.1850 | 0 | Logquantity | 0 |
| | AR1,1 | -0.18585 | 0.20208 | -0.92 | 0.3577 | 1 | Logquantity | 0 |
| | NUM1 | 1.85301 | 0.66110 | 2.80 | 0.0051 | 0 | logGDP | 0 |

Table 6.3.3-b: Fit Statistics - BLX

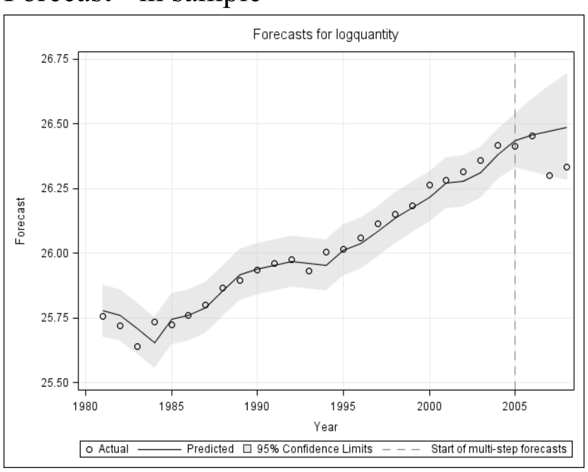
| Fit statistics | Model I | Model II | ModelIII | Model IV |
|---|---|---|---|---|
| Constant Estimate | -0.00761 | 0.0113 | 0.002544 | -0.02591 |
| Variance Estimate | 0.002515 | 0.002711 | 0.000562 | 0.002302 |
| Std Error Estimate | 0.050152 | 0.052062 | 0.023701 | 0.047978 |
| AIC | -85.2587 | -80.0986 | -127.25 | -87.7505 |
| SBC | -81.2621 | -76.2111 | -123.254 | -83.7538 |
| Number of Residuals | 28 | 27 | 28 | 28 |

Despite the obtained sub-optimal econometric properties of the models forecasts are now tested. The reason is that empirical research in forecasting has shown that a sub-optimal model fit is not necessarily restrictive given the objective of forecasting, in which case a model with limited explanatory power may still produce very good forecasts.

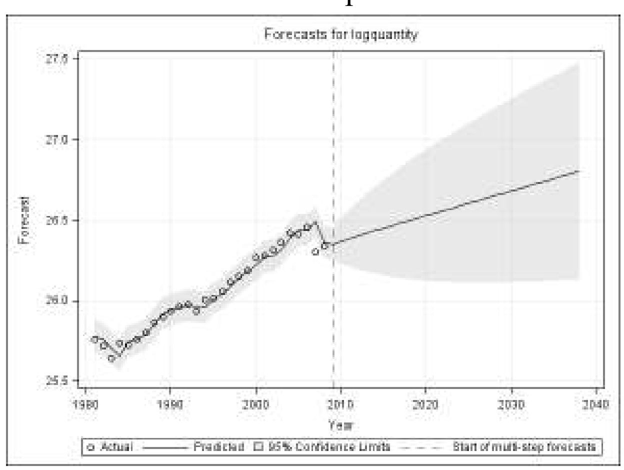
The in sample forecasts for BLX are shown in graphs 6.3.1-a and 6.3.1-b. The in sample forecasts are performed by re-estimating the models until the year 2005 and perform forecasts until the year 2008. Model I, the core model is shown separately from the other three models and it includes the out of sample forecast.

Graph 6.3.1-a: Forecast – BLX : $\Delta \log y_t = -0.006 - 0.209 \Delta \log y_{t-1} + 1.3 \log x_t$

Forecast - in sample

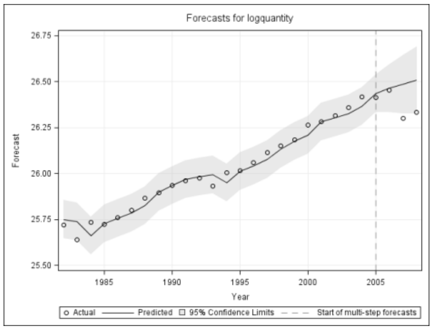



Forecast – out of sample

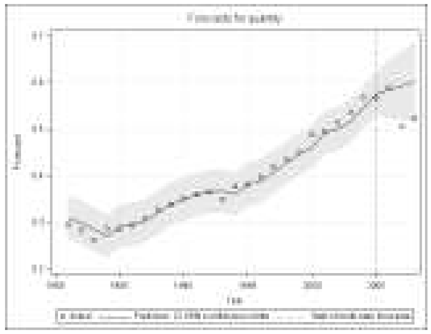


Graph 6.3.1-b: In sample Forecasts alternative model specifications - BLX

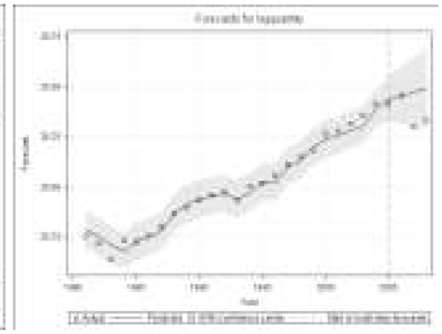
Model II




Model III



Model IV

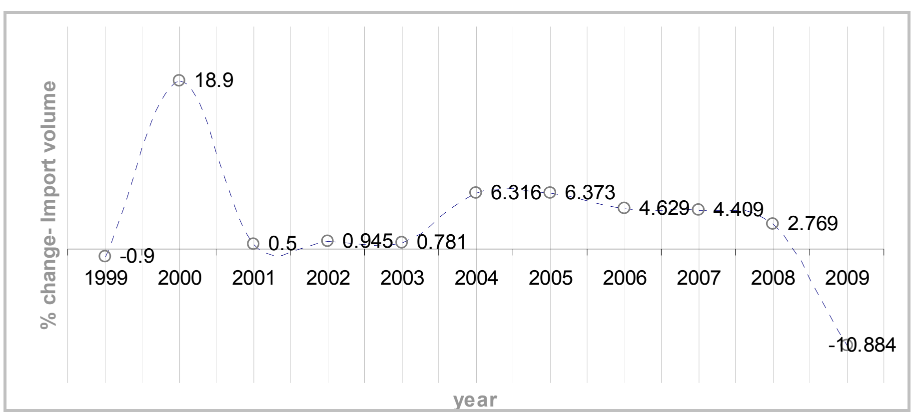


Graphically in the case of BLX the in sample forecasts for all models, core and alternative specifications perform equally well.

In particular the core and alternative models perform well for the year 2006 but do not predict well the dip in 2007 and 2008. While for the year 2008 the dip could be explained by the financial crisis this is not likely to be the case for 2007. What hence needs to be investigated is whether the value of 2007 is a statistical outlier. This is explored by the use of the alternative database used in chapter four, IMF's WEO database.

In particular, the data of the percent change of the volume of import[20] for only BLX (LUX values are unfortunately not available) are shown in graph 6.3.1-c.

Graph 6.3.1-c: WEO % change of Import volume of goods (BEL only)




Source: WEO, 2010

[20] Percent change of volume of imports of goods refers to the aggregate change in the quantities of imports of goods whose characteristics are unchanged. The goods and their prices are held constant, therefore changes are due to changes in quantities only (WEO, 2010).

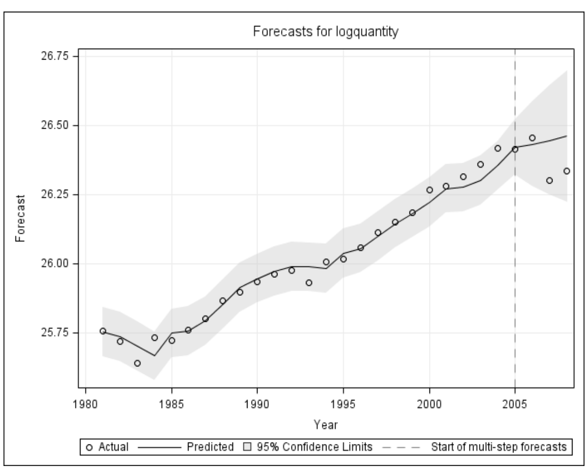
Graph 6.3.1-c explains the poorly fitted value for the year 2000 where it seems that import volume grew by 18.9 per cent. This extraordinary increase could be explained by the entry of Belgium in the European Monetary Union in 1999 (1st January). According however to the WEO figures the dip in 2007 is not justified. It could however be that LUX experienced a noticeable decline in imports during that year. For the purpose of this work the year 2007 will be regarded as an outlier bearing no economic importance. As in all cases acquiring data for 2010 will be most informative for the recovery from the crisis and hence also for future forecasts.

An alternative in sample forecast period by extending the in sample forecast from the year 2000 to 2008 is also tested. This alternative however leads to projections which continuously underestimate true values. What this outcome means is that Model I does not accurately predict the volume of imports. This situation can be explained by the fact that BLX is a particular case of an open economy which grows more than what its localized economic growth suggests. Since the data however include the imports of Belgium as final destination only, what such an assumption suggests is that some of the products imported by other countries but with BLX as transit country could be registered by the customs as imports of BLX while their final destination is outside BLX.

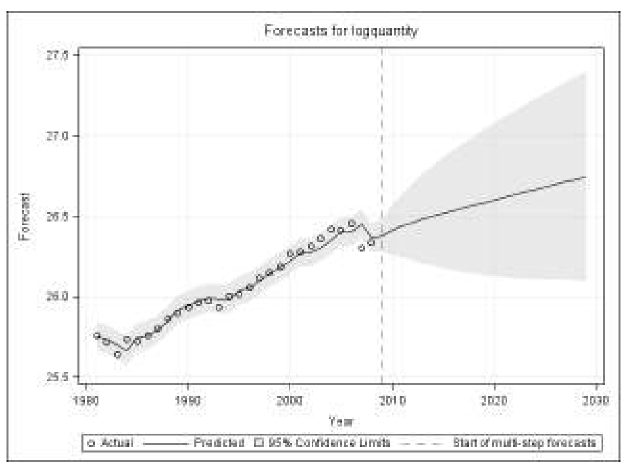
Finally the VEC model based forecast is introduced in figure 6.3.1. Both in sample and out of sample forecasts are illustrated. The stationarity of the error is confirmed by the Dickey Fuller test. Parameter estimates are significant. The graphical fit of the in sample forecast is good. It can therefore be concluded that the VEC model in the case of BLX is a sensible model for forecasting future import growth, although in this case too the forecasts for the year 2007 (and year 2000) do not perform well.

Figure 6.3.1: VEC – BLX

Forecast - in sample




Forecast – out of sample



| Variable | Parameter Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| Dlogdomestic_demand | 1.04264 | 0.35010 | 2.98 | 0.0029 |
| residual1 | -0.40620 | 0.15840 | -2.56 | 0.0103 |

#### 6.3.2.3 The case of Germany (DEU)

A similar pattern as in the case of BLX is observed for DEU. The series in levels are non-stationary and the white noise hypothesis is rejected very strongly. The differenced series are however stationary as confirmed by both the dickey fuller test and the graphical ACF plot.  The check for white noise indicates as for the BLX countries that the series is white noise (a purely random process), which means there is no need to fit simple AR(p) models. Such conclusion is further confirmed by the diagnostic check indicating and ARMA (0,0).

The models estimated are described in Tables 6.3.4. The application of specification I, is the best performing model according to the fit statistics (see Table 6.3.4-b). Model IV scores second after model I in terms of fit statistics.

According to the p values in Table 6.3.4-a models I and IV produce significant estimates of the lag of import quantity. The regressor domestic demand (NUM1) in model I is significant while the regressor GDP (NUM1) in model IV is not significant.  The untransformed specification model III performs well with all significant parameter estimates. The mean (MU) is not significant for neither model.

Finally model II performs poorly while subject to the same issue of collinearity as the case of BLX.

The signs are however not as expected with in particular a negative domestic demand and GDP (NUM1) coefficient.

Table 6.3.4-a: Parameter Estimates – DEU

| Maximum Likelihood Estimation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Model | Parameter | Estimate | Standard Error | t Value | Approx Pr > \|t\| | Lag | Variable | Shift |
| Model I | MU | 0.05450 | 0.03408 | 1.60 | 0.1098 | 0 | Logquantity | 0 |
| | AR1,1 | 0.60851 | 0.16103 | 3.78 | 0.0002 | 1 | Logquantity | 0 |
| | NUM1 | -2.10401 | 0.97923 | -2.15 | 0.0317 | 0 | Logdomestic_demand | 0 |
| Model II | MU | 0.0077937 | 0.02260 | 0.34 | 0.7303 | 0 | Logquantity | 0 |
| | AR1,1 | 0.24595 | 0.20056 | 1.23 | 0.2201 | 1 | Logquantity | 0 |
| | NUM1 | 1.49109 | 0.93581 | 1.59 | 0.1111 | 0 | Logdomestic_demand | 1 |
| Model III | MU | 0.03978 | 0.02156 | 1.84 | 0.0651 | 0 | Quantity | 0 |
| | AR1,1 | 0.56399 | 0.16995 | 3.32 | 0.0009 | 1 | Quantity | 0 |
| | NUM1 | -1.84167 | 0.82354 | -2.24 | 0.0253 | 0 | Domestic_demand | 0 |
| Model IV | MU | 0.04321 | 0.02953 | 1.46 | 0.1434 | 0 | Logquantity | 0 |
| | AR1,1 | 0.40086 | 0.18850 | 2.13 | 0.0335 | 1 | Logquantity | 0 |
| | NUM1 | -0.88778 | 1.07000 | -0.83 | 0.4067 | 0 | logGDP | 0 |

An explanation for the negative sign can be found in Table 6.1 listing possible triggers of change and in particular the identification of shift to service based economies. It is plausible that the DEU economy has already significantly shifted to services which are not included in the dataset given the focus on goods. An increase hence of domestic demand does not lead to higher volumes of trade in goods. Additionally, as income rises (and hence also GDP and domestic demand), the share of high valued goods with lower weight in trade will increase (similar to Engel's law) and therefore, the higher domestic demand will lead to higher imports in value, but not in volume (Meersman, 2011).

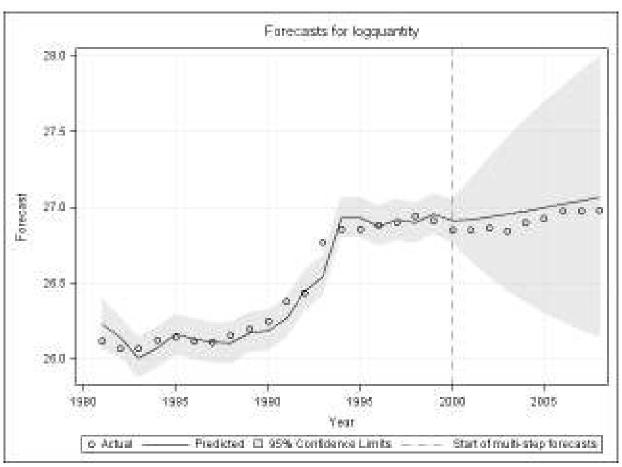
Table 6.3.4-b: Fit Statistics – DEU

| Fit Statistics | Model I | Model II | ModelIII | Model IV |
|---|---|---|---|---|
| Constant Estimate | 0.021335 | 0.005877 | 0.017342 | 0.025891 |
| Variance Estimate | 0.004674 | 0.004799 | 0.002167 | 0.005072 |
| Std Error Estimate | 0.068368 | 0.069277 | 0.046553 | 0.071215 |
| AIC | -67.4902 | -64.6561 | -89.091 | -65.4925 |
| SBC | -63.4936 | -60.7686 | -85.0944 | -61.4959 |
| Number of Residuals | 28 | 27 | 28 | 28 |

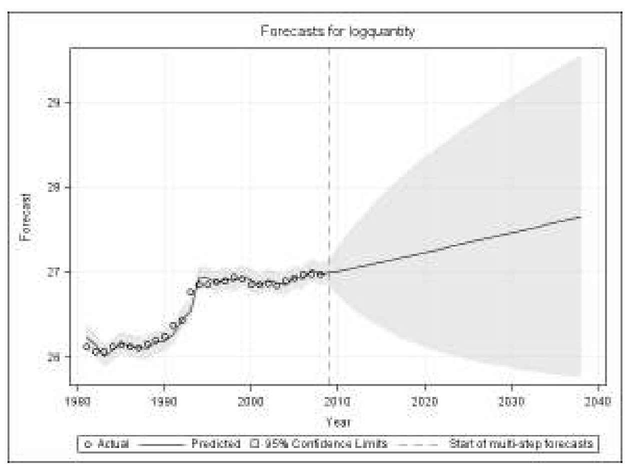
The same distinction between the explanatory power and predictive power of a model as explained in the case of BLX is valid in this case too. This is seconded by the forecast which performs reasonably well as shown by the in sample forecasts shown in Graphs 6.3.2. The graphs for the forecasts illustrate in sample forecasts from the year 2001 until 2008. Model I, the core model is shown separately from the other three models and it includes the out of sample forecast in Graph 6.3.2-a. The alternative models and their in sample forecasts are shown in Graph 6.3.2-b.

Graph 6.3.2-a: Forecasts – DEU: $\Delta \log y_t = 0.054 + 0.608 \Delta \log y_{t-1} - 2.104 \log x_t$

Forecast - in sample

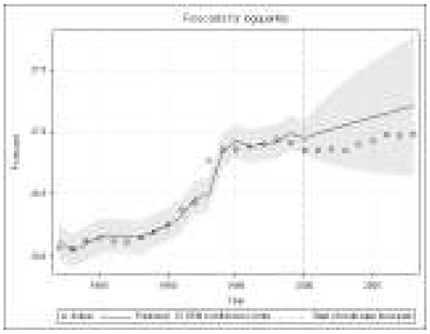
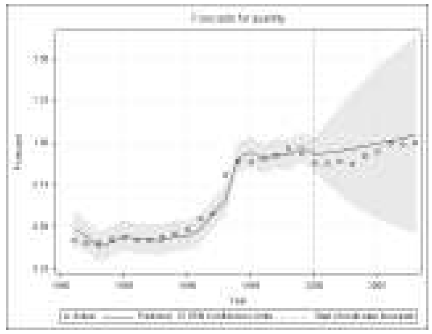
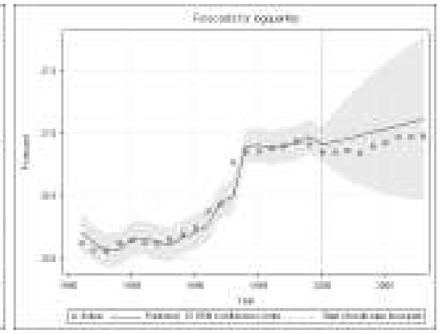



Forecast - out of sample



Graph 6.3.2-b: In sample Forecasts alternative model specifications - DEU

Model II Model III Model IV

The combination of unexpected signs and good forecasts points towards the presence of collinearity between the lag of import growth and domestic demand growth. The latter is investigated by the table of correlation of parameter estimates where no indication of collinearity is detected.

Projections however continuously slightly overestimate true values for the period 2001-2008. What this outcome means is that domestic demand growth and the lag of import growth do follow the growth of the volume of imports but they overestimate true import growth.

Such growth pattern can be explained by the German economic model of an export driven economy which stimulates its competitiveness by keeping wages and domestic demand lower that what is expected, as quoted and systematically indicated by the press (Financial times, 2011; 2010; 2008; 2005). This pattern is very well captured by the model. However, what is observed as stagnant domestic demand is even less expressed by the importing profile in quantities. Such slight overestimation is better understood by decomposing domestic demand to its components of gross capital formation, gross national expenditure and household final consumption. The inclusion of gross capital formation or alternatively gross domestic investment[21] in which the DEU performs well, could possibly be the reason for the overestimation. Another explanation could be that domestic demand in the case of DEU includes mostly demand for goods produced within DEU and not imports.

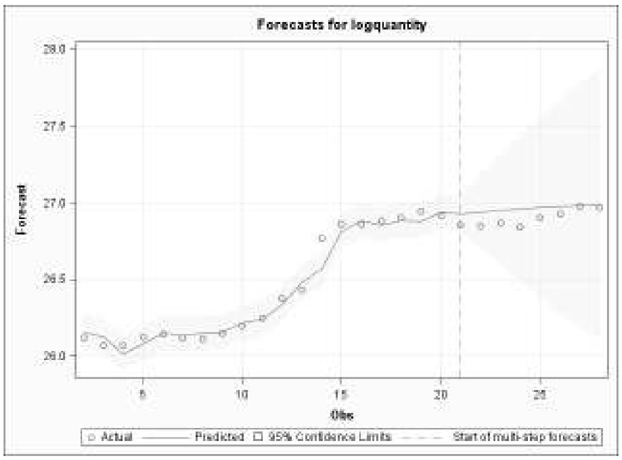
Graph 6.3.1-b illustrates the alternative specifications which confirm the results of the RMSFE and parameter estimates by attributing superiority to specification I. Model III performs equally well as expected given the good statistical properties of the model.

[21] Gross capital formation (formerly gross domestic investment) consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. Inventories are stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, and "work in progress." According to the 1993 SNA, net acquisitions of valuables are also considered capital formation (WDI, 2011).

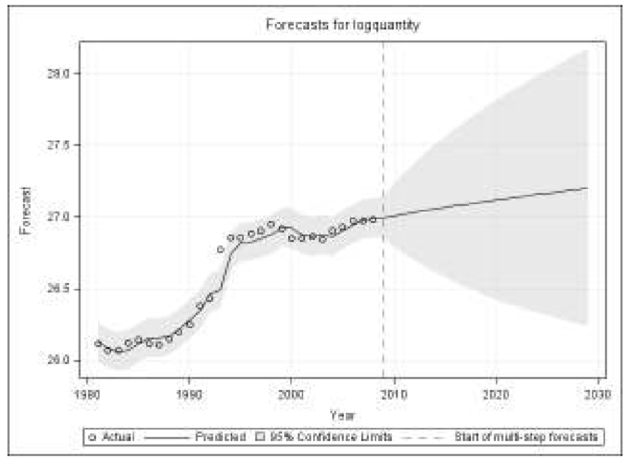
Finally the VEC model is introduced in figure 6.3.2. Both in sample and out of sample forecasts are illustrated. The stationarity of the error is confirmed by the Dickey Fuller test. The estimate for the log of domestic demand is not significant. The in sample forecast however performs well. It can therefore be concluded that the VEC model in the case of DEU is a sensible model for forecasting future import growth.

Figure 6.3.2: DEU – VEC

Forecast - in sample




Forecast – out of sample




| Variable | Estimate | Standard Error | t Value | Approx Pr > \|t\| |
|---|---|---|---|---|
| Dlogdomestic_demand | 0.83564 | 0.59422 | 1.41 | 0.1596 |
| Residual1 | -0.30390 | 0.11746 | -2.59 | 0.0097 |

#### 6.3.2.4 The case of the Netherlands (NLD)

Finally, in the case of the NLD in contrast to the cases of BLX and DEU the series in levels are found to be stationary. This is confirmed by the Dickey Fuller test and the ACF plot which displayed rapid decay after lag 1. Additionally, the white noise hypothesis with p value p=0.08 shows that the series is autocorrelated. Further testing with ARIMA diagnostic checks show that an ARMA (1, 0) or (2, 0) is most suitable. The fitting however of simple AR(p) models and in particular an AR(1) and AR(2) produce very poor forecasts. Such outcome might be due to the weakness of the Dickey Fuller test for small samples. Consequently all models are estimated with differenced series.

The models estimated are described in Table 6.3.5. The application of specification II is the best performing model according to the fit statistics (see Table 6.3.5-b). Model I scores second .

According to the p values in Table 6.3.5-a, the parameter estimates are insignificant in all models.

The signs are as expected with in particular a positive domestic demand and GDP (NUM1) coefficient. Only exception is model II where the lag of domestic demand has a negative sign.

Table 6.3.5-a: Parameter Estimates – NLD

| | | | Maximum Likelihood Estimation | | | | | |
|---|---|---|---|---|---|---|---|---|
| Model | Parameter | Estimate | Standard Error | T Value | Approx Pr > \|t\| | Lag | Variable | Shift |
| Model I | MU | 0.0031711 | 0.01401 | 0.23 | 0.8209 | 0 | Logquantity | 0 |
| | AR1,1 | 0.05460 | 0.20019 | 0.27 | 0.7850 | 1 | Logquantity | 0 |
| | NUM1 | 0.57395 | 0.50717 | 1.13 | 0.2578 | 0 | logdomestic_demand | 0 |
| Model II | MU | 0.03567 | 0.01018 | 3.50 | 0.0005 | 0 | Logquantity | 0 |
| | AR1,1 | -0.16373 | 0.20220 | -0.81 | 0.4181 | 1 | Logquantity | 0 |
| | NUM1 | -0.70476 | 0.37368 | -1.89 | 0.0593 | 0 | logdomestic_demand | 1 |
| Model III | MU | 0.0053646 | 0.0064507 | 0.83 | 0.4056 | 0 | Quantity | 0 |
| | AR1,1 | -0.04401 | 0.20053 | -0.22 | 0.8263 | 1 | Quantity | 0 |
| | NUM1 | 0.59891 | 1.48563 | 0.40 | 0.6868 | 0 | domestic_demand | 0 |
| Model IV | MU | 0.0048065 | 0.01613 | 0.30 | 0.7657 | 0 | Logquantity | 0 |
| | AR1,1 | -0.02438 | 0.20400 | -0.12 | 0.9049 | 1 | Logquantity | 0 |
| | NUM1 | 0.45572 | 0.56904 | 0.80 | 0.4232 | 0 | logGDP | 0 |

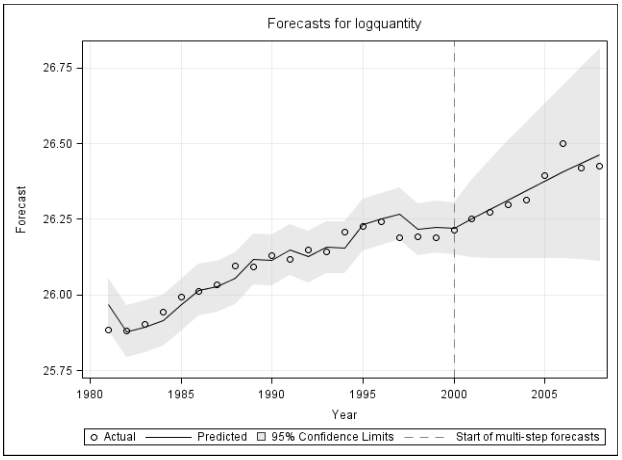
Table 6.3.5-b: Fit Statistics – NLD

| Fit statistics | Model I | Model II | ModelIII | Model IV |
|---|---|---|---|---|
| Constant Estimate | 0.002998 | 0.041509 | 0.005601 | 0.004924 |
| Variance Estimate | 0.001884 | 0.001319 | 0.000468 | 0.001921 |
| Std Error Estimate | 0.043402 | 0.036316 | 0.021644 | 0.043833 |
| AIC | -93.3953 | -99.5674 | -132.36 | -92.8445 |
| SBC | -89.3987 | -95.6799 | -128.363 | -88.8479 |
| Number of Residuals | 28 | 27 | 28 | 28 |

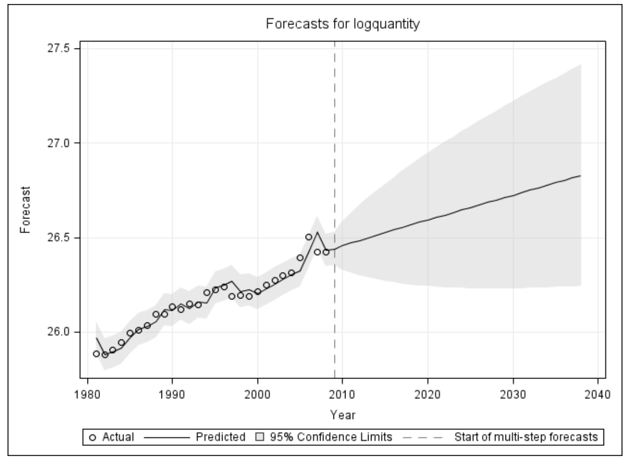
In this case too it is instructive to look at the in sample forecast plots. Graph 6.3.3 illustrates in sample forecasts from the year 2001 until 2008. Graph 6.3.3-a shows the forecasts for in sample and out of sample forecasts of Model I. Graph 7.3.3-b shows the in sample forecasts for the alternative specifications.

Graph 6.3.3-a: NLD – output: $\Delta \log y_t = 0.003 + 0.054 \Delta \log y_{t-1} + 0.574 \log x_t$

Forecast - in samle

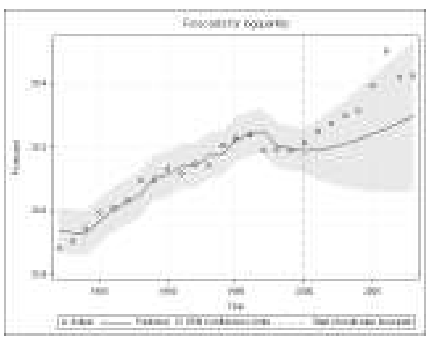



Forecast - out of sample

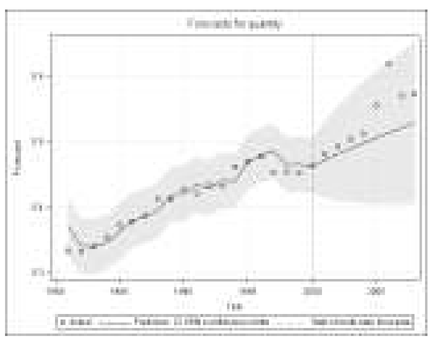



Graph 6.3.3-b: In sample Forecasts alternative model specifications - NLD

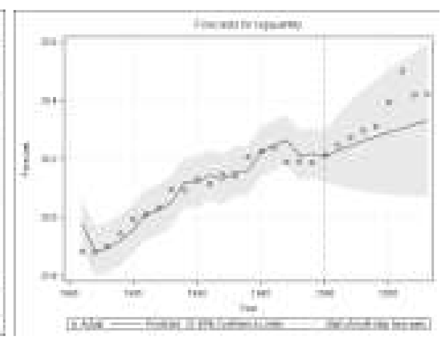
Model II



Model III



Model IV

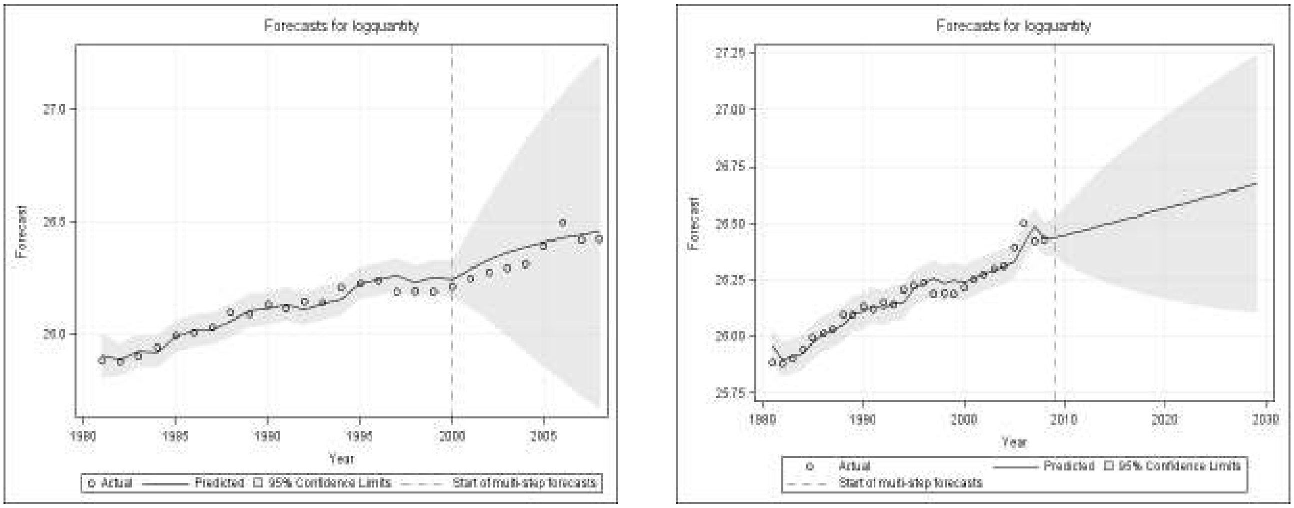


The forecast plots show that model I outperforms all other models. Projections accurately predict true values with the exception of years 2006 and 2008. The fact that Model I does not capture the growth in imports for these years can be explained by model misspecification whereby the intervention of other variables defining the growth of imports could have been especially expressed during the specific years of 2006 and 2008. The year of 2008 is however the year of the financial crisis which could have already affected importation growth which is not directly accountable by domestic demand.

Finally the VEC model is introduced in figure 6.3.3. The stationarity of the error is confirmed by the Dickey Fuller test. The estimates are significant. The in sample forecast performs well.
It can therefore be concluded that the VEC model in the case of the NLD is a sensible model for forecasting future import growth.

Figure 6.3.3: NLD – VEC

Forecast - in sample Forecast – out of sample




| Variable | Estimate | Standard Error | t Value | Approx Pr > \|t\| |
|---|---|---|---|---|
| Dlogdomestic_demand | 0.73696 | 0.27568 | 2.67 | 0.0075 |
| residual1 | -0.28232 | 0.13800 | -2.05 | 0.0408 |

#### 6.3.2.5 Sample country forecasts: Forecast evaluation

Theil's U statistic is used to evaluate the best performing models according to the analysis in chapter 6.3.2.4. The ARIMA model I and the VEC models are hence documented. The results are presented in table 6.3.4.

Table 6.3.4: Forecast Evaluation Statistics

| Forecast Evaluation Statistics - MODEL I | BLX | DEU | NLD |
|---|---|---|---|
| Theil's U1 | 0.00172 | 0.00145 | 0.00075 |
| Theil's U2 | 0.0005873 | 0.007228 | 0.00423 |

| Forecast Evaluation Statistics - VEC | BLX | DEU | NLD |
|---|---|---|---|
| Theil's U1 | 0.001667 | 0.000995 | 0.0009132 |
| Theil's U2 | 0.009234 | 0.005185 | 0.0047207 |

In particular Theil's U statistic is used in two ways. Firstly, to see how much two series (actuals and forecasts) are closer to each other and secondly whether forecasts produced by a model perform better than the naïve forecasts. This is done by calculating a U1 and U2 statistic respectively. The U1 statistic is bounded between 0 and 1. Values closer to 0 indicate greater forecasting accuracy. The U2 statistic takes the value 1 under the naïve forecasting method. Values less than 1 indicate greater forecasting accuracy than the naïve forecasts, values greater than 1 indicate the opposite (department of treasury, 2008). According to table 6.3.4 both model I and VEC perform very well for all countries.

## 6.4 Summary of findings

The objective of this chapter was to provide for forecasting models capable of addressing future growth potential and variability of the volume of imports of the countries and between the countries respectively.

Several specifications were tested and different estimation methods were used. The main indicators used were domestic demand, GDP and the oil price (although the latter only confirmed the expected no relevance to the forecasting accuracy of the models). A core specification was defined with the growth of import quantities being explained by the growth of domestic demand and the lag of the import quantities.

Domestic demand in particular was considered as an indicator adding economic considerations as suggested by Keck (2006) and Pain (2005). In this application too it is believed that expert opinion plays a crucial role. As already described in chapter five experts opinion is typically used when structural models are employed and the discussion concentrates on input parameters. Given the attractiveness of time series as baseline economic forecasts, it is believed that experts opinion can be used for the additional testing with explanatory variables which go beyond theory, to be based on in depth market intelligence.

Furthermore as previously mentioned, a number of other variables could potentially improve the results obtained in this research. Such process of trial and error even if based on time series need not be void of economic considerations and can be based on the variables used within structural models. This is to say that the analysis can be extended to cover a number of indicators according to either expert opinion or on the basis of common practices within the structural modeling approaches.

As a general remark concerning the ongoing sovereign debt crisis this approach is superior to the trend modeling approach under the assumption that domestic demand captures the effect of the crisis. Further testing when the data for 2010 becomes available will allow for an assessment of the explanatory power of domestic demand in this respect. In this case too a number of alternative variables could be tested and compared to each other.

The initial approach was to apply forecasting in the dynamic panel setting. While the models applied performed well, with significant estimators and no violation of the basic assumptions, an investigation of the variability between countries proved not to produce significant estimates. The lack of this dimension would limit the forecasting to a projection of the mean. Such forecasts add little value and do not justify the use of such a complicated approach. It was therefore decided to continue with the forecasting step through single country series.

The results of the single country estimations demonstrated that model fit often contradicts forecasting performance. Reasons for divergence between the countries' forecasting performance are attributed to the variability between the countries in terms of their economic development and the level of fragility of their economies to external factors.

Improvements of the selected as core specification, concentrated on, apart from the indicator of GDP which is the most widely applied input in trade applications, oil prices. In particular GDP seemed to significantly improve the forecasts for PRT. The addition of oil was expected to capture the volatility from year to year. The reason why it did not perform well might have been the measurement of it as yearly averages. It would thus mean that the oil price is better suited for analyses on a quarterly or monthly basis.

From the specific case studies presented in detail the alternative VEC model always at least matched the best performing VAR model. Although in this case the reliability of the models is severely compromised by the limited sample, theoretical considerations and existing studies provided the certainty of VEC modeling as a valid approach for the current applications.

Concerning the poor performance of the core and alternative specifications for some of the countries it can be attributed to data quality, especially for the countries of Eastern Europe for which data before 1996 should be viewed with caution.

## 6.5 Discussion on dynamic model suitability and impact on the transport sector

Dynamic time series models have a good track record of performance in forecasting. It is often quoted that they outperform structural models with typically strong explanatory power but less strong predictive power. Single time series techniques even the most simple ones can provide good forecasts while panel data forecasting is a growing field. By employing more complicated techniques the panel data methods incorporate the time dimension and the dimension of the individual, in this case being the different countries. Such dynamics are of high relevance to the trading patterns of countries throughout time but also to the interactions of countries trading with each other.

Given the derived nature of transport's demand such quantifiable solutions can be of great assistance to transport stakeholders' decision making processes. The way the current work contributes is by providing the information needed for policy designs or corporate strategies aimed at accommodating the future growth, stagnation or decline of transport volume flows as explained in chapters one, three and five. More specifically the added value as compared to chapter five is the addition of the dynamic element in the forecasts and the use of indicators. Such a methodology of single time series can be replicated for a number of indicators beyond the ones tested in this research, to serve the specific needs of transport stakeholders as they arise.

# 7. Two alternatives in linking Trade to Container flows

Chapter seven suggests two alternatives in linking trade to container flows. The reason why such information is important is due to the high demand in the measurement of TEU in studies modeling freight. The intention therefore is to construct tools directly usable by transport stakeholders including policy makers and the transport industry. It is anticipated that the methodologies developed allow for further exploitation of trade data for transport purposes. In particular, value is added through the level of detail trade models entail in terms of their coverage in product categories, trade flow direction (ODs) and modeling sophistication. Such potential is more pronounced in the case of container flows, where currently only exclusive freight or maritime applications are available, lacking linkages to product categories or total trade and hence also to trade modeling outputs.

This chapter is split according to the two alternatives. Chapter 7.1 includes the disaggregated approach while chapter 7.2 the aggregated illustrated with a pilot case. The chapter ends with a discussion on the use of the disaggregated versus the aggregated approach in chapter 7.3.

## 7.1 The step-wise conversion of Trade data into Container units: A disaggregated approach

In this chapter a mechanism of converting trade into container units is constructed. The objective is the construction of a practical and ready-to-use tool, which incorporates common practices as observed in the transport sector. The reason why it is important is due to the high demand in the measurement of TEU in studies modeling freight.

The problems encountered are data and sector related. The data barriers are a result of data availability, specifically the lack of input on volume indicators and stowage factors. Sector related limitations are a result of market conditions with respect to practices of mixed cargo (more than one type of good in a single container) and container loading inefficiencies. In both cases the provision of a measurement quantifying the relevance of such occurrences is not attainable.

The suggested solutions to the aforementioned limitations are based on a combination of assumptions and scenarios. As such the conversion mechanism developed provides for second best solutions. However, by following a step wise approach a flexible and practical tool easily adjustable depending on the level of detail available is attainable.

The structure of this chapter is as follows. Chapter 7.1.1 introduces the problem. In chapter 7.1.2 a review of the available inputs potentially contributing to the construction of the conversion mechanism are reported. Chapter 7.1.3 contains a description of the data used and chapter 7.1.4 explains the step-wise methodology. The findings of the pilot case are illustrated in chapter 7.1.5. Chapter 7.1.6 is an attempt to partially validate the obtained result. Concluding remarks are found in chapter 7.1.7.

### 7.1.1 Introduction

The link between trade and transport data necessitates the direct sourcing of trade data in terms of tonnages. A step further however is needed when considering the translation of tonnages into TEU, the standard container measurement. The problems in executing such a task are numerous. The most important ones include:

- The lack of volume indicators in trade databases;

Typically trade databases and their applications report data and apply models on values or on some volume index of goods and services. Additionally volume measurements are typically reported in weight and not in volume measurements, a three dimensional unit.

- The lack of information on stowage factors;

Stowage factors of goods simply do not exist. After the prevalence of the container, general cargo practices necessitating detailed information for vessel planning on the level of cargo were no longer necessary and the problem of how to load a container shifted to the shipper.

- The lack of information on the content of the containers and its content throughout time.

Information on the content of the container is available but not accessible. Customs collect such information through the bill of lading but this information is not further processed into their systems making it readily available. As a consequence the evolution in time of products shifting from their traditional way of transport to the container is also not accessible.

- The lack of information on market related conditions in terms of i) mixed cargo and ii) inefficient loading of containers;

Common practices point towards substantial inefficiencies in the loading of containers. Therefore one cannot assume that full utilization of every container is achieved and furthermore that one container only contains one type of good.

- The lack of information on empty containers;

The movement of empty containers is not recorded.

The available data which serve the purpose of the conversion best are trade flows measured in weight and more specifically in kilograms as provided by the UNcomtrade when sourced on a three digit level[22]. The unit measurement of kilograms while not being the only measurement available[23] , it is the most complete (after the measurement of value). While such a database in kilograms is directly convertible into tonnages it does not contain information on the volume measurements. This means that there is no information describing the three dimensional size of the goods and as a consequence by having weight figures one cannot draw any inferences on how much container capacity this translates to. Yet, even with available data on goods volume, in either net or gross terms (with the packaging accounted for or not) the stowage of the goods in the container would remain unknown. This is for example the case when pallets are being put into the container for which information is not available.

Furthermore, under the assumption of known container stowage factors, the problems become market related. These problems arise due to practices of mixed cargoes instead of containers exclusively loaded with a single type of good, or inefficiencies in loading the container in terms of the available container space not being fully optimized. Finally the unknown content of the containers does not allow for a dynamic estimation of the container volumes. This is due to a lack of historic information on the goods traditionally transported in containers and their differentiation from the occasionally containerized goods or the non containerized goods. In particular, what is being observed is that due to unforeseen events or specific market conditions (i.e. high/low freight rates) goods are occasionally being transported in containers. The extent and frequency, these situations occur remains unknown. Especially due to the crisis and the consequent pressures for capacity optimization this tendency has been even more pronounced. An interesting complication relevant to these dynamics is that during times of very high charter rates cargo shifts also vice versa i.e. from containers to bulk. As mentioned earlier, a large part of this information could be constructed from data, from the bill of lading collected by the customs, but is unfortunately not processed and hence not available.

Literature on this topic is extremely limited. A master thesis using a conversion factor by Cheung (2005) looked into the imports of manufactured goods of the Netherlands from China using trade value densities and the containerization degree together with the average container weight statistics of the Netherlands. Such an approach while novel it is OD specific and requires substantial amounts of data. The approach followed in this research addresses the lack of the link between trade and freight databases with main objective the realistic representation of the volume of trade in TEU by providing a flexible ready-to-use tool.

---

[22] The number of digits depends on the product classification and represents the level of detail in the product classification. This is explained in detail in chapter four.

[23] Other measurements include: Area in square meters, Electrical energy in thousands of kilowatt-hours, Length in meters, Number of items, Number of pairs, Thousands of items, Volume in cubic meters, Volume in litres, Weight in carats, Weight in kilograms

An illustration is made on the category of manufactured goods, in particular the sub-category of manufactured goods chiefly classified by material (category six)[24]. Ideally such study should be made on the data of the customs directly or with the cooperation of transport agents. Given the lack of both sources, this chapter describes and suggests a second best alternative which overcomes such barriers.

### 7.1.2 Available input

The availability of relevant input is limited and is either outdated or does not provide for the necessary coverage in product categories. An extensive research on stowage factors had been made in the 1920's, commissioned by the US government. The final output of that research was an impressive document of eighty pages listing the stowage factor of a number of products. This information used to be critical for the loading of general cargo vessels where the intention was to optimize cargo loading due to increased demand for cargo space. Despite its striking coverage, apart from the stowage factors being outdated (due to different packaging, use of pallets etc) it does not provide accurate information on container loadings. An example of such inaccuracies is that the stowage factor of a certain number of boxes changes when positioned on pallets.

Similar problems are faced by other industries like the air industry. Research has thus been performed in the air transport field with a different purpose however. In particular, a study was made with special interest the establishment of the accuracy of the 1/6 rule[25] used in cargo charging which is based on average product density (Van de Reyd et al, 2005). The motivation had been the curiosity in the sector on the evolution of the growth of volume constrained shipments. Two main objectives were defined, the determination of product densities and the investigation of entire aircraft pallets and the total aircraft loadings. The data used was directly sourced from a variety of air freight companies. Considerations on the direct use of the results of this research have been rejected due to the incomplete coverage in product categories and the differentiation of unit loading devises.

Another example of a different industry in need of such information is the rail industry. In particular a project with prime goal the quantification of emissions of freight transport called EcoTransit was carried out by a number of European railway companies in 2000. One of the elements under consideration has been the load factors of modes and of the container. Such information is relevant for that study since volume and average weight cargo are responsible for higher emissions.

[24] A more detailed description of category six is given in chapter four.

[25] This is a conversion factor and it means that 6 cubic meters of volume correspond to a weight of 1 ton. It is set arbitrarily and it has originally been defined to 1/5 then to the current 1/6 while in 2002 an amendment proposal for the adaptation of a 1/5 rule had been denied.

In particular a distinction between three container load classes was made, defined by a category of average, light and heavy load. The distinction was made since many cargoes shipped in containers are light weight consumer goods and should hence be differentiated by the heavier goods. The category of average cargo was defined on the basis of a study of port container statistics[26]. Under a set of assumptions for each of the categories, average tons per TEU were calculated.

### 7.1.3 Data: Trade

The trade data are sourced by the UNCOMTRADE. The pilot trade data include a database for disaggregated data on the SITC digit three level[27], which is the minimum level of disaggregation for which data in kilograms are available. It consists of European imports of category six, "manufactured goods chiefly classified by material", the database described in chapter four. In particular it includes imports of Western European countries (Austria, Belgium, France, Germany, Luxembourg, Netherlands and Switzerland) from the world and from China. The choice of China adds the maritime perspective, serving as an example of an important overseas located trading partner. The methodology is illustrated for the specific product category and as such the focus lies on the characteristics of the subcategories of the good. The products hence require further identification in terms of their transport characteristics and in terms of their volume and stowage.

### 7.1.4 Methodology: Disaggregated

The conversion of weight in TEU for the disaggregated database is made with the help of three additional databases: a classification database listing the product classification (code plus description of the product and digit level), a volume database splitting goods in Light Average and Heavy and a unitization degree database splitting goods according to Low, Medium and High probability of containerization.

All three databases are elaborated on the maximum number of digits (3 until 5 in the case under investigation). The final classification desired is the digit 3 and it is calculated as the mode[28] of digit 4, with the latter when further disaggregated calculated as the mode of digit 5. A detailed approach is hence followed of a highly disaggregated level in order to make the classifications in the databases.

26 The ports considered were: Amsterdam, Rotterdam, Hamburg, Bremerhaven, Seattle, Singapore, Hong-Kong and Sydney.

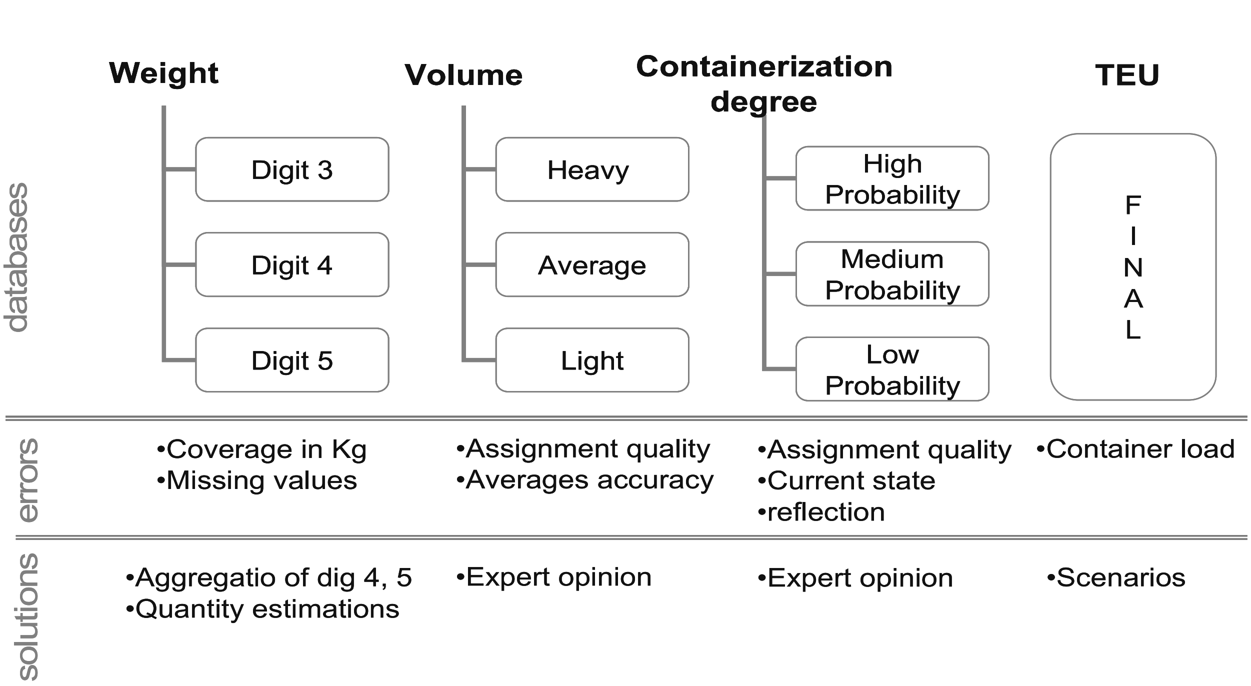
27 In particular the SITC revision 2 has ben chosen. This is due to the sourcing of historic data from the 1980's for which earlier classifications are appropriate.

28 Most frequently occurring value in the array of digit 4 and 5 .

Such a step wise approach, allows for flexibility by reflecting considerations of market imperfections. Assumptions could hence be made by means of scenarios reflecting market intelligence on for example i) empty containers, ii) non-fully loaded containers or iii) hypotheses of for example "what if all products would be containerized". Such interventions would be possible by manipulating the volume and unitization degree databases.

The process of obtaining container units from trade data is summarized in Figure 7.1.1. It is split in three blocks (indicated on the left hand side of the figure horizontally): the databases, the errors inherent in the databases and the solutions suggested.

Figure 7.1.1: The disaggregated methodology correct aggregation




The block databases, starts with the raw database "Weight" and describes the process in the following three steps:

**1.** The axis Volume describes the assignment of the sub-products of category six (on a three digit level) to the three levels of average ton/TEU which take the value 6 when classified as Low (L) ton/TEU, the value of 10.5 when classified as average (A) ton/TEU and lastly the value 14.5 when classified as Heavy. These figures are based on averages of tons per TEU as they have been estimated by the EcoTransit project. The created database (table: ton/TEU classification) includes three main elements:

i) the product code, ii) its description and iii) the value of ton per TEU plus some auxiliary information. A sample of that table is included in table 7.1.1. It illustrates how the table is organized showing specifically the way it is done for the category of “leather”.

Table 7.1.1: sample of table ton/TEU classification

| **Product code** | **Product Description** | Level of aggregation | **L/A/H** | Comments | **Average ton/TEU** |
|---|---|---|---|---|---|
| 611 | Leather | 3 | A | Calculation: Mode | 12.45 |
| 6112 | Composition leather, in slabs, sheets or rolls | 4 | A | Average weight non bulky | 12.45 |
| 6113 | Calf leather | 4 | A | Average weight non bulky | 12.45 |
| 6114 | Leather of other bovine cattle and equine leather | 4 | A | Average weight non bulky | 12.45 |
| 6115 | Sheep and lamb skin leather | 4 | A | Average weight non bulky | 12.45 |
| 6116 | Leather of other hides or skins | 4 | A | Calculation: Mode | 12.45 |
| 61161 | Goat and kid skin leather | 5 | A | Average weight non bulky | 12.45 |
| 61169 | Leather, nes | 5 | A | Average weight non bulky | 12.45 |

Source: own compilation, based on online sources

For a better understanding of the table further details on how the calculations made by the EcoTransIT project have been used in this research are described below.

In particular, the starting point of EcoTransIT was the definition of the average cargo category. The category of average cargo together with the Light and Heavy categories and the assumptions made are summarized in table 7.1.2.

Table 7.1.2: Volume cargo

| **Categories** | **Tons per TEU** | **Assumptions** |
|---|---|---|
| Light weight cargo | Net weight: **6**<br>Total weight:**7.9** | ▪ Typically 40’ feet containers<br>▪ 90% Max container load<br>▪ 50% use of carrying capacity |
| Average cargo | Net weight: **10.5**<br>Total weight:**12.45** | ▪ 20’and 40’ feet containers<br>▪ 2 to 5 transported cargo ratio<br>▪ 1.95 average empty weight |
| Heavy weight cargo | Net weight: **14.5**<br>Total weight:**16.5** | ▪ 20’and 40’ feet containers<br>▪ 90% max container load<br>▪ 90% use of carrying capacity |

Source: based on IFEU Heidelberg, Öko-Institut, IVE, RMCON, 2010 (see reference 28)

Concerning the category average according to the study of EcoTransIT, cargo is transported in 20' and 40' containers in the ratio of approximately 2 to 5 hence two 20's and five 40's, i.e. 2 TEU to 10 TEU. Thus for each lift (here meaning the number of containers loaded onboard of vessels) an average of 1.7 TEU is loaded (determined by comparing lifts and TEU handled from port statistics). The average empty weight of a container is 1.95 tons. Thus the average gross weight of a TEU is 12.45 tonnes.

Concerning light cargo a convention was used assuming that light weight cargo (or volume cargo) tends to be transported in 40' containers. Generally a maximum load of 90% of the capacity is assumed due to imperfect fit of the cargo in the container. The light weight is then assumed to be using 50 % of the carrying capacity. Thus, a 40' Container filled 45 % to its weight carrying capacity is assumed to represent a light weight cargo container. The latter results in 6.0 ton/TEU and an average empty container weight of 1.9 tons.

The heavy weight is similarly defined but with 90 % maximum carrying capacity. The average heavy weight is defined by applying the 1.7 ratio of 40' 20'. This results in 12 TEU (approximately 5 40' and 2 20' containers) In the set of 12 TEU and 7 containers, a ratio of 3x 40' containers filled with volume weight cargo and 2x 40' containers plus 2x 20' containers filled with heavy weight cargo result in the overall average weight of 10.5 tonnes. The heavy weight containers are then filled with 14.5 tonnes per TEU on average18[29] (EcoTransIT, 2010).

The approach of EcoTransIT is basically a way to technically approximate common market practice and indicators used by maritime stakeholders like the maritime agents, ship-owners and shipping lines. What is done in practice within the industry is that stakeholders use indicators of average weight per route expressed in tons/TEU.

Unfortunately, a database with average weight per route with some frequency either yearly/quarterly/monthly at least to the knowledge of the author does not exist. Some indicative figures of ton/TEU partly validating the EcoTransIT approach for around the period November 2010 were: a) Far East-Europe: 8 to10 tons/TEU (which is higher then what it was 5 years ago, of about 6.7 tons/TEU) and b) Europe-East-Coast USA: 14 to 15 tons/TEU (Paelinck, 2010). Given the lack of such information on the desired scale the EcoTransIT method is considered a valid approach.

**2.** The axis containerization degree describes the assignment of three levels of containerization probability: Low (LP: low probability of containerization), Medium (MP: medium probability of containerization) and High (HP: high probability of containerization). The created database (table: TEU probability) includes the product code, its description and the containerization probability. A sample of the TEU probability table is shown table 7.1.3.

[29] For further information the interested reader could consult the Methodology and Data document of the EcoTransIT Information Tool for Worldwide Transport found in URL: http://www.ecotransit.org/download/ecotransit_background_report.pdf

Table 7.1.3: sample of table TEU probability

| Product code | Product Description | Level of aggregation | Containerization probability |
|---|---|---|---|
| 611 | Leather | 3 | HP |
| 6112 | Composition leather, in slabs, sheets or rolls | 4 | HP |
| 6113 | Calf leather | 4 | HP |
| 6114 | Leather of other bovine cattle and equine leather | 4 | HP |
| 6115 | Sheep and lamb skin leather | 4 | HP |
| 6116 | Leather of other hides or skins | 4 | HP |
| 61161 | Goat and kid skin leather | 5 | HP |
| 61169 | Leather, nes | 5 | HP |
| 6118 | Leather, specially dressed or finished, nes | 4 | HP |
| 61181 | Chamois-dressed leather | 5 | HP |
| 61182 | Parchment-dressed leather pre-1978 | 5 | HP |
| 61183 | Patent leather and imitation patent leather; metalized leather | 5 | HP |

Source: based on expert opinion

As described in chapter three the category of average containerization probability is meant to reflect the market conditions of occasional containerization and route specific conditions of goods origin. The latter reflects the specificities in the OD's for which the origin of a certain good influences whether it's going to be transported in a container or not. The category of high probability includes the goods which are mature container goods, while the category of low probability includes goods which are typically transported in bulk. Clearly there is a level of arbitrariness in the attribution of high, average and low probabilities. The current version is partially based on the expert opinion of Prof. Honore Paelinck who has been kind enough to provide for valuable insights on the transportation of goods from the times of generalized cargo until today and of common practices in the maritime field. The author of this work takes however full responsibility for any "errors" within the database.

**3.** The matching of the observed data with the databases ton/TEU and TEU probability. The created database (table: final TEU) includes the product name, its code, the value of ton per TEU and the containerization probability.

The final database (final TEU) records the total TEU based on a set of assumptions, reflected by the so called errors in Figure 7.1.1.

The initial assumption made reflects data quality considerations. It should however be noted that the data quality affects the final outcome but it does not compromise the methodology itself which is based on the classification of goods and not the actual figures. It is nevertheless important to utilize as accurate and complete data as possible in order to acquire reliable results on the level of containers.

The second assumption made relates to the accuracy of the three level classification of ton/TEU as defined by the EcoTransIT project. Given their calculation as averages it should be taken into account that there is some inherent bias in the final result. Furthermore, the two assignments firstly of low, average and heavy ton/TEU and secondly low, medium and high probability of containerization to the digit 3 trade data are subject to further improvements. While the current assignment is valid, the use of an extended panel of experts willing to provide input on what would be a tedious task, would potentially improve the level of accuracy contributing hence to the overall quality of the database.

A third assumption of this approach regards mixed cargo practices. The assumption made assumes a single product per container. A fourth assumption made concerns inefficiencies in the loading of a container. While it is true that shippers would rationally strive for the optimization of container loadings, practice shows that this is not always true. The optimal solution to the aforementioned limitations would be by the acquisition of customs data. One of the barriers to such a task is the insertion of all the necessary information from the bill of lading into the system and the creation of databases which could become transferable without the need to reveal confidential information. It is however unknown what the quality of the database would be. The investigation of the existence of political will in doing so on a European scale goes beyond the scope of this research.

Solutions on the second best methodology presented in this chapter include the following suggestions:

Concerning missing data further estimations beyond the ones performed by the UNCOMTRADE can be made or aggregations from a deeper level of disaggregation can be performed.

Concerning the lack of experts opinion, a survey of forwarders, shipping lines or other agents could be designed. It should however be noted that such detailed insights on a product level only limited people possess today, since currently it is the shipper who makes the decisions. As a consequence a survey of shippers might prove to be more appropriate. Incentives for participation would be the database itself.

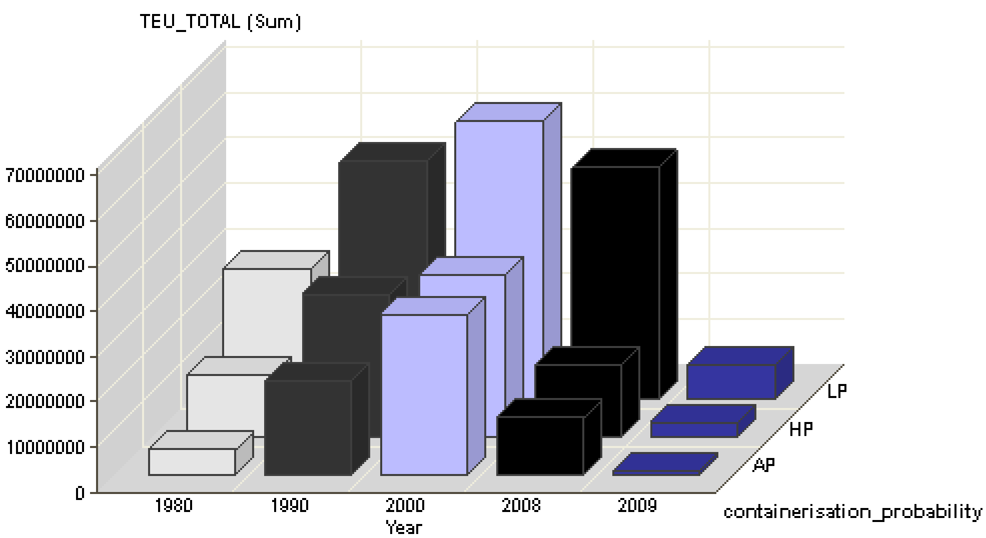
Finally, market practices could be captured by means of scenarios. For example ranges of a 2 to 10 per cent penalties can be imposed on the categories of ton/TEU reflecting the expectations of the level of inefficiencies. By doing so the approach is not compromised in the case where substantial inefficiencies are observed. Another example could be on future expectations of the degree of containerization of products which have been traditionally transported in bulk, ranging from all goods to what is believed to be the current situation.

### 7.1.5 Findings: Disaggregated

The findings of this methodology are illustrated by summarizing the output for the two cases under consideration, the imports of the European countries from the world and from China. Graph 7.1.1 represents the imports of category six from the world while graph 7.1.2 isolates the imports from China. These figures summarize the result of the combination of the three databases as described in the methodology. They are hence the output of the process of transforming weight in tons, tons in TEU and TEU split according to the containerization probability.

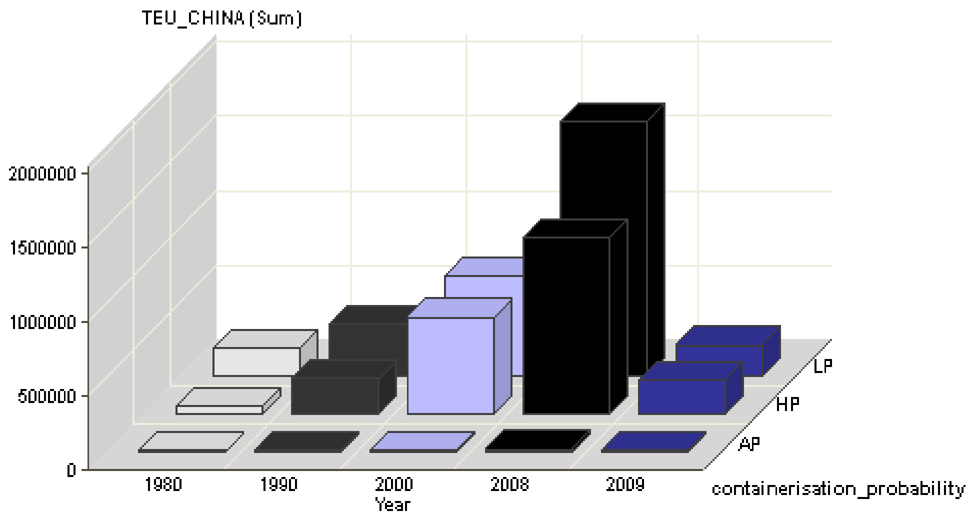
In Graphs 7.1.1 and 7.1.2 the x axis is the year and the y axis the TEU, while the third dimension of depth represents the degree of containerization. Although the graphs include historic observations it should not be interpreted as the evolution of the containerization degree. The graphs only reflect the growth in total volumes. The analysis on historic series would require an additional database attributing the containerization degree per category per year which would for example only be possible through the acquisition of customs data.

Graph 7.1.1: WESTERN European Imports of category 6 from the WORLD




Source: own compilation based on UNCOMTRADE data and additional sources

Graph 7.1.2: WESTERN European Imports of Category 6 from CHINA




Source: own compilation based on UNCOMTRADE data and additional sources

The most noticeable observation regarding the subdivision in AP, HP and LP from Graph 7.1 is that actual volumes of the category with a low probability of containerization rank highest. For example during the year 2008 the total importing mix of category 6 products of the Western European countries was divided in 61.% LP, 20% AP and 19% for HP. This is explained by the characteristics of the goods classified as LP which includes bulk products. This is shown in Graph 7.1.3.

Graph 7.1.3 shows the disaggregation on the two digit scale. This however can be further broken down on the three and four digits. For illustrative purposes only the two digit scale is reported in this chapter.

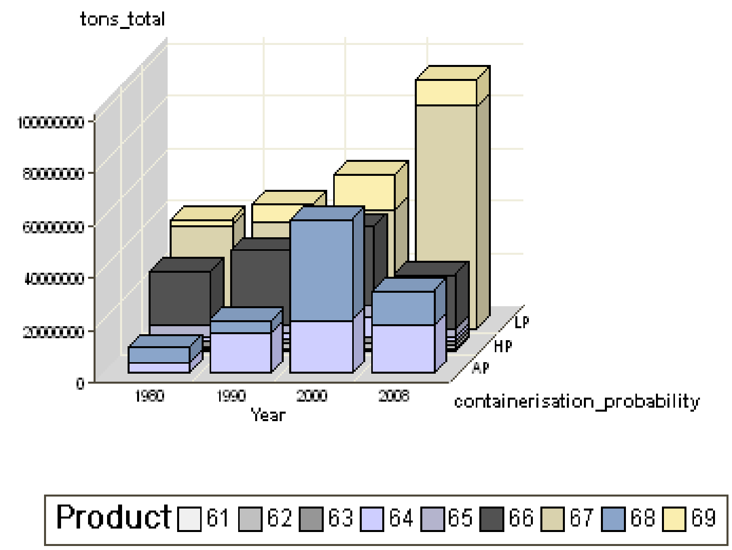
What Graph 7.1.3 shows is that the categories of low probability represent iron and steel (category 67) and manufactures of metals (category 69) which are products typically transported in bulk[30]. Irrespective of the actual volumes it has been shown in chapter four that category six is 81% composed of BEC code 22 products i.e. processed industrial supplies.

In the case of having had the possibility to chart the historic trend of the containerization degree the category of generalized cargo would have been incorporated. The graphs would then show the transition from generalized cargo to the container.

[30] For a further break of category six into the three, four, five digits kindly see URL: http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=14&Lg=1

The effect on the current graphs as they are depicted in this research would have been that the early years would then have attributed fewer volumes to the container trade.

Graph 7.1.3: Category 6 Product Disaggregation (per digit 2)




| Manufactured goods classified chiefly by material | |
|---|---|
| 61 | Leather, leather manufactures, n.e.s., and dressed furskins |
| 62 | Rubber manufactures, n.e.s. |
| 63 | Cork and wood manufactures (excluding furniture) |
| 64 | Paper, paperboard and articles of paper pulp, of paper or of paperboard |
| 65 | Textile yarn, fabrics, made-up articles, n.e.s., and related products |
| 66 | Non-metallic mineral manufactures, n.e.s. |
| 67 | Iron and steel |
| 68 | Non-ferrous metals |
| 69 | Manufactures of metals, n.e.s. |

Source: own compilation based on UNCOMTRADE data

What Graph 7.1.1 furthermore suggests is that the degree of containerization for category six shows further potential since tendencies to put more and more goods in containers are continuing. Another interesting feature illustrated by Figure 7.1.1 is the sharp fall of the crisis year 2009 which has been more pronounced for the LP subdivision. The year the crisis begun in 2008 the LP products did yet not react, which could be a result of the type of contracts signed or just a result of expectations on the basis of a short lived turmoil. In the case of HP and AP according to the graphs the crisis had started influencing imports already in 2008. Once again the characteristics of the products play a crucial role.

On the other hand the most striking observation in Graph 7.1.2 is the growth of importation for both LP and HP goods from China. What this trend suggests is that China is growing exponentially in goods categories which have been typically classified as intra European trade. It should be noted that the actual volumes represented a maximum of 6% of the total volumes of imports for the last two years before the crisis. The products of average containerization probability are products China does not yet significantly trade with Europe.

The above illustrations showed the type of results attainable by such a methodology. Further depth of analysis can be achieved by means of disaggregation of the product category (in the digits 2 to 5 as shown in tables 7.1.1, 7.1.3) depending on the requirements of the transport stakeholder. Under the assumption of the reliability of the TEU attained further calculations on for example the number of vehicles/vessels or econometric modeling can be performed.

### 7.1.6 Evaluation

One of the biggest bottlenecks of this analysis is the lack of validation. This approach could only get properly validated after having been applied for the full range of products and then compared to a database like the one of Containerization International (CI). It would hence require sourcing a significant amount of trade data especially since CI includes only extra trade and not intra trade while double counting biases results. The latter double counting occurs since port container throughout is not split per direct or transshipment. This means that the same container can be counted more than once, one at the hub port and another time at the port of final destination. This problem could be resolved if ports would report on transshipment flows. An alternative would be to have all steps be thoroughly reviewed by experts.

The only information available in TEU to use as a benchmark to evaluate the results is TEU throughput of the ports in the Hamburg Le Havre range, available in the CI database. Such data correspond to aggregated goods (total trade), for both imports and exports and exclusively extra trade. As such a comparison of the obtained results can only provide with a very vague idea on the dimension of the data. The data are included in table 7.1.4 for selected years. The results under "TEU own calculation" correspond to the methodology developed in this chapter for the categories of high and average containerization probability and their summation in the third column.

Table 7.1.4: Technical translation evaluation

| **YEAR** | **TEU - Own methodology** | | | **TEU – CI Hamburg-Le Havre range** | **Ratio** (in %) **TEU_TOTAL/TEU CI** |
|---|---|---|---|---|---|
| | **TEU_HP** | **TEU_AP** | **TEU_TOTAL** | | |
| 1990 | 3 938 073.00 | 1 822 449.00 | 5 760 522.00 | 10 285 191 | 56.0 |
| 1995 | 3 242 609.00 | 1 349 424.00 | 4 592 033.00 | 140 59 603 | 32.7 |
| 2000 | 4 739 490.00 | 1 988 579.00 | 6 728 068.00 | 20 970 030 | 32.1 |
| 2005 | 3 190 654.00 | 4 874 946.00 | 8 065 600.00 | 32 350 605 | 24.9 |
| 2008 | 4 248 053.00 | 5 042 250.00 | 9 290 303.00 | 40 938 426 | 22.7 |

Although it is extremely difficult to assess the accuracy of the data in table 7.1.4 the figures do not seem unrealistic. Some facts that may help include the following: While the CI database includes all containerized goods, the TEU obtained by the so called "own methodology" correspond to a category which is on average 70% of total manufactured goods (see table 4.3) which on its own is the category

often directly linked to the container trade. Hence one expects that the CI includes more volume than the “own methodology” although not of an extreme level. The fact that the CI incorporates imports and exports while the “own methodology” total imports, i.e. intra and extra trade means that the latter includes much more volume of goods. The fact that the hinterland of the Hamburg Le Havre range serves more than the countries included in the HW country group (BLX, CHE, DEU, FRA, NLD) means that that the CI should include more volume of goods than the “own methodology”.
While all the points described provide for a better understanding of the differences between the two databases the only way of providing a better assessment of the quality is through replicating the methodology for all goods categories.

### 7.1.7 Concluding remarks: Disaggregated

This chapter described a disaggregated approach for the translation of trade into containerized volumes. The results obtained showed that converting trade into TEU data is worth pursuing, especially considering the spectrum of research which would benefit from such information. As such the replication of this approach to other product categories although resource intensive, it adds value to transport analyses.

The set of assumptions build reflect reality to the extent possible and are possible to construct from the available information used within the methodology. Additionally, variations of these assumptions can be captured through scenarios assuring the flexibility of the conversion tool. The main disadvantage of the disaggregated approach is that validation of the final outcome can become possible if the exercise would be repeated for all product categories. However, validation can occur on the build in steps, mainly through the assessment of the properties of the assumptions made by experts in the transport field.

It is anticipated that the current methodology could eventually be incorporated within freight models, a type of tool intensively used by policy makers. It would be especially suitable for applications using the traditional four stage freight models[31] given the importance and existing interest in modeling flows in TEU. For example, the incorporation of the “container” product category is one of the expected developments planned for the “Freight Model Flanders”[32].

[31] Freight transport models are mathematical-empirical models that describe and explain the performance of a freight transport system. They also allow one to make predictions about the future assuming that certain changes are made to that system in consequence of, for example, exogenous developments or policy decisions (De Jong and Van de Riet, 2004a). As such, they can be used to determine the direct and indirect impact of new infrastructure projects (Tavasszy, 2003). Pauwels (2007) provides a general outline of a number of freight transport models currently and/or recently applied in Belgium and/or the Netherlands.Four stage model: Flow Generation, Distribution of flows, Mode choice, Assignment.
[32] The Freight Model for Flanders has been developed at the request of the public authorities (Kenniscentrum Verkeer en Vervoer, afdeling Verkeerscentrum) and in cooperation with the University of Antwerp, by K+P Transport Consultants, Tritel and Mint. The Freight Model Flanders (FMF) is used to determine the impact of hypothetical scenarios on future freight transport.

Furthermore, shippers could particularly benefit from a disaggregated approach since the methodology incorporates more detail on the disaggregated product level. In general modeling of flows on the level of TEU becomes possible on a level of detail which is currently not attainable.

## 7.2 The Relation between Container and Trade flows and the Conversion Mechanism

In this chapter the relation between container and aggregated total trade flows is measured. It represents the complete work of the submitted paper of Markianidou and Weeren (2012). objective is to draw inferences on the link between Twenty-foot Equivalent Units (TEU) and trade volumes and estimate a model for the conversion of the latter to the container unit. This approach draws inferences on the aggregate level of flows. The problems encountered are data and sector related. Data barriers are a result of the limited information regarding container units such as the distinction in the direction as inbound or outbound and the lack of specific origin/destination data. Issues of time series availability, stationarity and error autocorrelation are also encountered. Additionally, sector practises like the overlapping hinterlands of ports does not allow for a match of port specific throughput with individual countries.

The structure of this chapter is as follows. Chapter 7.2.1 introduces the problem and the inherent limitations. Chapter 7.2.2 describes the methodology while chapter 7.2.3 includes the findings of the model estimations. Chapter 7.2.4 applies and evaluates the conversion mechanism. This chapter ends with a short conclusion.

### 7.2.1 Introduction

This chapter analyzes the relation between container and total trade flows in order to draw inferences on the link between TEU and trade volumes and obtain a conversion mechanism of trade into containers. The motivation lies in the need to measure container units in studies modeling freight which is the expected unit, given the dominance of the container as a means of transport for all modes.

The application is made on the aggregated level of trade which is independent of specific origins-destinations (ODs) or the specificities linked to product categories. The question raised is whether these measurements can be used in analyses on aggregated flows. The analysis relies purely on time series of trade volumes and container units. As such the time series approach employed does not involve considerations on the variables explaining container demand as discussed by de Langen (2003), rather it is purely data driven.

The evaluation of the conversion factor is made on the basis of the econometric properties of the model. The construction of a conversion factor for container volumes with trade as the starting point on an aggregated level has, to the knowledge of the author, not yet been explored. A master thesis using a conversion factor by Cheung (2005) looked into the imports of disaggregated flows and in particular the manufactured goods of the Netherlands using trade value densities and the containerization degree together with the average container weight statistics of the Netherlands.

### 7.2.2 Trade and Container Data

The two types of trade and transport data needed are volumes of trade and unitized transport data in twenty foot equivalent units (TEUs). The time series cover the period between 1980 and 2009, the crisis year. The trade data used is weight measurements in kilograms available by the UNCOMTRADE when sourced on a three digit level[33]. This is the minimum level of disaggregation for which data in volumes are available. The unit measurement of kilograms while not being the only measurement available[34], it is the most complete (after the measurement of value). Such database in kilograms is directly convertible into tonnages. The transport database used is Containerization International (CI) which is composed of container port throughput data in TEU.

For the applications in this paper decisions on the direction of trade, country and port composition are made. In particular concerning trade direction two different sets of databases are composed. The core database is the one of extra trade. It represents the trade of the European countries with non European partners and is calculated as the subtraction of intra from total trade. By intra trade reference is made to the trade of each European country with its European counterparts. It is a database which proxies' maritime trade since extra trade includes European trading partners who are located overseas and hence necessitate seaborne transport and in particular deep sea transport for their trading activities with Europe. The second database derives from the application of a filter to the core database classifying products according to their containerization degree.

In particular three levels are defined: low probability (LP), average probability (AP) and high probability (HP) of the goods being containerized. The final classification of products is the result of targeted expert opinion covering the entire product range of 0 to 9 product codes on a digit two level. The latter is an aggregation of the digit 3 level. This database is found in Annex VI. The filtered database is the sum of products with a high and average probability of containerization. The selection of the countries to be included in the two databases is made on the grounds of matching transport with trade databases. The UNCOMTRADE is a database constructed on trade while the CI is a database constructed on a port basis.

[33] The number of digits depends on the product classification and represents the level of detail in the product classification. Digit 1 is the highest level of aggregation followed by digit 2, 3 and so on.
[34] Other measurements include: Area in square meters, Electrical energy in thousands of kilowatt-hours, Length in meters, Number of items, Number of pairs, Thousands of items, Volume in cubic meters, Volume in liters, Weight in carats, Weight in kilograms

The final choices made are summarized in table 7.2.1. The intention of this table is not to make divisions in groups but to illustrate the composition in terms of countries of both trade and port databases. To demonstrate this, table 7.2.1 is split in two blocks, per database, trade on the left hand side and freight on the right hand side. The geographic divisions per block show the country data availability in terms of trade and the port data availability in terms of freight in TEU. For example Eastern and Southern European countries in terms of trade are specified within the port blocks of East Med, West Med, Black Sea and the Iberian Peninsular. The countries included in each case, under the "trade" and "freight" column, are the ones which are considered in the database of the UNCOMTRADE and in the database of CI respectively. The countries which are either landlocked or do not have a port are naturally only included in the trade block.

Table 7.2.1: Trading and Port countries

| TRADE | | FREIGHT | |
|---|---|---|---|
| **Country division** | **Countries included[35]** | **Port Division** | **Port countries included[36]** |
| Eastern Europe | Belarus, Bosnia, Bulgaria, Czech Republic, Georgia, Hungary, Bosnia Herzegovina, Moldova, Poland, Romania, Ukraine, Slovakia | East Med, West Med, Black Sea, Iberian Peninsular | Bulgaria, Croatia, Cyprus, Georgia, Greece, Italy, Malta, Portugal, Romania, Slovenia, Spain, Ukraine |
| Southern Europe | Cyprus, Croatia, Greece, Italy,Slovenia, Spain | | |
| Western Europe | Austria, Belgium, France, Germany, Luxembourg Netherlands, Switzerland | Northern Europe | Belgium, France, Germany, Iceland, Netherlands |
| Northern Europe | Estonia, Denmark, Finland, Iceland, Latvia, Lithuania, Poland, Norway, Sweden | Scandinavia Baltic | Denmark, Estonia, Finland, Latvia, Lithuania, Norway, Poland, Sweden |

Source: own compilation based on CI and UNCOMTRADE coverage

In the making of these choices problems occur in both the trade and transport databases. Concerning trade, data quality problems need to be addressed given the unit of volumes of data processed. Difficulties occur since the analysis is made on quantities, where several quantification units exist, including missing values. An assessment of the coverage in kilograms is therefore necessary. The evaluation is based on frequency tables for the pilot cases summarized in table VI-2 in Annex VI.

[35] The countries excluded in Southern Europe are Andorra, Gibraltar, Holy Sea, San Marino, Montenegro, Serbia and Monaco. The countries excluded in Northern Europe are the UK, the Aland islands, the Channel islands, the Faeroe islands, Guernsey, Ireland, Isle of Man, Jersey, Svalbard and the Jan Mayen islands. No countries were excluded from Easter Europe.
[36] The European port countries excluded are the UK and Ireland.

What the table shows is the number of observations per quantity unit for the period of 1980 to 2009 and a percentage of each unit's contribution to the total. In all pilot cases the coverage of Kg is on average 80 per cent. In addition to coverage the quality of the final database is of equally high importance especially given the use of solely data driven techniques. While typically when aggregating, patterns smoothen out, what is observed in the current case is that extreme outliers present in the individual country datasets disrupt the aggregated patterns. An investigation of the patterns in detail revealed extreme values in the cases of the first years of reporting for Eastern European countries. In particular the countries subject to such outliers are summarized in table VI-3 in annex VI. The observed extreme patterns are noticeable on the aggregate level of total trade per country which is corrected by removing the years specified in Annex Table VI-3.

In the transport database the major complexity is defining clear geographic borders of the ports' hinterlands. Obviously, ports have overlapping hinterlands and the trade of a country cannot be solely attributed to its national ports. For this reason the aggregation includes the widest possible range of countries in Europe for which data is available on trade and the total number of European ports listed in the CI database. This approach is a second best solution. The ideal situation requires the availability of databases including the OD's of the cargo handled and in particular the final destination of cargo for each port. Such databases however do not exist. This is due to the creation of the EU's customs union whereby internal border controls are no longer made. An additional limitation, results from double counting, as previously mentioned in chapter 7.1. It occurs due to the lack of distinction of transshipment cargo which means that transshipment ports (Hubs) count the data first and the final destination ports count the data a second time. Such considerations are not taken into account in the CI database where distinctions between domestic, international and transshipment are not made.

### 7.2.3 Methodology: Aggregated

The objective of the econometric estimation is to model the link between TEU and trade volumes and to predict the TEU from the tons of trade, which ideally provides for a conversion factor from tons to TEU. By estimating the equations with for example simple linear regression, predictions of the TEU or conversions to TEU can be made if the tons of trade are known. Ideally, one would thus want to estimate the data in levels and obtain the predictors and parameter estimates which could directly be used to convert data from tons to TEU. An important assumption validating such an approach is that the time series modeled are stationary. In this application however the stationarity assumption is doubtful, e.g. the Dickey Fuller test performed for the series suggests the presence of unit roots. The results obtained by modeling non-stationary time series are proven to be misleading (Greene 2002). In particular using conventional t and F tests the hypothesis of no relationship is rejected too often.

Typically in (traditional) time series applications, data are de-trended often leading to stationary time series which can consequently be modeled using linear regression. Also in this case, by differencing the data once stationary time series are obtained. The models for the differenced data are then estimated with the first-order autoregressive model using the Yule Walker (Y-W) method. Alternatively the single step Error Correction Model (ECM) approach is used.

The former method ignores the presence of a possible long term relationship between the variables. If long term relations can be ignored, it is a method proven to be about as efficient as the maximum likelihood method for estimating AR models and is proven to be particularly suitable for small samples (Harvey and McAvinchey, 1978). In this Y-W approach, the traditional regression model is augmented with an autoregressive model for the random error, thereby accounting for the autocorrelation of the errors (otherwise present in applications made using ordinary regression analysis).

Alternatively, the possibility of long run relationships is taken into account. Since the expectation in the application is that long run relationships are very likely to exist, given the growing containerization degree of transporting goods, the ECM Model is also considered. As is e.g. shown in (Banerjee et al. 1986, 1993), this model is at least theoretically to be preferred over the Y-W approach, since it allows for the identification of the long run relationship. In particular Single Equation ECMs estimate a long term effect for each independent variable, thus allowing for the evaluation of the contribution of each.

In this chapter the two approaches, namely the use of the Y-W model and the ECM are applied. For each approach, three model specifications are considered, to be called model I, II and III. The models are estimated using the two different databases described in chapter two. Model I estimates how much container trade changes when total extra trade volume in tons changes by one unit. Since not all extra trade represents containerized goods the aforementioned aggregated database is filtered under the assumption that not all goods are containerized.

The assumptions made for the filtering can be found in Annex VI in Annex table VI-1. The latter table shows goods categories on a digit two level, split in low average and high probability of containerization as explained in chapter three. This database was build with the help of expert opinion[37]. Evidently the aggregation excludes the goods with a low containerization probability.

An additional content related assumption made is that containers are fully loaded. Inefficiencies in the loading of containers are thus not taken into account nor are empty containers. Model II estimates the effect of growth of containerized trade explained by a 1% growth of total extra trade.  This is the so called log-log model with both variables (dependent and independent) integrated of order one. Model III is the same as model II estimated for total trade. It hence estimates how much containerized trade grows when total trade increases by 1%.

The YW and VEC models are specified in equations (7.1) and (7.2) respectively as defined in econometric textbooks (Verbeek, 2008; Greene, 2002):

[37] This database is a result of consultations with Professor Honore Paelinck, with many years of experience in the maritime industry and academia. Any “errors” found fall under the exclusive responsibility of the author.

$y_t = \beta_0 + \beta_1 x_t + v_t$, where (7.1)

$v_t = \varepsilon_t - \phi_1 v_{t-1}$

and

$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \beta_2 x_{t-1} + \beta_3 y_{t-1} + \varepsilon_t$ (7.2)

Where $y_t$ is the response variable, $x_t$ is a column vector of regressor variables, β is a column vector of structural parameters, and  is normally and independently distributed with a mean of 0 and a variance of $\sigma^2$. In the parameterization of equation 1 the signs of the autoregressive parameters are reversed from the parameterization documented in most of the literature. Equation 2 shows the Error Correction Model estimated directly instead of using the classical Engel and Granger two-step approach (see Annex box VI-1 for more details).

Given the nature of derived demand, model I leads to a conversion mechanism from trade to TEU since it models the same variable of trade, measured in two different units, tons and TEU. Models II and III are added because they can be used to add insight to the relation between the growth of the container trade and the growth of extra trade (model II) and total trade (model III).

### 7.2.4 Findings

The results of the VEC and the Yule Walker estimated models are described in table 7.2.2 and residual tests together with the diagnostic statistics are documented in annex VI.

The Y-W estimations in all three cases produce significant parameter estimates with the exception of the intercept in model I. Model I obtains an R-square value of 0.55 while models II and II obtain the value of 0.4. Mean Squared Errors (MSE) are low and in particular lower than the ones estimated with regular regression. The QQ plots and histograms show that the errors are normally distributed while residual scatter plots indicate that the errors are homoscedastic. The Durbin Watson values are above the critical value of 1 but do not allow us to exclude the presence of autocorrelation. The graphical inspection with the sample correlation plots, the autocorrelation function (ACF) and the partial autocorrelation function (PACF), does not suggest any significant violations of the whiteness assumptions on the residuals. What could compromise the results however is the presence of outliers, which is a result of the more violent fluctuations present in the trade database compared to the much smoother growth patterns observed in the transport database in TEU. Given the current results of the Y-W estimates it is suggested that the models fit the data reasonably well and are therefore useful tools in understanding the relationship between the different trade expressions (extra trade, extra trade growth and total trade growth) and TEU.

Table 7.2.2: Model results

| **MODEL** | **Variable** | **Parameter Estimate** | **Standard Error** | **T Value** | **Pr > \|t\|** |
|---|---|---|---|---|---|
| MODEL I | VEC | | | | |
| | Intercept | 0.01133 | 0.01205 | 0.94 | 0.3561 |
| | Dif_EXTRA_TRADE_tons | 0.61572 | 0.08804 | 6.99 | <.0001 |
| | Lag_EXTRA_TRADE_tons | 0.32585 | 0.11168 | 2.92 | 0.0074 |
| | Lag_TOTAL_TEU | -0.33620 | 0.11095 | -3.03 | 0.0056 |
| | Y-W | | | | |
| | Intercept | 0.0162 | 0.0107 | 1.51 | 0.1433 |
| | Dif_EXTRA_TRADE_tons | 0.4910 | 0.0901 | 5.45 | <.0001 |
| MODEL II | VEC | | | | |
| | Intercept | -0.54841 | 2.65733 | -0.21 | 0.8382 |
| | Dif_logEXTRA_TRADE_tons | 0.63303 | 0.17080 | 3.71 | 0.0010 |
| | Lag_logEXTRA_TRADE_tons | 0.07537 | 0.17378 | 0.43 | 0.6682 |
| | Lag_logTOTAL_TEU | -0.05807 | 0.06369 | -0.91 | 0.3706 |
| | Y-W | | | | |
| | Intercept | 0.0559 | 0.0144 | 3.87 | 0.0007 |
| | dif_logEXTRA_TRADE_tons | 0.5594 | 0.1393 | 4.02 | 0.0004 |
| MODEL III | VEC | | | | |
| | Intercept | -8.99114 | 4.48993 | -2.00 | 0.0562 |
| | dif_logTOTAL_TRADE_tons | 0.95403 | 0.19835 | 4.81 | <.0001 |
| | lag_logTOTAL_TRADE_tons | 0.59187 | 0.28186 | 2.10 | 0.0460 |
| | lag_logTOTAL_TEU | -0.23633 | 0.10387 | -2.28 | 0.0317 |
| | Y-W | | | | |
| | Intercept | 0.0505 | 0.0137 | 3.70 | 0.0010 |
| | *dif_logtotal_trade_tons* | *0.7396* | *0.1824* | *4.05* | *0.0004* |

The Y-W estimation results described in table 7.2.2 correspond to the following equations:

Model I $\Delta y_t = 0.0162 + 0.4910 \Delta x_t + v_t$

$v_t = 0.2 v_{t-1} + \varepsilon_t$

Model II $\Delta \log y_t = 0.0559 + 0.5594 \Delta \log x_t + v_t$

$v_t = 0.1 v_{t-1} + \varepsilon_t$

Model III $\Delta \log y_t = 0.0505 + 0.7396 \Delta \log x_t + v_t$, where

$v_t = 0.04 v_{t-1} + \varepsilon_t$

The VEC estimation results described in table 7.2.2 correspond to the following equations:

Model I $\Delta y_t = 0.01133 + 0.61572 \Delta x_t + 0.32585 x_{t-1} - 0.33620 y_{t-1} + \varepsilon_t$

Model II $\Delta y_t = -0.54841 + 0.63303 \Delta x_t + 0.07537 x_{t-1} - 0.058070 y_{t-1} + \varepsilon_t$

Model III $\Delta y_t = -8.99114 + 0.95403 \Delta x_t + 0.59187 x_{t-1} - 0.236330 y_{t-1} + \varepsilon_t$

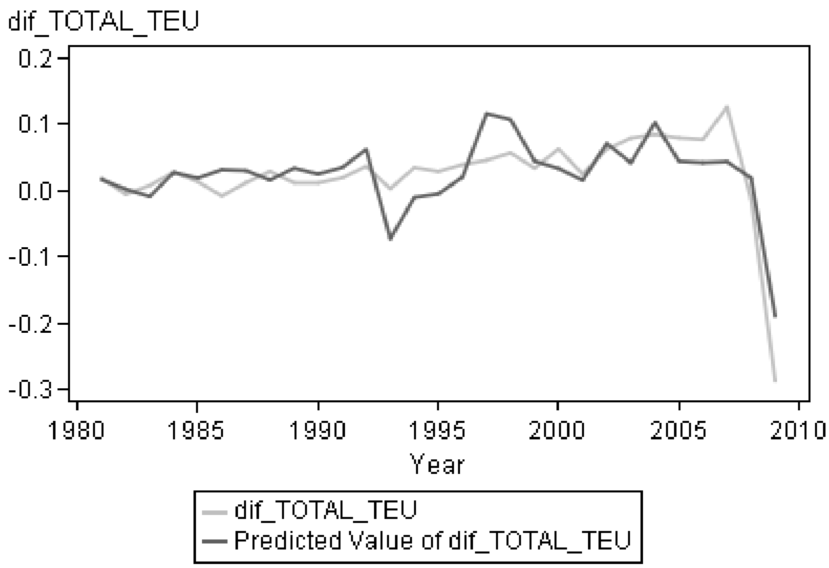
The VEC models produce significant parameter estimates with the exception of the intercept. The R square of 0.6 for model I is quite good. Models II and III produce R square values of about 0.4 as in the case of the Y-W estimations. Errors are normally distributed. However the error analysis confirmed the presence of outliers. This is visible in both the plots of residuals versus predicted and dependent versus predicted values. Three possible outliers are identified using Cook's D plot. The model is re-estimated excluding the observations 2007 to 2009 which are identified as outliers. The errors perform well but the model parameters are no longer significant. The presence of outliers may explain the poorer performance of models II and III. In this case too however no further action is taken.

Based on the findings the best model linking trade to containers is the ECM model. It is from an econometric perspective the most appropriate model given its good performance and the fact that it captures the long run relationships between trade and containers. Models II and III perform best when applied with the Y-W method.

### 7.2.5 The conversion mechanisms: application and evaluation

After having quantified the link between trade and containers it is necessary to check how well the chosen model performs as a conversion mechanism. The first step is a graphical assessment of the fit of the model. This is shown in graph 7.2.1 which shows the predicted versus observed values. It provides for an evaluation of the fit of the model. On average the model fit is good. It is however observed that the model systematically under- or overestimates observed values.

Graph 7.2.1: Model FIT – Model I




For the purpose however of using and evaluating this relation as a conversion mechanism an additional step is required. It is obtained from the ECM equation itself (see annex VI for a detailed description of the derivation). The final relation obtained provides the long run equilibrium in levels which is given by equation 7.3:

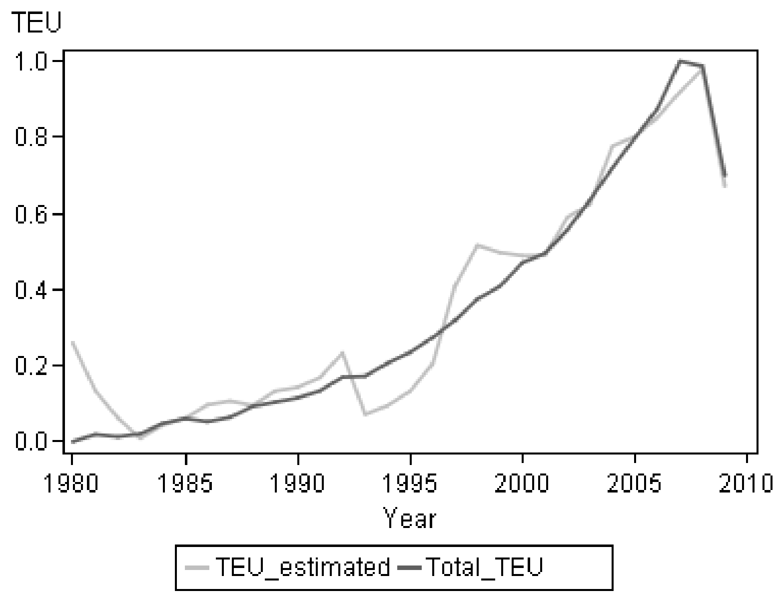
$$y_t = \frac{\beta_0}{1-\beta_3} - \frac{\beta_2}{\beta_3} x_t \tag{7.3}$$

And finally from the current VEC application it is derived that:

$$y_t = 0.008479 + 0.96921 x_t \tag{7.4}$$

By simply plugging in equation 7.4 to the data, it is now possible to obtain the TEU from the trade figures. The evaluation of the conversion mechanism is performed by means of graphical assessment in Graph 7.2.2. What the latter shows is a plot of the original TEU series against the series obtained by applying the conversion mechanism.

Graph 7.2.2: Conversion Mechanism output – Model I

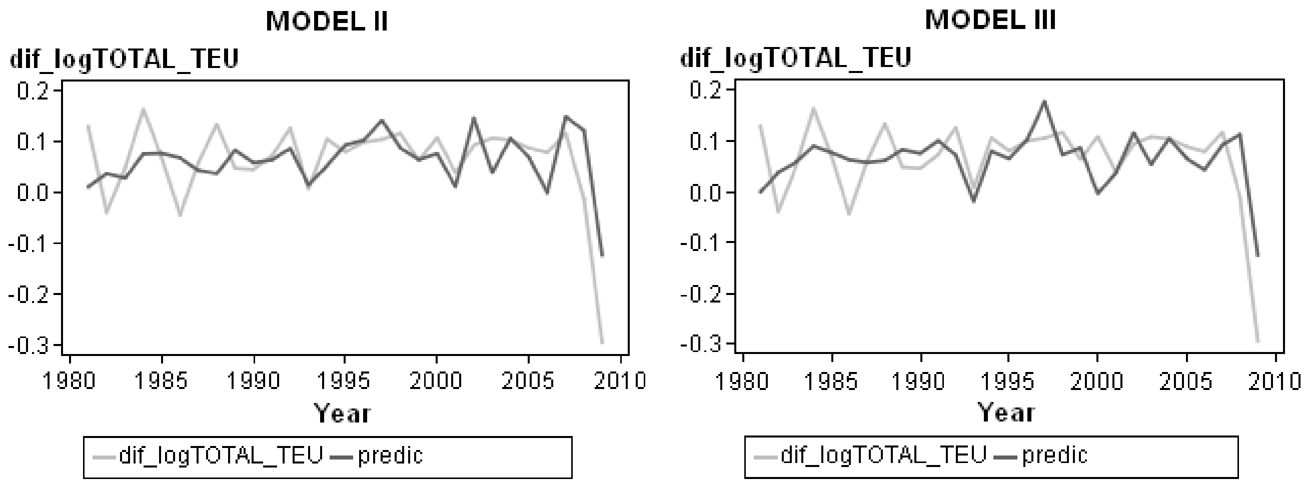



As mentioned in the error analysis, the deviations from the original TEU values are attributed to outliers in the trade database. On average however the conversion mechanism performs well.

The practical use of such a conversion mechanism is appropriate in cases where the intention is to quantify goods in the unit of TEU which are known to be containerized. It can thus be applied to aggregates or to specific products.

A conversion mechanism can also be obtained from the Y-W growth estimations. The first step is a graphical assessment of the fit of the model. This is shown in graph 7.2.3 which shows the predicted versus observed values for models II and III. It provides for an evaluation of the fit of the model. On average the model fit is reasonably good.

Graph 7.2.3: Model FIT- Model II & Model III




For the purpose however of using this relation as a conversion mechanism an additional step is required. It is obtained from the Y-W equation itself. The process is described in the following way:

Under the assumption of v zero mean estimate model (7.1) can be written as

$$\log y_t = a_0 + \log y_{t-1} + a_1(\log x_t - \log x_{t-1}) \qquad (7.5)$$

By taking the exponential one transforms into the original scales

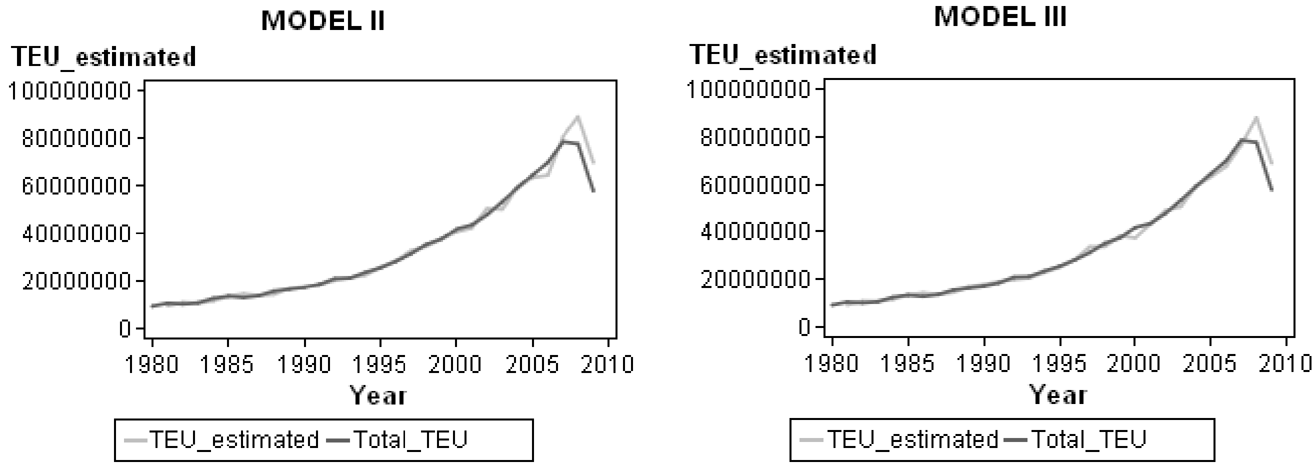
$$y_t = \exp(a_0 + \log y_{t-1} + a_1(\log x_t - \log x_{t-1})) \qquad (7.6)$$

Finally this can be simplified to

$$y_t = e^{a_0} y_{t-1} \left( \frac{x_t}{x_{t-1}} \right)^{a_1} e^{v_t} \qquad (7.7)$$

By simply plugging in equation 7.6/7 to the data, it is now possible to obtain the TEU from the trade figures. The evaluation of the conversion mechanism is performed by means of graphical assessment in Graph 7.2.4. What the latter shows is a plot of the original TEU series against the series obtained by applying the conversion mechanism. Bothe models perform very well.

Graph 7.2.4: Conversion Mechanism output – Model II and Model III




In the case of the Y-W estimations and in particular model II, the results of the estimation show that a 1 per cent growth in extra trade leads to 0.55 per cent growth in containerized trade, in the case of the database where the entire extra trade volume is considered. The result is plausible given the fact that not all products traded between the European Countries and its extra European trade partners are currently containerized. It also reflects the volumes of dry and liquid bulk goods imported by European countries which in terms of volume are significant but are not transported in containers.

A similar result is obtained in the case of model III, where a 1 per cent increase of total trade leads to a 0.72 per cent increase in containerized trade. In the case of total trade the presence of containerized volumes of goods is more pronounced. Since total trade includes intra trade (trade between the European countries) it principally reflects the large volumes in general traded between European countries.

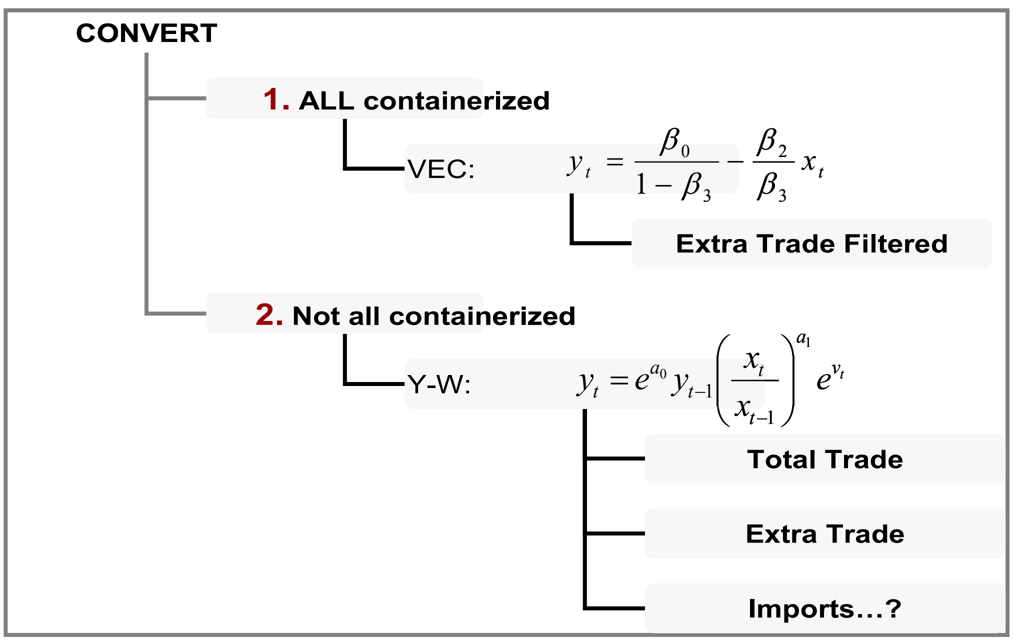
To illustrate the importance of intra trade, according to the EU (data from May 2011) trade in goods between the member states of the EU was valued in terms of dispatches at EUR 2 538 393 million in 2010 which is almost twice the value of exports from the EU-27 to non-member countries. Although these figures are in values, it still provides with some indication of the importance of intra trade. Besides the sheer volumes of trade what the relation shows is that a high degree of containerization is achieved in terms of total trade.

### 7.2.6 Concluding remarks: Aggregated

This chapter illustrated an aggregated methodology to establish the link between trade volumes and containerized trade, when the final objective is the definition of a conversion mechanism between the two units.

The model based conversion mechanisms developed were evaluated with respect to their econometric properties and their ability to accurately convert trade units into TEU units. The results showed that the ECM is the most appropriate model to serve as a conversion mechanism when the assumption is made that all goods are containerized. The Y-W models were found suitable for the modeling of the link between the growth of TEU and two cases, the case of extra trade and total trade. The case of imports indicated with a questionmark is applied in chapter eight since it is directly applicable to the empirical work presented in the previous chapters. These models were also used as conversion mechanisms. The aforementioned options are illustrated in figure 7.1.

Figure 7.1: Conversion options overview




Further information on the relation between trade and containerized volumes showed that the container trade is estimated to grow by about 0.5 per cent when extra trade (intra subtracted by total trade) grows by one per cent and about 0.7 per cent growth when total trade grows by one per cent.

Improvements of this approach from a modeling perspective were considered by extending the sample to quarterly or monthly observations where alternatives of GARCH models become possible. When searching for the necessary data it quickly became clear that the sourcing of data for shorter intervals currently represents a barrier. This is due to the fact that TEU need to be sourced directly by the Port Authorities and the availability of such data is not to be taken for granted across all European ports. UNCOMTRADE data of volume measurements on the other hand are not yet provided for. For this reason it is suggested that the current modeling approach is used for linking trade to container flows.

## 7.3 Discussion: Aggregated versus Disaggregated applications

The choice on which approach to apply depends on the level of detail required by the final user. Hence, while specific product analysis and a higher level of detail is achieved by the technical approach, the econometric is more suited for the investigation of trends on an aggregated scale. As such the latter is more suited for port authorities where the composition of trade is not of prime interest. On the other hand land transport stakeholders dealing with specific product niches would require the technical translation and hence benefit from the disaggregated approach. Shipping lines are predominantly interested in aggregated flows. However a better understanding of the derived demand is instructive to their business given trends of vertical integration. As such both aggregate and disaggregated approaches can become of use.

Policy makers on the other hand require information on all levels especially since such input is not only directly usable for the making of transport policy but it serves as input in the fields on energy, environment and a for market analyses of a number of economic sectors.

# 8. Practical Implementation of suggested approach

In chapter eight the applicability of this PhD is demonstrated. The purpose is to provide evidence for what is claimed to be a complete tool in the hands of transport stakeholders. This is achieved by combining the results obtained from the preceded analysis. Such a step is necessary, since the modeling output described thus far in chapters 5 and 6 is provided in volume. While the latter is already the type of output directly usable for transport purposes the objective of this analysis has been to additionally provide the link to the container unit. This is specifically addressed in chapter seven by suggesting two alternative mechanisms of translating volume into TEU. This chapter hence demonstrates how to feed chapter seven into chapters 5 and 6 and show what type of output is attainable.
Chapter eight is split in two parts, according to the level of disaggregation. Chapter eight.1 describes the disaggregated approach and chapter eight.2 the aggregated approach. Hence in 8.1 TEUs are obtained from the analysis performed for manufactures (category six) and in 8.2 TEUs are obtained from the analysis for total trade.

## 8.1 Disaggregated output in TEU

The disaggregated output refers to the analysis made on the digit 1 level and in particular the analysis of manufactures (chiefly classified by material-category six). The application which is illustrated is made for the group of Western European countries (HW) which includes BLX, CHE, DEU, FRA and NLD. The final result shown includes import aggregates of the HW group of countries.

The reason why the latter group is selected is because it corresponds to the case study applied in chapter 7. In particular it links to the disaggregated approach which uses the step wise conversion mechanism. It should be noted that while no other cases were applied in chapter seven, the analysis could however be replicated for any other country group. Examples include the cases of the HS or HE groups or for the database including the complete set of countries, HWHSHE.

The objective is to combine the output of chapter five with the methodologies suggested in chapter 7. In particular chapter five refers to the trend forecasts made for the imports of the HW countries of category six. The forecasts hence performed until the years 2020 and 2030 which are made on the unit of volume are in this instance converted into TEU.

The starting point of this analysis is obtaining the forecasts from the applications of the different growth specifications. This means that TEUs are obtained per growth specification, linear, logarithmic and logistic. The forecasts however are in volumes of trade. In order hence to obtain the TEUs from the forecasted volumes of trade it is necessary to obtain a relation which will provide the link between the TEUs and the volumes of category six. The main reason why the step wise methodology cannot be used for the forecasted figures is because the latter are aggregated figures of category six.

This means that having estimated with aggregated figures it is no longer possible to disaggregate the forecasted figures into the two or three digit level.

In order to estimate the link between containers and trade of category six, the TEU obtained by the stepwise methodology and the trade figures of the UNCOMTRADE are used. The process involves the use of the Yule Walker estimation and its conversion mechanism as explained in chapter 7.

A summary of the steps taken is given below:

1. Obtain category six imports in TEUs calculated with the stepwise approach and category six imports in volume;
2. Apply Y-W model;
3. Obtain category six forecasts for Linear, Logarithmic and Logistic trend models;
4. Un-standardize predictions;
5. Transform to logarithms and obtain first differences;
6. Insert in the Y-W conversion mechanism;

Step 2, the estimation of the Y-W model is described in equation 8.1.1. The data used are the TEUs and the volumes of category six. Both variables are transformed in logarithms and differences are taken. This is a convenient transformation because it amounts to growth rates and reads as the effect of a 1 per cent growth of imports on the growth of TEU but is also necessary in order to obtain stationary series.

The obtained model is the following:

$$\begin{aligned} \Delta \log y_t &= 0.001743 + 1.0691 \Delta \log x_t + v_t \\ v_t &= 0.25 v_{t-1} + \varepsilon_t \end{aligned} \tag{8.1.1}$$

$$Est.\operatorname{var}(\varepsilon_t) = 0.003$$

The results of the model are described in Table 8.1.1. The model performs well with a significant model parameter for the logarithm of quantity.  The intercept is not significant but it will be kept for the purpose of the conversion. The Durbin Watson statistic returns a value of 2.18 which does not raise concerns of autocorrelation. The R square of 0.9 (see table 8.1.2) means that the model performs very well.

Table 8.1.1: Cat6 - Yule- Walker model output

| Variable | DF | Estimate | Standard Error | t Value | Approx Pr > \|t\| |
|---|---|---|---|---|---|
| Intercept | 1 | 0.001743 | 0.0109 | 0.16 | 0.874 |
| dif_loqquantity | 1 | 1.0691 | 0.052 | 20.57 | <.0001 |

Table 8.1.1 (continued): Cat6 - Yule- Walker model output

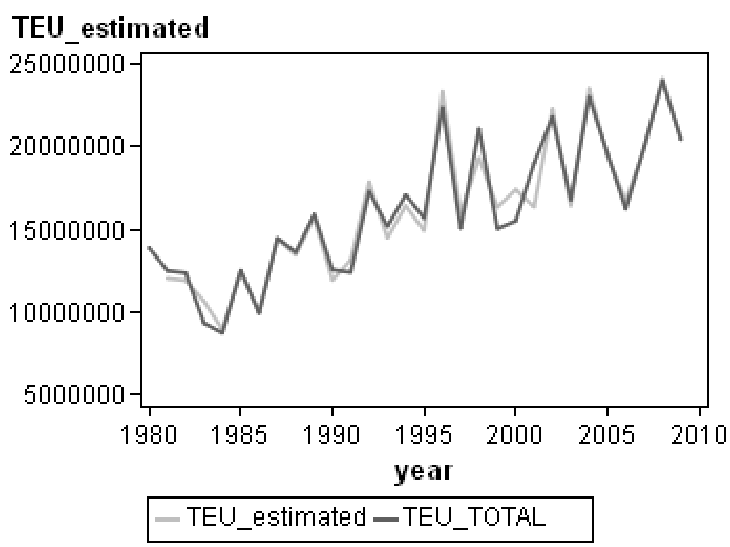
| Estimates of Autoregressive Parameters | | | |
|---|---|---|---|
| Lag | Coefficient | Standard Error | t Value |
| 1 | 0.249849 | 0.189896 | 1.32 |

Table 8.1.2: Car6 - Yule- Walker model Statistics

| Yule-Walker Estimates | | | |
|---|---|---|---|
| SSE | 0.08663513 | DFE | 26 |
| MSE | 0.00333 | Root MSE | 0.05772 |
| SBC | -76.122246 | AIC | -80.224134 |
| MAE | 0.04104881 | AICC | -79.264134 |
| MAPE | 62.8235991 | Regress R-Square | 0.9277 |
| Durbin-Watson | 2.1823 | Total R-Square | 0.9439 |

The evaluation of the model and resulting conversion mechanism is performed by means of graphical assessment in Graph 8.1.1. What the latter shows is a plot of the TEU series obtained by the step-wise methodology of chapter seven against the series obtained by applying the conversion mechanism. Clearly the conversion performs well and can now be used to convert the volume based forecasts to TEU.

Graph 8.1.1: Conversion mechanism evaluation – Imports of category six




Model 8.1.1 provides all the necessary information for the Y-W conversion mechanism. It is hence now possible to obtain the forecasted TEUs. The result is shown in table 8.1.3. Column one indicates that only TEUs for two selected years are shown, the years 2020 and 2030. Column 2 differentiates those results according to model specification, linear, logarithmic and logistic.

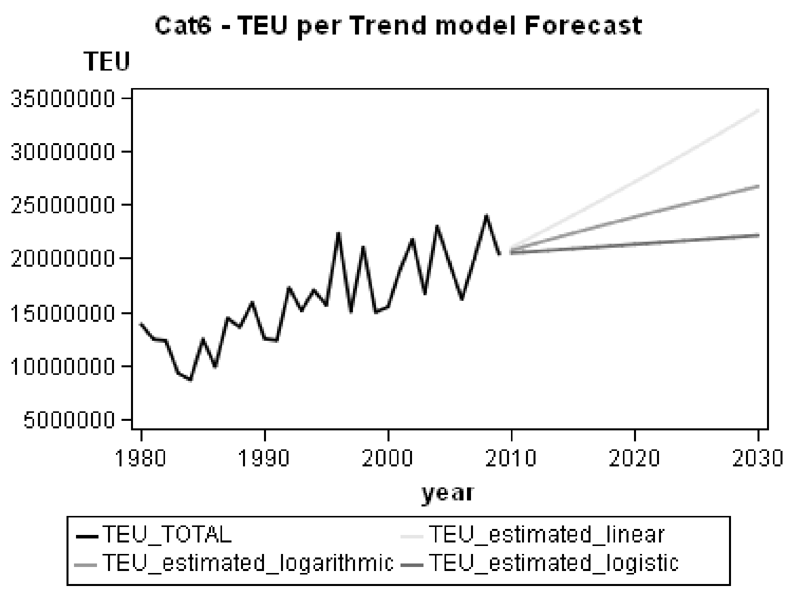
Column three is a calculation of the growth in volume of the imports of category six with 2008 as the basis year. Finally column four reports on the TEU obtained.

Table 8.1.3: TEU Trend forecasts – Cat 6

| Forecast Year | Model Specification | Growth (in % from basis year=2008) | TEU |
|---|---|---|---|
| 2020 | Linear | 29 | 27 170 651 |
| | Logarithmic | 13 | 23 906 564 |
| | Logistic | 4 | 22 074 772 |
| 2030 | Linear | 53 | 33 798 416 |
| | Logarithmic | 21 | 26 748 754 |
| | *Logistic* | *5* | *23 108 984* |

The graphical illustration of the entire series from 1980 until 2030 is shown in graph 8.1.2 below.

Graph 8.1.2: Disaggregated conversion output




The different colors from year 2010 onwards demonstrate the differences in the forecasted container values between the linear, logarithmic and logistic growth model. The volatile black line until the year 2009 shows the number of containers obtained by the conversion. It has therefore been shown that obtaining TEU figures with the disaggregated approach can prove to be very informative and very flexible considering the fact that the growth models can be substituted by any other modeling exercise.

## 8.2 Aggregated output in TEU

The aggregated output refers to the analysis made on total goods. The application is made on the largest group of countries (HWHSHE), the single database including all sample countries. The results presented are import aggregates of the HWHSHE group of countries. The analysis could however be replicated for any other country group (HW or HS or HE).

The objective is to combine the output from chapters five and six with the methodologies suggested in chapter 7. In particular chapter five refers to the trend forecasts and chapter six to the dynamic forecasts. A similar reasoning as in 8.1 is followed whereby the forecasts performed until the years 2020 and 2030 which are made on the unit of volume are in this instance converted into TEU.

The starting point is hence the forecasts obtained by the applications of the different growth specifications and the ARIMA applications per country. This means that TEUs are obtained per growth specification, linear, logarithmic and logistic and per ARIMA application for the three countries. The forecasts however are in volumes of trade in both trend and dynamic forecasts. In order hence to obtain the TEUs from the forecasted volumes of trade two approaches are followed.

In the case of the trend models the same process as described in 8.1 is applied which is based on the methodology suggested in chapter 7. it is therefore necessary to obtain a relation which will provide the link between the TEUs and the total import volumes.

In the case however of the dynamic forecasts the TEUs for the countries of BLX, DEU and NLD are not available. For this reason the only alternative is to apply the VEC conversion mechanism described in chapter seven and titled "All containerized" in figure 7.1. This means that the output provided by this methodology assumes that all the imports of the three countries are containerized.

### 8.2.1 Trend model conversion output

The process of acquiring the TEUs from the application on total trade involves the use of the Yule Walker estimation and its conversion mechanism as explained in chapter 7. A summary of the steps taken for the trend model based conversion is given below:

1. Obtain total imports in TEUs sourced by the CI database as described in chapter five and total imports in volume;
2. Apply Y-W model;
3. Obtain forecasts for the Linear, Logarithmic and Logistic trend models;
4. Un-standardize predictions;
5. Transform to logarithms and then obtain first differences;
6. Insert in the Y-W conversion mechanism;

Step 2, the estimation of the Y-W model is described in equation 8.2.1. Both dependent and independent variables are transformed in logarithms and differences are taken. This is a convenient transformation because it amounts to growth rates and reads as the effect of a 1 per cent growth of imports on the growth of TEU but is also necessary in order to obtain stationary series. The obtained model is the following

$$\Delta \log y_t = 0.05 + 0.89 \Delta \log x_t + v_t \qquad (8.2.1)$$

$$v_t = 0.02 v_{t-1} + \varepsilon_t$$

$$Est. \operatorname{var}(\varepsilon_t) = 0.004$$

The model performs well with significant model parameters (including the intercept) as shown in Table 8.2.1. The Durbin Watson statistic returns a value of 1.5 which does not raise concerns of autocorrelation. The R square of 0.46 means that there is about 50 per cent residual variability. However, alternative model specifications where the series are modeled either in levels or only differenced are not recommended since the series become non-stationary.

Table 8.2.1: Yule- Walker model output

| Variable | DF | Estimate | Standard Error | t Value | Approx Pr > \|t\| |
|---|---|---|---|---|---|
| **Intercept** | 1 | 0.0564 | 0.0124 | 4.54 | 0.0001 |
| **dif_logtotalimp_tons** | 1 | 0.8907 | 0.1893 | 4.71 | <.0001 |

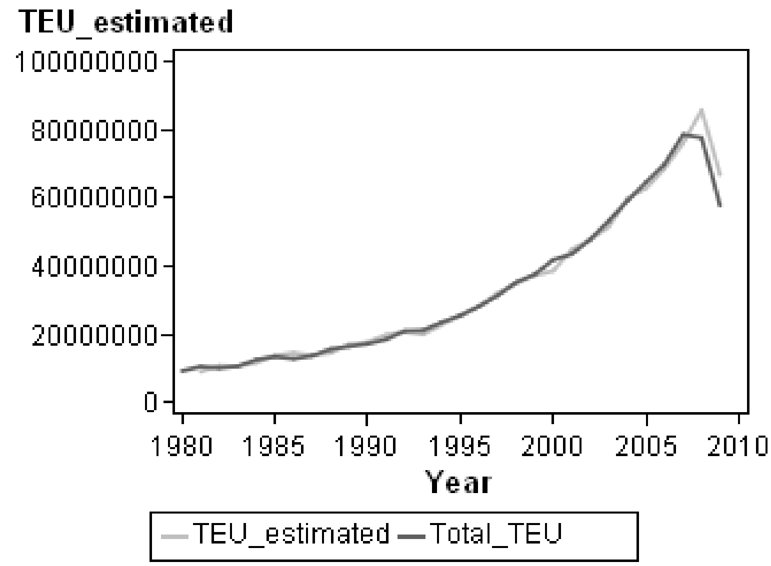
| Estimates of Autoregressive Parameters | | | |
|---|---|---|---|
| **Lag** | **Coefficient** | **Standard Error** | **t Value** |
| **1** | -0.025995 | 0.196050 | -0.13 |

Table 8.2.2: Yule- Walker model Statistics

| Yule-Walker Estimates | | | |
|---|---|---|---|
| **SSE** | 0.10926231 | **DFE** | 26 |
| **MSE** | 0.00420 | **Root MSE** | 0.06483 |
| **SBC** | -69.456691 | **AIC** | -73.558578 |
| **MAE** | 0.04553264 | **AICC** | -72.598578 |
| **MAPE** | 103.981361 | **Regress R-Square** | 0.4599 |
| **Durbin-Watson** | 1.5757 | **Total R-Square** | 0.4624 |

The evaluation of the model and resulting conversion mechanism is performed by means of graphical assessment in Graph 8.2.1. What the latter shows is a plot of the original TEU series against the series obtained by applying the conversion mechanism.

Graph 8.2.1: Conversion mechanism evaluation – Imports




According to Graph 8.2.2 the conversion mechanism performs very well with the exception of the years of the financial crisis in 2008 and 2009. Nevertheless the quality of the conversion is considered of good enough quality to be used in the applications of chapters five and six.

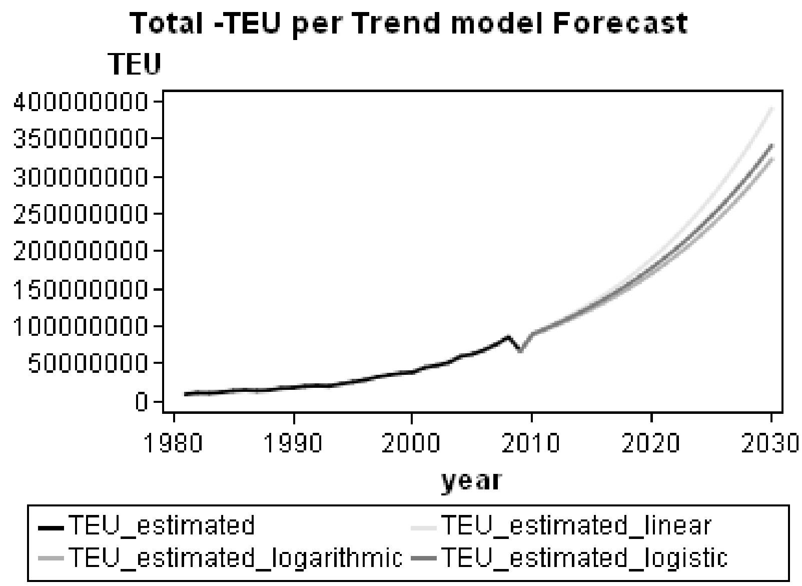
Model 8.2.1 provides all the necessary information for the Y-W conversion mechanism. It is hence now possible to obtain the forecasted TEUs. The result is shown in Table 8.2.3 for the trend model based forecasts of chapter five. Column one indicates that only TEUs for two selected years are shown, the years 2020 and 2030. Column 2 differentiates those results according to model specification, linear, logarithmic and logistic. Column three is a calculation of the growth in volume of total imports with 2008 as the basis year. Finally column four reports on the TEU obtained.

Table 8.2.3: TEU Trend forecasts – Total Trade

| Forecast Year | Model Specification | Growth (in % from basis year=2007) | TEU |
|---|---|---|---|
| 2020 | Linear | 27 | 96 100 563 |
| | Logarithmic | 12 | 83 369 634 |
| | Logistic | 18 | 88 648 198 |
| 2030 | Linear | 49 | 112 043 464 |
| | Logarithmic | 18 | 88 484 059 |
| | *Logistic* | *27* | *95 387 493* |

The graphical illustration of the entire series from 1980 until 2030 is shown in graph 8.2.2 below.

Graph 8.2.2: Aggregated conversion output




The different colors from year 2010 onwards demonstrate the differences in the forecasted container values between the linear, logarithmic and logistic growth model. What is visible is that there are only small differences between the different specifications.

### 8.2.2 Dynamic Model Conversion output

In the case of the dynamic forecasts for the specific countries the conversion is performed under the hypothesis that the total imports of those countries are containerized. The conversion hence used is the one described by equation 7.3 in chapter 7. Table 8.2.4 shows the results obtained for the BLX, DEU and NLD countries including forecasted years. Growth figures are included at the end of the table calculating the growth for the years 2020 and 2030 with 2008 as the basis year.

The figures correspond to the anticipation that eventually, all goods will be transported in containers. Systematic reasons justifying such a scenario could be observed within specific supply chain routines. It is possible that given cost efficiency objectives the intention to realize fully loaded round trips may lead to goods traditionally transported in bulk to shift to containers. An example of such goods is waste. Furthermore, occasionally, goods traditionally transported in bulk have shifted to containers as a result of freight rate volatility. Very low freight rates for example tend to make shippers more creative which results in goods shifting mode of transport from bulk to container. Such practices have been observed during the peak years of the crisis, 2008 and 2009.

These results should be viewed as the upper threshold, the maximum possible potential of containerized cargo for the imports of those countries.

Table 8.2.4: TEU Dynamic forecasts – Total Trade

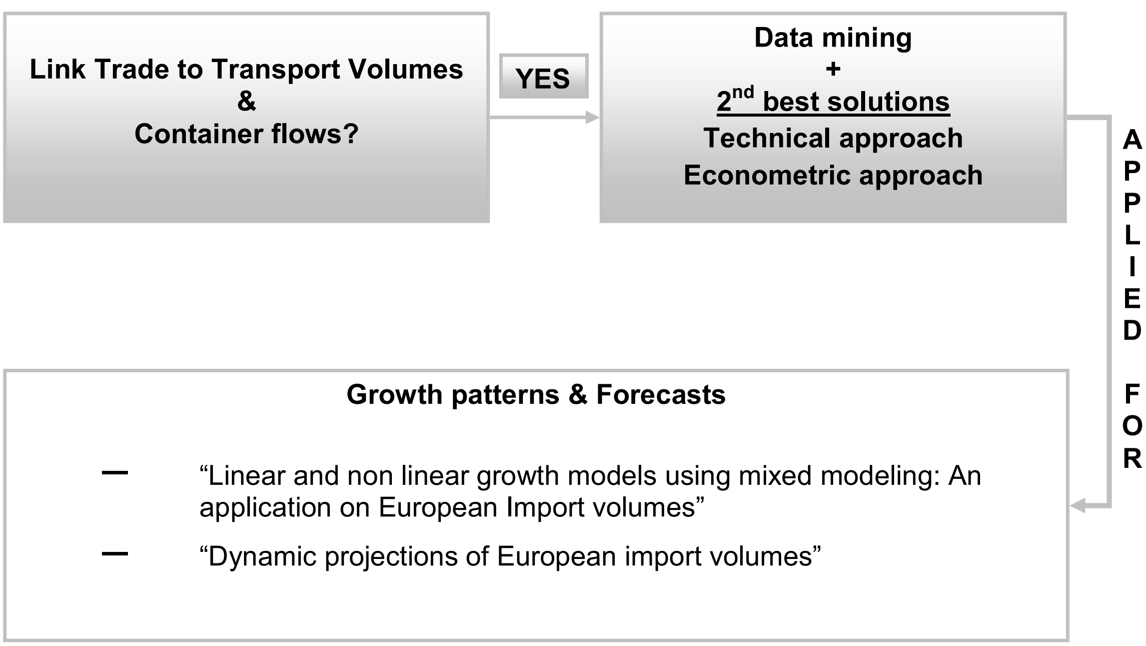
| YEAR | TEU estimated with the VEC conversion | | |
|---|---|---|---|
| | **BLX** | **DEU** | **NLD** |
| 1985 | 147 053 828 | 224 114 444 | 183 601 730 |
| 1990 | 178 704 492 | 228 708 225 | 212 722 361 |
| 1995 | 191 989 418 | 482 959 605 | 239 240 322 |
| 2000 | 235 972 095 | 470 692 788 | 232 655 835 |
| 2001 | 248 700 242 | 446 318 427 | 238 442 024 |
| 2002 | 250 788 014 | 469 096 845 | 245 024 312 |
| 2003 | 258 781 695 | 454 673 123 | 251 142 140 |
| 2004 | 278 097 797 | 447 807 948 | 256 717 913 |
| 2005 | 293 467 012 | 488 964 863 | 262 499 638 |
| 2006 | 293 287 004 | 474 533 934 | 289 233 823 |
| 2007 | 308 375 767 | 533 860 274 | 320 919 083 |
| 2008 | 271 996 047 | 504 611 561 | 292 179 229 |
| 2009 | 269 210 850 | 512 769 164 | 294 655 229 |
| 2010 | 274 205 960 | 521 662 871 | 299 190 336 |
| 2011 | 278 862 394 | 531 939 335 | 303 656 561 |
| 2012 | 283 488 106 | 543 194 368 | 308 071 022 |
| 2013 | 288 078 017 | 555 176 713 | 312 454 798 |
| 2014 | 292 674 600 | 567 731 061 | 316 825 310 |
| 2015 | 297 297 201 | 580 762 503 | 321 196 667 |
| 2016 | 301 961 297 | 594 214 203 | 325 580 293 |
| 2017 | 306 677 253 | 608 053 337 | 329 985 466 |
| 2018 | 311 452 519 | 622 262 247 | 334 419 743 |
| 2019 | 316 292 476 | 636 832 861 | 338 889 309 |
| 2020 | 321 201 134 | 651 763 191 | 343 399 255 |
| 2021 | 326 181 585 | 667 055 132 | 347 953 800 |
| 2022 | 331 236 306 | 682 713 082 | 352 556 470 |
| 2023 | 336 367 368 | 698 743 081 | 357 210 240 |
| 2024 | 341 576 572 | 715 152 272 | 361 917 648 |
| 2025 | 346 865 546 | 731 948 567 | 366 680 883 |
| 2026 | 352 235 805 | 749 140 438 | 371 501 864 |
| 2027 | 357 688 799 | 766 736 789 | 376 382 292 |
| 2028 | 363 225 934 | 784 746 880 | 381 323 697 |
| 2029 | 368 848 600 | 803 180 279 | 386 327 479 |
| 2030 | 374 558 179 | 822 046 837 | 391 394 930 |
| **Growth 2020** | **18.1** | **29.2** | **17.5** |
| **Growth 2030** | **37.7** | **62.9** | **34.0** |

# 9. Conclusions: Summary and Contribution

The research question posed in this thesis was whether trade data could be adequately used to capture patterns in transport volumes and containerized freight flows. For this purpose seven auxiliary steps were built. They were addressed in chapters two until eight.

The conclusion of this research is presented schematically below in figure 9.1. What the figure points out is that it is possible to link trade to transport volumes and to container flows. The way this is done is by employing a variety of tools starting with data mining and followed by either a good understanding of product characteristics (reflected by the technical approach) or reliance on econometric specifications (reflected by the econometric approach). The applications illustrate what are believed to be suitable approaches that add insight to the modeling of transport demand. In particular, static and dynamic models in the panel or single time series framework address the patterns of growth of transport volumes and containerized flows. The specific choices were made bearing in mind gaps in the literature and more practical issues of data availability and level of sophistication.

Figure 9.1: Final Conclusion




The contribution of this work is described per-chapter within the summary below in chapter 9.1 and more broadly with respect to its societal and sector related relevance in chapter 9.2.

## 9.1 Contribution per chapter

The gaps in the literature were identified in chapter two. What was observed was that the demand for transport volumes and container flow research on the international level is substantial and has in particular grown considerably in the recent years. Moreover it regularly makes part of research as primary input like for example in freight models where the final objective varies from mode choice to routing, to calculating emissions and so forth. At the same time it often represents a weak part of the latter type of analysis due to data constraints. Problems arise due to the need to collect OD data from ports all over the world, the lack of sufficiently long time series and the lack of information on the OD's within the hinterlands.

The main observation was that there is a lack of dynamic time series approaches in the modeling of container flows as applied within the academic contributions of modeling freight. Moreover the methodologies of converting trade data or tons into containers were barely documented.

Having established the need for such research the interest shifted to investigating to what extent the existing literature could contribute to this work and vise versa. What was quickly established was that there is a vast variety of tools and models available to the final user being the transport stakeholders and in particular policy makers and the transport industry. Tools have been traditionally constructed by the international organizations, academia, consultancies and the industry itself. The level of sophistication of those tools ranges from very complicated and highly resource intensive structural models/General Equilbrium Models (GEM) to simple regression analyses assuming for example a one to one relation of GDP to transport and the container trade. Typically the former are constructed by international organizations while the latter by consultancies.

The highly demanding approaches of General Equilibrium models incorporate a level of detail which as mentioned in chapter 2 substantially exceeds the requirements of this research. However bearing in mind the value of such structural approaches while their replication is not considered appropriate the translation of their output for the transport context represents an additional implementation possibility of the current work. In particular this is possible by applying the conversion mechanisms suggested in this research to the typically scenario based, output of the GEM models in order to obtain container flows. As such the current research apart from its contribution as a complete methodology, it additionally serves fragmented in this occasion with regards to the conversion mechanisms specifically. A GEM model for the Belgian economy for example could thus be complemented by the conversion mechanism externally through which container flows would be obtained.

On the other hand, tools concerning patterns of growth of container traffic are constructed by consultancies and internally by PAs and liner companies/ship-owners. The methodologies behind the available reports are however unknown and hence no straight forward comparison of their methodologies to the methodologies used in this research can be done. However judging from the type of output reported it is safe to assume that in their modeling applications no panel techniques are employed.

The use of dynamic models cannot be ruled out although during the current investigation no documentation implying the use of dynamic models was found. Putting the discussion on the modeling superiority of this research aside several other issues in the traditional approach should be mentioned.

The forecasting on the basis of container flows that is sourced by ports requires the incorporation of port competition with all the factors impacting port choice. This is on its own a very complicated and resource intensive element which if ignored reduces the realism of the forecast. In the current approach of trade as the starting point such implications do not need to be incorporated reducing thus the complexity of the model. This does not mean that port choice is not important, on the contrary. It does however mean that it constraints the applications within forecasting given especially the data constraints. Under the assumption that port competition and forecasting can be constructed simultaneously an additional limitation should be considered, that of the lack of OD input.

The forecasts hence produced in the traditional freight approach using the input from ports typically cannot provide for ODs. As a consequence the forecast does not differentiate per container's origin that is crucial information for PAs strategic decision-making processes. Such limitation does not exist in this research's approach due to the global coverage of trade data per OD. The Flemish ports for example would thus benefit from gaining insight on extended coverage of extra European flows to European countries and therefore assess according to their market share strategic decisions on investments, cooperations and so forth.

Finally the traditional freight forecasting exercises of consultancies are of limited use to transport stakeholders interested in specific category of products like for example manufactures. This is a result of the unknown content of the container boxes.

The suggestion of a methodology was made in chapter three. It represents the impact of this work from a methodological perspective. The methodological contribution is thus a result of the construction of a step-wise approach for obtaining container flows. An approach, which results in time series of container flows on different levels: per aggregate product level, per disaggregate product level and per specific ODs which can be country to country, region to region, or total. The specific choices per step were made bearing in mind issues of data availability and level of sophistication.

In particular, the modeling using time series techniques, was applied with trade data. Data availability considerations were taken into account, thus addressing data shortage problems typically encountered in transport research. As such panel data techniques, which maximize the number of available data, were used whenever possible and appropriate. The level of sophistication is closely related to the latter issue of data availability. This means that more data allow for a higher level of sophistication in modeling transport. There is hence a maximum level of sophistication defined by the availability of data.

In this research this is further refined in such a way as to assure a level of practicality which also minimizes the loss of insight. This work is therefore replicable and can be used on a practical level by either policy makers or the industry itself.

Furthermore the construction of such step wise methodology makes possible the creation of a tool readily usable by final users. It can result in a very flexible mechanism easily adjustable at all stages given the step-wise approach in the programming steps followed. In practice, starting from the raw database of trade, a tool is easily built by connecting the entire set of programs within the data mining (chapter four), the applications (chapters five and six) and the conversion mechanism steps (chapters seven and eight).

In chapter four the practical feasibility of the contribution of trade for transport was assessed. For this reason an extensive data mining exercise was performed on several databases on the level of volume in kilograms. The main conclusion drawn from the data mining was that a variety of high usability databases could be created to serve the needs of transport research. The existence of data on an OD level for long time series (depending on the countries of interest), extended cross sectional series and for a high level of detail in terms of goods could be even further exploited for transport purposes. Especially the anticipation of shorter time intervals becoming available in the near future by the UNCOMTRADE will allow for the construction of sophisticated time series models with the potential of significantly superior model performance to what can be applied currently with the available resources.

The patterns of growth were investigated in chapter five. The analysis was made for freight and not containers. The reason why such decision was taken was in order to minimise the level of bias introduced in the models. It was therefore considered that the assessment of growth patterns and of the variability between the countries should be kept on the level of freight for estimation quality and interpretability purposes. The suggested approach for modeling growth and variability of trade was the mixed model from the family of panel models, a different approach from the until now fixed model approaches. This approach was justified by the characteristics of the sample countries and was believed to add realism to the growth models. In general the advantage of the panel modeling technique is that it addresses variability in both the dimension of time and cross section which is particularly suitable for applications with European countries.

The growth specifications chosen are economically interpretable and when used for trend extrapolations they reflect different levels of market confidence. Market confidence refers to different expectations of market growth, which correspond to the growth specifications as specified in this research. The main conclusion drawn from the estimations was that no single growth specification could be attributed with a clear superiority from an econometric point of view while in all cases the growth pattern varied in terms of volume and rate of growth between the countries. The suggestion made within this research was to assume the likelihood of all specifications being possible and make decisions based on the range of market confidence.

The use of the growth models for trend extrapolations, represent static trend models and are recommended as a tool for estimating future growth under the different ranges of future market confidence.

Having performed static forecasting exercises the focus in chapter six extended to dynamic forecasting with firstly a dynamic panel model, complemented with single series of ARIMA's and VEC models. The initial approach of using panel data opted to overcome the data availability barrier and provide for a two dimensional analysis. However given the defined specification the panel model produced very good results which would however have made little sense for forecasting. The conclusion hence drawn was that for the specific specification, single country forecasting would be more appropriate for forecasting purposes. For this reason ARIMAX models were estimated with results which varied in quality per country. The final conclusion drawn was that single country forecasts are useful tools which perform well even with limited number of observations. Concerning the VEC models the justification for their use was based on external sources and theoretical support of the cointegration between the dependent and input variables. The models performed as well as the best performing ARIMA models in each country case.

In chapter seven the constructed databases of solely trade had to be converted into freight data and in particular the TEU unit. The lack of customs data led this research into second best solutions applying two different methodologies differentiated according to the level of aggregation. The main conclusion drawn was that they both represent realistic quantifiable solutions which add value to research which requires input of freight flows. The rigidity resulting from the reliance on assumptions for especially the disaggregated approach was overcome by means of scenarios thus adding the necessary flexibility, a particularly desirable feature given the dynamics in trading patterns. The aggregated approach is heavily data dependent and has been mainly evaluated by econometric testing.

Finally chapter eight demonstrated the result of the suggested methodology. It is the chapter that brought all the different steps/chapters together and empirically illustrated how the methodology is put in practice and what type of output can become available.

The different steps followed in this research relied heavily on empirical work. Such empirical analysis however typically leads to continuous experimentation with new specifications, new models and so for forth, despite data limitations in terms of coverage and quality. There exists always some spectrum for improvement and since models are only approximations of reality and the notion of a single perfect model does not exist it thus leads to a continuous search for the best possible outcome given the available resources. The results achieved in this research are directly usable practical applications as long as they are used as complementary information, as is typically the purpose of modeling human behavior.

An example of the limitations of modeling and reasons why exclusive reliance on their output is not recommended is the ongoing economic crisis. It should be noted that in the applications made in this research, a recovery is assumed for the year 2010.

This is based on alternative sources of trade for that year, which were available at the time. There are two points which require attention. Firstly, predicting the timing of occurrence and extent of the crisis if possible at all, it could not have been done with any of the currently available models as demonstrated by the recent facts and their short history. Secondly, the complexity of the dynamics between the multiple actors make it impossible to predict the duration of the crisis or even model the different outcomes based on for example game theory since mathematical solutions to such problems beyond three players are very complicated.

What is however most important from a research thesis in the field of transport is the provision of the link to the final beneficiary, society and industry, which is described in chapter 9.1.

## 9.2 Societal and sector specific relevance

Two major pending structural question-marks facing Europe and the World are the environment and the current account imbalances of countries. The challenge focuses on building the foundations for a sustainable type of economic growth, without compromising growth. More research is hence needed in a wide spectrum of fields, to enrich current insights, assess the impact of best practices and promote innovations. The current work addressed the need for better quality and quantity of information in transport research. Bearing in mind the challenges facing the transport sector as specified in the 2011 White Paper of the EU, this work contributes by adding sophistication and detail to freight transport-related studies.

Concerning range of applicability, given the empirical choices made, the methodology can be replicated for different datasets reflecting different aggregation levels. It hence serves as input for a multitude of studies. The implementations could therefore range from studies on total freight volumes to freight volumes per economic sector, like for example the case of the automotive sector or the manufacturing sector among others. Furthermore implementations can be specified according to geographic coverage, either for the sum of all partners or per specific trading partner, or per groups of partners.

With respect to the typology of users, policy makers specialized in the field of transport are the target beneficiaries. In particular the contribution of this work to policy makers is the provision of a methodology and the basis for a tool utilizable for policies requiring input of trade volumes and/or container flows. The contribution explained in chapter nine applies directly in the case of policy makers too given the direct interest of policy makers in transport and the impact transport has on a number of policy fields. Further clarifications of the current research's contribution for policy makers on the specific topics of values versus volumes, synergies between policy areas and possible implementations are given below.

What is clarified to policy makers is that in understanding freight flows, monitoring volumes instead of values provides more reliable insights. The reason is that values distort the understanding of the true growth of freight. This is demonstrated by the mere fact that increases in values do not give an indication of the growth in the volume of goods being traded and hence also the physical movement of goods. This is especially pronounced for example in the case of aggregated flows, were extreme fluctuations in the values of some goods may completely distort the perception of policy makers regarding growth. This is particularly relevant in evaluating investment decisions especially since typically freight transport investments are resource intensive and the decisions often need to be made years before, in anticipation of future growth. In today's times where access to public money is limited the opportunity cost of such decisions is high.

Furthermore values are reported in CIF (Cost Insurance Freight) for imports and in FOB (Free On Board) for exports. This is an important distinction and should always be carefully addressed especially when aggregating flows across trade direction. Finally it should be noted that values do not reflect the end price of the goods. Hence, even in the case of CIF values one cannot assume that the complete cost of the transport chain is accounted for, since hinterland costs are not incorporated. Quantities on the other hand are free of such complications and are therefore a more straightforward measurement of growth.

However the typology of policy related users extends beyond the transport sector. This is due to the multifaceted nature of transport activities which causes a spillover effect to other policy fields. As such transport research is often complemented or even instigated by economic, environmental, energy related considerations among others. The main reason for existing synergies between transport policy making and other policy fields is the high integration of transport with other economic activities of modern societies and its direct and visible impact on society. It additionally represents a quantifiable indicator of economic activity which can thus be plugged into policy simulation tools.

Regarding potential implementations for policy makers, the contribution of this PhD is in studies necessitating a) future growth projections of trade volumes or containers, b) comparative analyses of the trading patterns of different countries and c) a freight generation input either on tons or containers for a broad range of ODs and product categories.

Examples of forecasts and comparative growth analyses of trading patterns have been demonstrated within this PhD by the trend and dynamic forecasts and the mixed modeling applications. A direct implementation for the Flemish government for example concerns port investments. Based on the projected growth of freight volumes in tons and container units, decisions on financing investments in its Flemish ports can be supported. Furthermore, by looking at the growth of the neighboring countries and countries further in the South and East of Europe, decisions linked to hinterland connectivity can be supported.

Examples of studies where a freight generation input is required include the impact assessment of road pricing, or infrastructure investments on the current and future traffic or mode split. In these cases input on tons or containers for specific Origins-Destinations and for either aggregated or disaggregated flows become possible. Implementations for the Belgian government concerns especially the addition of flows on the container unit which is one of the future implementation planned for the Freight Model Flanders[38].

Such studies can either be exclusively dealt within a transport framework, or on a societal framework, either directly, or indirectly. In the latter case, the effect of road pricing on traffic/mode split, is extended to include effects on economic growth. Furthermore, the effect of infrastructure investments on traffic/mode split is extended to considerations of maximizing added value of public expenditure. In the case of direct societal effects, freight generation contributes to the discussions on global warming and pollution, by serving as input for estimations on $CO_2$ emissions and pollutants, emitted by transport activities.

In addition to policy makers, transport agents in the different fields of either maritime and/or land transport and/or logistics represent final users benefiting from this PhD's output. This is due to their involvement in a sector of derived demand in nature and the fact that the sector is organized in supply chains. Summarized in a nutshell (since this field is quite extensive and has not been directly addressed in this research) transport agents organized in supply chains transport the goods demanded by society. Given their common purpose and strong interdependencies the same type of information on freight flows must be shared across agents. The contribution of this work in such framework is through the provision of freight volumes per supply chain that can be used by logistics platforms. Efficiency gains can thus be realized for entire supply chains and for individual agents. Furthermore, especially since supply chains involve the different modes of transport where the container plays a predominant role, input in the container unit is of high importance. Information flows on the level of container and tons could thus lead to a more efficient consolidation of flows. Furthermore an investigation of such flows for example on a local or regional level would assist in the assessment of the most appropriate location of logistics platforms. More detailed information could also be obtained on the types of goods typically transported in the area(s) under consideration. Although no specific analysis in relation to the supply chains is performed in this work it would certainly be very interesting to extend the current work to that level. The latter is therefore referenced in the chapter on future work.

In the case of individual transport companies the necessity of market analysis, or specific product analysis, typically makes part of their long term strategic planning. The contribution of this work is that customized input on the specific services of the individual companies can be provided through the suggested methodology. The input in tons or containers could include either exclusively product-based analysis or a combination of products with specific ODs. Broader data accessibility, allows for the making of more informed decisions.

[38] See footnote 24, 25.

In particular market analyses can in this way combine and compare the data on own-performance with a) total potential of the specific services and b) more exploratory analysis on the expansion of services to other products or geographic areas. As such transport stakeholders obtain information beyond their own market share and hence gain insight on the total current potential and future growth. Furthermore an exploratory approach in terms of adding geographic coverage can be pursued and in the case where specific product niches are served adding product coverage can also be assessed. In terms hence of strategic planning transport stakeholders benefit the most in terms of discovering new markets.

# 10. Future work

This last chapter of future work reflects i) some of the topics which were not addressed in detail within this research, ii) case studies which were not applied but which have a significant relevance to transport stakeholders and iii) ideas which resulted from the process of drafting this research but which have to be postponed for a later point in time.

Alternative topics which were not addressed in detail but which could contribute to achieving better results involve different model specifications. As such further experimentation with other indicators for the dynamic models could be considered. An example of an indicator which was initially explored in this research but never reached application due to the unsatisfactory quality of the detail is data on prices and in particular the unit value of goods and/or the unit value of goods across partners. Additionally the indicator of oil price was used in this research but the results achieved were if not inferior, equally good as the ones achieved with a simpler specification and for this reason the indicator of oil price was abandoned. Evidently a continuous process of trial and error is inevitable and could involve a multitude of indicators and combinations thereof. The major barrier to such experimentations runs down to data quality and availability.

Having said that, the topic of data coverage and quality emerge as part of future work. While the attempt made in this research was already quite extensive there is more that can be done. Further elaboration to improve the coverage of an average of 80% can be made by a) going deeper into the disaggregation of product categories and b) by converting data reported on other units (i.e. liters), into kilograms by the construction of proxies to the extent possible. Furthermore with regard to coverage, data of either longer yearly time series or of shorter time intervals (monthly or quarterly) would definitely contribute to the spectrum of usable candidate models. As a consequence and due to the fact that typically time series models require substantial amounts of data, more sophisticated time series models could be employed. While the latter does not necessarily guarantee better results it could contribute to the validation of results achieved with simpler techniques, to the improvement of their reliability or it could provide for new breakthroughs in the field.

In particular data of shorter intervals on the unit of weight are anticipated by the UNCOMTRADE. To the extent that input data exist on equivalent time intervals the modeling options would substantially expand. Finally it should be said that given the sharp declines observed in 2009, the availability of data for 2010 will immediately improve the forecasting power of the models applied in this research.

Outliers should also be addressed in more detail but only after the evaluation of the perceived added value from doing so. By that what is meant is that in the cases where large databases are aggregated (like the application of total trade in this research) going through the database in detail to identify and interpret outliers might result in an extremely time consuming task without significant added value.

While this process on its own is very valuable the resources it will consume need to be taken into account before such an attempt is made.

Case studies and pilots were used in this research given the numerous alternatives which could have been considered. Different cases studies and pilots could have been chosen depending on the specific needs of the transport stakeholders as a result of the market they are active in or their objective to expand in different markets or geographic areas. Some examples include the following:

- **Flow**: Exports, Total (imports plus exports);
- **Partners:** BRIC countries, countries of specific liner company loops, like for example countries belonging to the Europe-Asia loop, countries/regions served by logistics platforms;
- **Product categories:** Total manufactured goods, total agricultrural goods, or any other specific product categories;
- **Aggregation level:** Extra trade (Total trade minus Intra European Trade);

One of the biggest challenges in doing research is to define the "end" and allow for ideas which are created during the process to be pursued outside of the PhD framework. Two of the topics which belong to the immediate future work planned include the following:

(1) Non linear growth with emission target as a limiting factor;

---

Further elaboration for example of the logistic growth function could be considered for future research through an interpretation of the carrying capacity as the ecological restriction, imposed by the economies to the economies themselves by means of emission targets. Under this assumption, the qualitative interpretation of the logistic function follows the original approach of Verhulst[39] (Verhulst, 1845/1847) which states - when the wording is adjusted for trade - that the rate of trade growth is proportional to both the existing trade and the amount of available resources, all else being equal. Hence, finally trade growth slows down asymptotically as resources get depleted given no further actions in terms of technology or km reduction or shifts to greener modes.

[39] The model of population growth (Verhulst, 1845/1847) is the in the continuous logistic model described by the differential equation: $dN/dt = r N (K – N)/k$. The carrying capacity represents the maximum sustainable population denoted by k and the constant r is the population growth rate. In the equation, the early, unimpeded growth rate is modeled by the first term $+rN$. The value of the rate $r$ represents the proportional increase of the population $P$ in one unit of time. Later, as the population grows, the second term, which multiplied out is $-rN^2/K$, becomes larger than the first as some members of the population $P$ interfere with each other by competing for some critical resource, such as food or living space. This antagonistic effect is called the *bottleneck*, and is modeled by the value of the parameter $K$. The competition diminishes the combined growth rate, until the value of $P$ ceases to grow (this is called *maturity* of the population).

(2) Panel VEC applications;

Panel VEC are models which are particularly suitable for research which suffers from a lack of data and where capturing long term relationships is the objective. They are however models which are quite complex and require substantial amount of data. Currently, software packages do not readily provide for the necessary procedures which hence requires own programming.

The topics intended for future work have been selected on the basis of potential impact and usability. The reason why the expected impact is high is because of their relevance to current issues of sustainable growth and the dynamics between country interactions. While drivers of historic and current growth are put under scrutiny, the recognition of interdependencies between countries is clearly demonstrated by today's turmoil within the EU and globally. Such considerations need to be supported by appropriate empirical tools in the hands of policy makers with final objective the well being of both societies and the business world.

The research performed thus far has therefore served the additional purpose of stimulating the curiosity and motivation to investigate ways of understanding transport demand further, beyond the PhD framework.

## SAMENVATTING

De interesse van het beleid voor goederenvervoer is sterk toegenomen niet enkel door de sterke groei van de volumes maar ook door het meer uitgesproken effect dat goederenvervoer heeft of zou kunnen hebben op een aantal aspecten van de socio-economische activiteit en vice versa. De complexiteit van deze groei en de interacties met de omgeving, hebben in de onderzoekswereld reeds heel wat interesse opgewekt. Vooral de huidige en toekomstige vraag naar goederenvervoer spelen een belangrijke rol omdat zij mee bepalen welke maatregelen noodzakelijk zullen zijn om het transport op een duurzame wijze te kunnen realiseren. Gezien de belangrijke positie die de container inneemt als facilitator van het vervoer, is het belangrijk dat bij het onderzoek van de vraag naar goederenvervoer de beweging van containers opgenomen wordt als aanvulling op de traditionele product-based benadering.

Het probleem is echter dat de relatie tussen enerzijds de handelsstromen en anderzijds de containerstromen zeer complex en zeker niet eenduidig is. Oorsprong en bestemming van handelsstromen zijn beschikbaar voor zeer gedetailleerde goederencategorieën. Het grote probleem is echter dat, wanneer men dit wil vertalen naar containerstromen, men meestal niet weet wat er precies in een container zit. Gedetailleerde informatie over de inhoud, de bestemming en de oorsprong van containerstromen zal leiden tot een betere kwantificering van de relatie tussen containers en goederen en de bouw van steeds meer geavanceerde tools voor beleidsondersteuning.

Dit onderzoek wil een alternatieve benadering bieden voor de traditionele geaggregeerde analyse van de vraag naar goederenvervoer door te focussen op de vervoerde volumes en de containerstromen. Hierbij wordt niet louter gebruik gemaakt van gegevens over het vrachtvervoer, maar vooral ook van gegevens over internationale handel. Het gebruik van handelsstatistieken om zicht te krijgen op containerstromen en vrachtvervoer, laat een sterkere opsplitsing toe naar herkomst en bestemming en naar productcategorie.

De voorgestelde aanpak is tweeledig. Ten eerste wordt de handel in volume-eenheden gemodelleerd, in tegenstelling tot de traditionele aanpak van het modelleren van de handel in waarde. Op deze manier wordt de output direct bruikbaar voor transport stakeholders. Ten tweede wordt het verband tussen handelsstromen in volumes en de containerstromen gekwantificeerd, omdat dit tot op heden zo goed als niet gebeurd is. Hierbij wordt gewerkt op een geaggregeerd niveau voor de totale handel en op een meer gedetailleerd niveau voor specifieke goederencategorieën. Tenslotte kunnen beide benaderingen gekoppeld worden om vertrekkend van het model voor de handelsvolumes via de conversie van handelsvolumes naar containerstromen, voorspellingen te krijgen van TEU's.

De toepassingen van het modelleren van de handelsstromen maken gebruik van handel uitgedrukt in volumes. Bij het modelleren en verklaren van handelsvolumes wordt gebruik gemaakt van landengroepen en productcategorieën. Deze landengroepen en productcategorieën worden elk gekenmerkt door specifieke transporteigenschappen. Om de replicatie van de onderzochte transportmodellen door transport stakeholders te vereenvoudigen, werd tevens het niveau van complexiteit en detail aangepast. Er wordt dus voorkomen dat de modellen worden gekenmerkt door een buitensporig niveau van complexiteit en detailniveau. Het onderzoek kadert binnen het domein van de vraag naar vervoer, waarbij de aandacht ligt op de groei, de variabiliteit en het voorspellen van handelsvolumes.

Het onderzoek naar het verband tussen de handel en de container volumes is uitgevoerd met twee alternatieve benaderingen die vooral gericht zijn op de verschillende niveau's van aggregatie of desaggregatie. De eerste is in een eerder "technische" weg door de bouw van een stap-voor-stap methode. De laatste is gebaseerd op econometrische schattingen met behulp van tijdreeksen.

Dit doctoraat levert het bewijs dat het mogelijk is om handel, vervoerde volumes en containerstromen te linken met behulp van een stapsgewijze methode die in een volledig instrument kan worden omgezet voor transport stakeholders.

# BIBLIOGRAPHY


(1) Ahn, S.C., Schmidt, P. 1995. Efficient Estimation of Models for Dynamic Panel Data. Journal of Econometrics, 68: 5-27.

(2) Anderson, J.E., Van Wincoop, E. 2004. Trade Costs. Journal of Economic Literature, 423, 691-751. Available at: http://www.ecotransit.org/download/ecotransit_background_report.pdf [Accessed 18 August 2011]

(3) Anderson, T.W., Hsiao, C. 1982. Formulation and Estimation of Dynamic Models Using Panel Data. Journal of Econometrics, 18: 47-82.

(4) Apergis, A, Payne, J.E. 2010. Energy consumption and growth in South America: Evidence from a panel error correction model . Energy Economics 32: 1421–1426.

(5) Arellano, M., Bover, O. 1995. Another Look at the Instrumental Variable Estimation of Error Components Models. Journal of Econometrics, 68: 29-51.

(6) Arellano, M.,Bond, S.1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", Review of Economic Studies. 58: 277-297.

(7) Baldwin, R., Taglioni, D. 2006. Gravity for dummies and dummies for gravity equations, NBER working papers, No.12516.

(8) Ballabriga, F., Sebastian, M., Valles, J.1999. European asymmetries. Journal of International Economics, 48:233-253

(9) Baltagi, B.H. 2008. Forecasting with panel data. Journal of Forecasting, 27(2): 153-173.

(10) Baltagi, B.H., Kao C. 2000. Nonstationary panels, cointegration in panels and dynamic panels: A survey. In Nonstationary panels, cointegration in panels and dynamic panels, Advances in Econometrics. North-Holland: Elsevier.

(11) Banerjee, A., Dolado, J. Hendry, D.F., Smith, G.W. 1986. Exploring equilibrium relationships in econometrics through static models: Some Monte Carlo evidence. Oxford Bulletin of Economics and Statistics 48, pp.253-277.

(12) Banerjee, A., Dolado, J., Galbraith, JW. and Hendry, DF.1993. Co-Integration, Error-Correction, and the Econometric Analysis of Non-Stationary Data. Chichester: Oxford University Press.

(13) Barber, T., & Wiesmann, G. 2010. Germans urged to boost demand. Financial Times, pp. 8. Available at: http://search.proquest.com/docview/250284147?accountid=14480

(14) Ben-Akiva, M. 2008. Freight Demand, Transportation Systems Analysis: Demand & Economics. MIT lecture notes. Available at: ocw.mit.edu/courses/civil-and-environmental-engineering/1-201j-transportation-systems-analysis-demand-and-economics-fall-2008/lecture-notes/MIT1_201JF08_lec06.pdf - 2011-07-24 [Accessed 18 December 2011]

(15) Besseling, P., Francke, J., Nistal, R.S. 2006. Aanpassing WLO scenario's voor het containervervoer. Centraal Planbureau, Den Haag.

(16) Blundell, R. and S. Bond, (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models", Journal of Econometrics, Vol. 87, pp. 115-143.

(17) Borges, A.M. 1985. Applied General Equilibrium Models: an assessment of their usefulness for policy analysis. OECD Economic Studies No. 7

(18) Bröcker, J., orzhenevych, A. & Riekhof, M. 2011. Predicting freight flows in a globalising world. Research in Transportation Economics, 31, 37e44.

(19) Bundesbank, (2000), Macro-Econometric Multi-Country Model:MEMMOD

(20) Canova, F., Ciccarelli, M. 2003. Panel Index VAR Models: Specification, Estimation, Testing and Leading Indicators. CEPR Discussion Papers 4033.

(21) Cheung, C.L. 2005. A Framework for Estimating Container flow: The Case of Manufacturing Import from China. Master Thesis. Erasmus University Rotterdam.

(22) Containerization International. Available at: http://www.ci-online.co.uk/ [Accessed April 2011]

(23) Darity, W. Jr., Davis, L.S. 2005. Growth, Trade and Uneven Development. Cambridge Journal of Economics 29(1): 141–70.

(24) De Langen, P.W. 2003. Forecasting Container Throughput: A method and implications for port planning. Journal of International Logistics and Trade, 1(1): 29-39

(25) De Langen, P.W.2003. Forecasting Container Throughput: A method and Implication for Port Planning. Journal of International Logistics and Trade, 1 (1), pp.29-39.

(26) Deardorff. 2005. Deardorffs' Glossary of International Economics. Available at: http://www-personal.umich.edu/~alandear/glossary/ [Accessed 18 December 2011]

(27) Department of Treasury, 2008. Forecasting Accuracy of the act budget estimates. Available at: http://www.treasury.act.gov.au/documents/Forecasting%20Accuracy%20-%20ACT%20Budget.pdf [Accessed 07 October 2011].

(28) Diggle, P. J., Heagerty, P., Liang, K. Y. and Zeger, S. L. 2002. Analysis of Longitudinal Data. Oxford: Clarendon Press.

(29) EconTransIT, 2010. Ecological Transport Information Tool for Worldwide Transports Methodology and Data. Available at: http://www.ecotransit.org/download/ecotransit_background_report.pdf [Accessed 18 December 2011]

(30) ESPO. Statistics: The Rapid Exchange System (RES). Available at: http://www.espo.be/index.php?option=com_content&view=article&id=95&Itemid=90 [Accessed 18 December 2010]

(31) European Commission. COM2011 144 of 2011 White Chapter: Roadmap to a Single European Transport Area-Towards a competitive and resource efficient transport system.

(32) European Shipping and Port Competition? Maritime Policy and Management 27(4): 363-373

(33) EUROSTAT. 2010. Extra-EU trade in manufactured goods. Available at: http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Extra-EU_trade_in_manufactured_goods [Accessed December 2010]

(34) EUROSTAT. External trade detailed data. Available at: http://epp.eurostat.ec.europa.eu/portal/page/portal/external_trade/introduction [Accessed December 2010]

(35) Evans, D. J. 2005, The Elasticity of Marginal Utility of Consumption: Estimates for 20 OECD Countries. Fiscal Studies, 26: 197–224.

(36) Fagan, G., Henry, J., Mestre, R. 2001. An area wide model AWM for the Euro area. European Central bank. Working chapter No. 42.

(37) Free, E.W., Miller, T.W.2004. Sales forecasting using longitudinal data models. International Journal of forecasting 20: 99-114.

(38) Groen, J. J., Kleinbergen, F. 2003.Likelihood-based Cointegration Analysis in Panels of Vector Error Correction Models. Journal of Business and Economic Statistics, 21(2): 295–318.

(39) Grossman, G. and Helpman, E.1991. Innovation and Growth in the Global Economy, Cambridge: MIT Press.

(40) Heaver, T., Meersman, H., Moglia, F.,Van de Voorde, E. 2000. Do Mergers and Alliances Influence

(41) Hoogstrate, A.J., Palm, C., Pfann, G.A. 2000. Pooling in dynamic panel data models: An application to forecasting GDP growth rates. Journal of Business and Economic Statistics 18: 274-465

(42) IMF. World Economic Outlook (WEO) - Rebalancing Growth. 2010. Washington, DC : International Monetary Fund.

(43) International Monetary Fund. 2004. GEM: A new international Macroeconometric model, Research department. Washington: International Monetary Fund

(44) Jakaitiene, A., Stéphane, D. 2009. Forecasting the World economy in the Short-term. European Central bank. Working chapter series No. 1059.

(45) Janssen, L.H.J.M., Okker, V.R., Schuur, J. 2006. Welvaart enLeefomgeving: een scenariostudie voor Nederland in 2040. Centraal Planbureau, Milieu- en Natuurplanbureau en Ruimtelijk Planbureau. Centraal Planbureau, Den Haag.

(46) Judson, R.A., Owen, A. L.1999. Estimating dynamic panel data models: a guide for macroeconomists. Economics Letters, 65(1): 9-15

(47) Keck, A., Raubold, A. 2006. Forecasting Trade. WTO Staff Working Chapter No. ERSD-2006-05

(48) Khamis, A., et al. 2005. Nonlinear Growth Models for Modeling Oil Palm Yield Growth. Journal of Mathematics and Statistics, 1 3: 225-233

(49) Kincaid,C. 2005. Guidelines for Selecting the Covariance Structure in Mixed. In SUGI 30 Proceedings.

(50) King, R., Plosser, C., Stock, J., and Watson, M. 1987. Stochastic Trends and Economic Fluctuations. Working Paper No. 79. Rochester Centre for Economic Research.

(51) Le Fouler, L., W. Suyker & Turner, D. 2001. Trade Linkages and the Trade Matrices in the OECD Interlink Model. OECD Economics Department. Working Chapters No. 310.

(52) Lejour, A. Veenendaal,P., Verweij, G. van Leeuwen, N. 2006. WorldScan: a Model for International Economic Policy Analysis. CPB document No.111.

(53) Levine, B., Nozick, L., Jones, D. 2009. Estimating an origin–destination table for US imports of waterborne containerized freight. Transportation Research Part E 45, 611–626

(54) Littell, R. C., G. A. Milliken, W. W. Stroup, R. D. Wolfinger, and O. Schabenberger. 2006. SAS System for Mixed Models, Second Edition. Cary, NC: SAS Inst. Inc.

(55) Luo, M., Grigalununas, T. 2003. Spatial-Economic Multimodal Transportation

(56) Markianidou, P.,Weeren, A. (2011). Linear and non linear growth models using mixed modeling: An application on European import volumes. Working papers University of Antwerp.

(57) Markianidou, P.,Weeren, A. (pending review). The Relation between Container and Trade flows and a Conversion Mechanism.

(58) Masanao, A., Yoshikawa, H. 2002. Demand saturation-creation and economic growth. Journal of economic behavioud and organization, volume 48, issue 2, pages 127-154

(59) McKinnon, A. 2007. Decoupling of road freight transport and economic growth trends in the UK: an exploratory analysis. Transport Reviews, 271, pp. 37-64.

(60) Meersman, H., Francesca, M., Van de Voorde, E. 2002. Forecasting potential throughput. In: Port competitiveness: an economic and legal analysis of the factors determining the competitiveness of seaports. Antwerp: De Boeck.

(61) Meersman, H., Van de Voorde, E, 2008, The relationship between Economic Activity and Freight transport, in: Recent developments in Transport Modeling. New York: Springer.

(62) Melander, A., Sismanidis, G. and Grenouilleau, D. 2007. The track record of the Commission's forecasts - an update. European Commission Directorate General for Economic and Financial Affairs Economic Papers 291

(63) Meyermans, E., Van Brusselen, P. 2001. The nime model a macro econometric World model, Federal Planning Bureau Economic analyses and forecasts.

(64) MIT Sloan. 2011. The art of forecasting. MIT Sloan School of Management lecture notes. Available at: http://ocw.mit.edu/courses/sloan-school-of-management/15-761-operations-management-summer-2002/lecture-notes/lec10forecasting.pdf [Accessed 18 December 2011]

(65) Munchau, W. 2010. Gaps widen in the eurozone 'football league'. Financial Times, pp. 9. Retrieved from http://search.proquest.com/docview/250265882?accountid=14480

(66) Murata, K. et al. 2000. Modeling Manufacturing Export Volumes Equations: A System Estimation Approach, OECD Economics Department Working Papers, No. 235.

(67) Office for National Statistics-UK. 2008. Methodology of the Monthly Index of Services-Annex VI: The Cubic Spline Interpolation Method.

(68) Olivier, J., Subramanian, A., & Williamson, J. 2011. Germany owes more to prodigal periphery. Financial Times, pp. 1. Retrieved from http://search.proquest.com/docview/868720691?accountid=14480

(69) Osenton, T. 2004. The Death of Demand, , Upper Sadle River: Financial Times Prentice Hall Metz, D. 2010. Saturation of Demand for Daily Travel. Transport Reviews, 30: 5, 659 -674

(70) Pain, N. et al. 2005. The New OECD International Trade Model. OECD Economics Department Working Papers, No. 440.

(71) Pedroni, P. 1999. Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors. Oxford Bulletin of Economics and Statistics, 61: 653–670.

(72) Perrin, J-F., Tavasszy, L., van Meijeren, J. Minderhoud, M., Burgess, A., Bowden, N. 2008. Worldwide container model, in ETC proceedings.

(73) Pinheiro, J., and Bates, D., M. 2000. Mixed effects models in S and S-PLUS. Statistics and Computing. New York: Springer.

(74) Rae, D. and Turner D. 2001, A Small Global Forecasting Model, OECD Economics Department Working Papers, No. 286.

(75) Rattoa, M., Werner, R., Jan in ’t , V. 2008. QUEST III: An Estimated Open-Economy DSGE Model of the Euro Area with Fiscal and Monetary Policy , Economic Papers, No.335.

(76) Rothengatter, W., 2011. Preliminary defense comments. [e-mail] (Personal communication, 24 November 2011).

(77) SAS Institute Inc. 2008. SAS/STATR 9.2 User’s Guide. Cary, NC: SAS Institute.

(78) Schade W. 2005. "Strategic Sustainability Analysis: Concept and application for the assessment of European Transport Policy". PhD, NOMOS-Verlag, ISBN 3-8329-1248-7, Baden-Baden.

(79) Schmalense, R., Stoker, T.M., Judson, R.A.1998. World carbon dioxide emissions:1995-2050. Review of Economics and Statistics 80: 137-160.

(80) Sen, S. 2005. International Trade Theory and Policy: What Is Left of the Free Trade Paradigm? Development and Change 36(6): 1011–29.

(81) Silverstovs, B. and Schumacher, D. 2008. Disaggregated Trade Flows and the 'Missing Globalization Puzzle'. KOF Working Chapter No. 209.

(82) Simulation Model For US Coastal Container Ports, Maritime Economics & Logistics, 5, 158–178.

(83) Singer, J., Willett D., J., B. 2003. Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence. New York: Oxford University Press.

(84) Stock, J. H.. 2002.Time Series: Economic Forecasting. Available at:http://www.economics.harvard.edu/faculty/stock/files/isb201120.pdf [Accessed 18 December 2011]

(85) UNcomtrade. International Merchandise Trade Statistics (IMTS), [online] Available at: http://comtrade.un.org/ [Accessed December 2010]

(86) UNCTAD. Review of Maritime Transport. Available at: http://www.unctad.org/Templates/Startpage.asp?intItemID=2614 [Accessed 12 February 2010]

(87) UNESCAP.2007. Container Traffic Forecast.

(88) Veenstra, A., Charalambides. 2001. Multivariate autoregressive models for forecasting seaborne trade flows, Transportation Research Part E37, 311-319

(89) Verbeeke, M. 2008. A Guide to Modern Econometrics.3rd ed. Chichester: John Wiley and Sons

(90) Verbeke, G. and Molenberghs, G.2000. Linear Mixed Models for Longitudinal Data.

(91) Weeren, A., 2011. Discussions on modeling and software applications. [e-mails] (Personal communication, 2011).

(92) Willman, A., Estrada, A. 2002. The Spanish block of the ESCB Multi country model, European Central bank working paper series, No. 149.

(93) Wolf, M. 2008. The eurozone depends on a strong american recovery. Financial Times, pp. 13. Retrieved from http://search.proquest.com/docview/250147438?accountid=14480

(94) Wolfinger, R., D. Fitting Nonlinear Mixed Models with the New NLMIXED Procedure. Cary, NC: SAS Institute Inc.

(95) Zheng, M. 2010. Fitting Linear and Nonlinear Growth Curve Models Using PROC NLMIXED. Cary, NC: SAS Institute Inc.

## ANNEX I – List of Abbreviations

| | |
|---|---|
| ACF | Autocorrelation Function |
| AIC | Akaike Information Criterion |
| AICC | Corrected Akaike Information Criterion |
| AR1,1 | Autoregressive parameter |
| ARIMA | Autoregressive Integrated Moving Average |
| ARIMAX | Auto Regressive Integrated Moving Average with Exogenous Input |
| AUT | Austria |
| BGR | Bulgaria |
| BIC | Bayesian Information Criterion |
| BLX | Belgium and Luxembourg |
| CHE | Switzerland |
| CI | Containerization International |
| CPB | Central Plan Bureau |
| CPB_BE | Central Plan bureau of Belgium |
| CPB_NL | Central Plan Bureau_Netherlands |
| CSK | Czechoslovakia |
| CYP | Cyprus |
| DB | Deutsche Bundesbank |
| DEU | Germany |
| DF | Degrees of freedom |
| EC | European Commission |
| ECB | European Central Bank |
| ESP | Spain |
| FRA | France |
| GRC | Greece |
| HE | Country group Easter Europe |
| HS | Country group Southern Europe |
| HUN | Hungary |
| HW | Country group Western Europe |
| HWHSHE | single dataset with all country groups |
| IMF | International Monetary Fund |
| IMF | International Monetary Fund |

| | |
|---|---|
| ITA | Italy |
| M&A | Merger and Acquistion |
| MU | Mean |
| NLD | the Netherlands |
| NUM1 | Numerator 1 |
| NUM2 | Numerator 2 |
| OD | Origin-Destination |
| OECD | Organization for Economic Cooperation and Development |
| PA | Port Authority |
| PACF | Partial Autocorrelation Function |
| POL | Poland |
| Pr | Probability |
| PRT | Portugal |
| RMSE | Root Mean Squared Error |
| ROM | Romania |
| UNCOMTRADE | United Nations Commodity Trade Statistics Database |
| VAR | Vector Autoregressive |
| VEC | Vector Error Correction |
| WTO | World Trade Organization |

## ANNEX II – Statistical bottlenecks

Annex Table II-1: Sources and data type definitions

| Source | Data type |
|---|---|
| UN comtrade | Records all goods which add to or subtract from the stock of material resources of a country by entering (imports) or leaving (exports) its economic territory. Goods simply being transported through a country (goods in transit) or temporarily admitted or withdrawn (except for goods for inward or outward processing; see para. 28 below) do not add to or subtract from the stock of material resources of a country and are not included in the international merchandise trade statistics |
| | Imports can be distinguished as imports of foreign goods and imports of domestic goods. Import of domestic goods is referred as re-imports. In UN Comtrade, imports contain both the imports of foreign goods and domestic goods. However, import of domestic goods is available separately under the heading re-imports. Imports figures always include Re-imports. |
| | Exports of a country can be distinguished as exports of domestic goods and exports of foreign goods. The second class is generally referred to as re-exports. The exports shown in our database contain both the exports of domestic and foreign goods. As a help to our users we show the exports of foreign goods also separately under the heading re-exports. Exports figures **always** include Re-exports. |
| | Re-exported goods were imported by the country in the first place. However, at the time of imports it is not necessarily clear if a good will stay in the country or will be re-exported. UN Comtrade does not have information that would link re-exports of goods to the imports of these goods. |
| Eurostat | Arrivals are goods in free circulation within the European Union which enter the statistical territory of a given Member State. |
| | Dispatches are goods in free circulation within the European Union which leave the statistical territory of a given Member State to enter another Member State. |
| | Article 23 EC Treaty stipulates free circulation for Community goods throughout the European Community (EC). This principle applies not only to goods made in the Community but also to imported goods which have been released for free circulation after payment of the import duties to which they are liable |

Two examples are given one for each database:

**UN**

- Belgian imports of foreign goods from China includes all goods:
  - Produced in china and exported to BE
  - Re-exports of china to BE
- Belgian exports to China include all goods:
  - Produced in BE
  - Re-imports of BE from the EU

**EC**

- E.g. Arrivals in Belgium are all goods with origin: EU and destination:BE being already labeled as goods in free circulation hence all goods:
  - Produced by EU member states
  - Extra European cargo that entered the EU by any port or land EU border

- E.g. Dispatches from Belgium are all goods with origin:BE and destination:EU, being already labeled as goods in free circulation hence all goods:
  - Produced in Belgium
    - Extra European cargo that exits Belgian ports (either by transshipment, rail or road) or land EU border (which for Belgium does not matter since it has not borders with non EU countries).

# ANNEX III– Alternative classifications of category six

## Category six

Annex Table III-1: ISIC-6

| ISIC2 | ISIC | Total |
|---|---|---|
| 200 | 200 | 1 |
| 500 | 500 | 2 |
| 1429 | 1429 | 3 |
| Fashion | 1711 | 121 |
| | 1721 | 28 |
| | 1722 | 12 |
| | 1723 | 3 |
| | 1729 | 33 |
| | 1730 | 7 |
| | 1810 | 2 |
| | 1820 | 6 |
| | 1911 | 13 |
| | 1912 | 3 |
| 2010 | 2010 | 1 |
| 2021 | 2021 | 13 |
| 2022 | 2022 | 4 |
| 2023 | 2023 | 3 |
| 2029 | 2029 | 9 |
| 2101 | 2101 | 42 |
| 2102 | 2102 | 7 |
| 2109 | 2109 | 19 |
| 2221 | 2221 | 6 |
| 2411 | 2411 | 2 |
| 2430 | 2430 | 12 |
| 2511 | 2511 | 11 |
| 2519 | 2519 | 21 |
| 2610 | 2610 | 33 |
| 2691 | 2691 | 7 |
| 2692 | 2692 | 5 |
| 2693 | 2693 | 5 |
| 2694 | 2694 | 7 |
| 2695 | 2695 | 6 |
| 2696 | 2696 | 7 |
| 2699 | 2699 | 16 |
| 2710 | 2710 | 171 |
| 2720 | 2720 | 81 |
| 2811 | 2811 | 7 |
| 2812 | 2812 | 4 |
| 2893 | 2893 | 39 |
| 2899 | 2899 | 56 |
| 2930 | 2930 | 4 |
| 3691 | 3691 | 4 |
| 3699 | 3699 | 1 |
| ISIC | ISIC | 1 |
| Grand Total | | 838 |

Annex Table III-2: BEC-6

| Description | BEC | Total | % |
|---|---|---|---|
| primary industrial supplies not elsewhere specified | 21 | 8 | 0.965018 |
| processed industrial supplies not elsewhere specified | 22 | 672 | 81.06152 |
| capital goods except transport equipment | 41 | 21 | 2.533172 |
| cqpital goods parts and accessories | 42 | 16 | 1.930036 |
| transport equipment parts and accessories | 53 | 13 | 1.568154 |
| durable consumer goods not elsewhere specified | 61 | 18 | 2.171291 |
| semi durable consumer goods not elsewhere specified | 62 | 52 | 6.272618 |
| non durable consumer goods not elsewhere specified | 63 | 29 | 3.498191 |
| | Grand Total | 829 | 100 |

## Category five

Annex Table III-3: ISIC 5

| Description | ISIC2 | ISIC | Total |
|---|---|---|---|
| Manufacture of food products and beverages | Group1 | 1520 | 0.21% |
| | | 1532 | 1.70% |
| | | 1551 | 0.42% |
| Manufacture of coke, refined petroleum products and nuclear fuel | 2330 | 2330 | 0.85% |
| Manufacture of chemicals and chemical products | Group2 | 2411 | 44.16% |
| | | 2412 | 5.94% |
| | | 2413 | 10.62% |
| | | 2421 | 1.06% |
| | | 2422 | 2.34% |
| | | 2423 | 12.53% |
| | | 2424 | 5.10% |
| | | 2429 | 9.34% |
| Manufacture of rubber and plastics products | 2520 | 2520 | 4.88% |
| Manufacture of other non-metallic mineral products | Group3 | 2695 | 0.21% |
| | | 2699 | 0.42% |
| Electricity, gas, steam and hot water supply | 4010 | 4010 | 0.21% |
| | Grand Total | | 100.00% |

Annex Table III-4: BEC 5

| Description | BEC | Total |
|---|---|---|
| processed food and beverages mainly for industry | 121 | 0.21% |
| primary industrial supplies not elsewhere specified | 21 | 1.05% |
| processed industrial supplies not eslewhere specified | 22 | 91.14% |
| processed fuels and lubricants | 322 | 0.84% |
| non durable consumer goods not elsewhere specified | 63 | 6.75% |
| | Grand Total | 100.00% |

## Category seven

Annex Table III-5: ISIC 7

| Description | Group | ISIC | % |
|---|---|---|---|
| | 32 | 32 | 0.15% |
| Publishing, printing and reproduction of recorded media | 2222 | 2222 | 0.15% |
| Manufacture of coke, refined petroleum products and nuclear fuel | 2330 | 2330 | 0.15% |
| Manufacture of rubber and plastics products | 2520 | 2520 | 0.15% |
| Manufacture of other non-metallic mineral products | Group1 | 2610 | 0.46% |
| | | 2691 | |
| Manufacture of fabricated metal products, except | Group2 | 2813 | 1.37% |
| | | 2899 | |
| Manufacture of machinery and equipment n.e.c. | Group3 | 2911 | 57.08% |
| | | 2912 | |
| | | 2913 | |
| | | 2914 | |
| | | 2915 | |
| | | 2919 | |
| | | 2921 | |
| | | 2922 | |
| | | 2923 | |
| | | 2924 | |
| | | 2925 | |
| | | 2926 | |
| | | 2929 | |
| | | 2930 | |
| Manufacture of office, accounting and computing machinery | 3000 | 3000 | 4.72% |
| Manufacture of electrical machinery and apparatus n.e.c. | Group4 | 3110 | 10.05% |
| | | 3120 | |
| | | 3130 | |
| | | 3140 | |
| | | 3150 | |
| | | 3190 | |
| Manufacture of radio, television and communication equipment | Group5 | 3210 | 10.81% |
| | | 3220 | |
| | | 3230 | |
| Manufacture of medical, precision and optical | Group6 | 3311 | 1.37% |
| | | 3312 | |
| Manufacture of motor vehicles, trailers and semi-trailers | Group7 | 3410 | 5.02% |
| | | 3420 | |
| | | 3430 | |
| Manufacture of other transport equipment | Group8 | 3511 | 8.52% |
| | | 3512 | |
| | | 3520 | |
| | | 3530 | |
| | | 3591 | |
| | | 3592 | |
| | | 3599 | |
| | Grand Total | | 100.00% |

Annex Table III-6: BEC 7

| Descirption | BEC | Total |
|---|---|---|
| primary industrial supplies not elsewhere specified | 21 | 0.15% |
| processed industrial supplies not elsewhere specified | 22 | 3.21% |
| capital goods except transport equipment | 41 | 52.14% |
| capital goods parts and accessories | 42 | 24.77% |
| transport equipment passenger motor cars | 51 | 0.15% |
| other industrial transport equipment and parts and accessories thereof | 521 | 5.50% |
| other non industrial transport equipment and parts and accessories thereof | 522 | 2.60% |
| transport equipment parts and accessories | 53 | 6.42% |
| durable consumer goods not elsewhere specified | 61 | 3.98% |
| semi durable consumer goods not elsewhere specified | 62 | 0.46% |
| non durable consumer goods not elsewhere specified | 63 | 0.31% |
| goods not elsewhere specified | 7 | 0.31% |
| | Grand Total | 100.00% |

**Category eight**

Annex Table III-7: ISIC 8

| Description | Groups | ISIC | % |
|---|---|---|---|
| Manufacture of textiles | Group1 | 1721 | 1.80% |
| | | 1730 | |
| Manufacture of wearing apparel; dressing and | Group2 | 1810 | 19.37% |
| | | 1820 | |
| Tanning and dressing of leather; manufacture of | Group3 | 1912 | 6.53% |
| | | 1920 | |
| Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials | 2029 | 2029 | 0.90% |
| Manufacture of paper and paper products | 2109 | 2109 | 0.23% |
| Publishing, printing and reproduction of recorded media | Group4 | 2211 | 4.95% |
| | | 2212 | |
| | | 2213 | |
| | | 2219 | |
| | | 2221 | |
| Manufacture of chemicals and chemical products | 2429 | 2429 | 2.25% |
| Manufacture of rubber and plastics products | Group5 | 2519 | 3.38% |
| | | 2520 | |
| Manufacture of other non-metallic mineral | Group6 | 2610 | 0.68% |
| | | 2691 | |
| Manufacture of fabricated metal products, except | Group7 | 2811 | 1.13% |
| | | 2812 | |
| | | 2899 | |
| Manufacture of machinery and | Group8 | 2927 | 3.83% |
| | | 2930 | |
| Manufacture of electrical machinery and apparatus n.e.c. | 3150 | 3150 | 2.25% |
| Manufacture of medical, precision and optical instruments, watches and clocks | Group9 | 3311 | 27.25% |
| | | 3312 | |
| | | 3313 | |
| | | 3320 | |
| | | 3330 | |
| Manufacture of furniture; manufacturing n.e.c. | Group10 | 3610 | 22.75% |
| | | 3691 | |
| | | 3692 | |
| | | 3693 | |
| | | 3694 | |
| | | 3699 | |
| Other business activities | Group11 | 7421 | 0.68% |
| | | 7494 | |
| Recreational, cultural and sporting activities | Group12 | 9211 | 2.03% |
| | | 9214 | |
| | Grand Total | | 100.00% |

Annex Table III-8: BEC 8

| Description | BEC | Total |
|---|---|---|
| processed industrial supplies not elsewhere specified | 22 | 17.38% |
| capital goods except transport equipment | 41 | 16.03% |
| parts and accessories | 42 | 5.42% |
| transport equipment parts and accessories | 53 | 0.68% |
| durable consumer goods not elsewhere specified | 61 | 11.74% |
| semi durable goods not elsewhere specified | 62 | 34.54% |
| non durable goods not elsewhere specified | 63 | 12.19% |
| Goods not elsewhere specified | 7 | 2.03% |
| | (blank) | 0.00% |
| | Grand Total | 100.00% |

# ANNEX IV – Data mining: coverage and quality

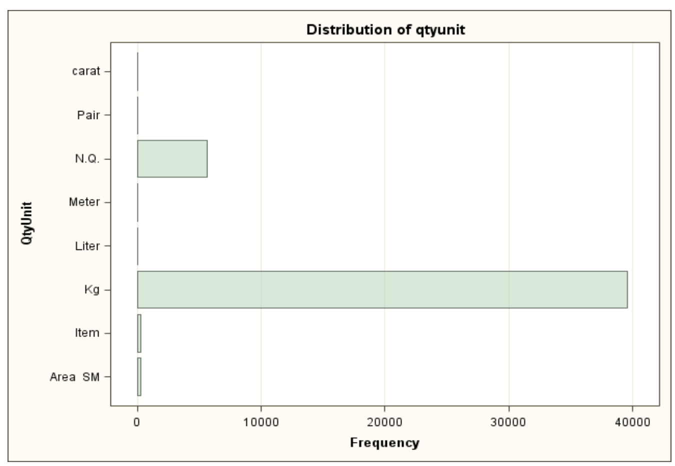
**Category six: How complete is the database?**

Although the patterns of growth coincide with the trends published in communications and documentations of the EUROSTAT. the quality and coverage of the data needs to be further evaluated. The reason is that poor data quality will compromise the forecasting exercises and the translation into container volumes. An unsatisfactory assessment of the data coverage on the SITC dig-3 level which is used in this application will lead to the sourcing of data from a SITC digit 4 level which itself will need to be checked for its "completeness" and quality. Further aggregation than the one performed in the current application (the digit-3 level), will in that case be needed. However, according to the UN, the volume data provided includes data directly provided by the countries themselves (following the UNCOMTRADE guidelines) or estimated figures by the UNCOMTRADE. Although the organization states that the estimation provides better quantity information to most end users, the data are not aggregated in order to provide the option to users who only want to use data reported by country's statistical bureaus. Practically what this means is that the more one is forced to aggregate the bigger the mix of both types of data.

The evaluation is based on an estimation of missing values. This has been done through the creation of frequency tables for all geographic groups together (HWHSHE) and separately (see figure 4.1) for the full dataset hence covering the years 1980 until 2009.

Annex-Figure IV-1: data quality assessment HWHSHE

| QtyUnit | | |
|---|---|---|
| **Qtyunit** | **Frequency** | **Percent** |
| **Area SM** | 243 | 0.53 |
| **Item** | 282 | 0.62 |
| **Kg** | 39585 | 86.41 |
| **Liter** | 33 | 0.07 |
| **Meter** | 45 | 0.10 |
| **N.Q.** | 5603 | 12.23 |
| **Pair** | 6 | 0.01 |
| **Carat** | 12 | 0.03 |




What the graph and table shows is the number of observations per quantity unit. Since in the analysis only observations measured in kilograms (kg) have been used, an assessment of the completeness of the data provided in this measurement needs to be estimated. The comparison between the different measurements (which are the available ones from the UNCOMTRADE itself) is done in order to avoid a situation where there would be a lot of missing values because of the choice of kg as the desired measurement. According to the graph, kg scores the highest of all measurements. This is also true in the case of the geographic groups HW, HS and HE. The database was alternatively sourced as category six imports of the selected countries from the world. In that case the results of the coverage are less satisfactory than the current 86 per cent of coverage in kg.

**Category six: What has been done with the outliers?**

The graphical exploration of the data revealed the presence of outliers. The level of detail available by this type of disaggregated analysis allows the tracing of outliers on the three digit level. Practically this means that outliers can be traced and evaluated which would have been impossible on a more aggregated level. An example of the process is documented in table 4.1 for the HW group only. The specifics of each case and the actions taken are explained within the notes.

Annex Table IV-1: HW outliers

| Partner | Product | Description | Year | Quantity | *Change* |
|---|---|---|---|---|---|
| NLD | 634 (1) | Veneers, plywood, "improved" wood and other wood, worked, nes | 1992 | 749982926 | |
| | | | 1993 | 6296284386 | *547336266,4* |
| | | | 1994 | 854225210 | |
| AUT | 612 (2) | Manufactures of leather or of composition leather, nes; etc | 1993 | 5237419 | |
| | | | 1994 | 54575630 | *5457563* |
| | | | 1995 | 6639965 | |
| CHE | 681 (3) | Silver, platinum and other metals of the platinum group | 1995 | 29949510000 | *Fully eliminated for all countries* |
| | | | 1996 | 34885682000 | |
| | | | 1997 | 182022722000 | |
| | | | 1998 | 1409179 | |
| | | | *1999* | *2532000* | |

**Notes**

(1) For category 634 the mean of the time series has replaced the original value.

(2) For category 612 there seems to be a typo hence the zero is removed. The complete time series has been checked before making this assumption.

(3) Category 68 and 667 have been completely eliminated from the dataset since apart from the irregularity in the trade pattern for this category (an example is given in table 4.1) they do not make part of the manufactured goods category according to the definition of UNCTAD.

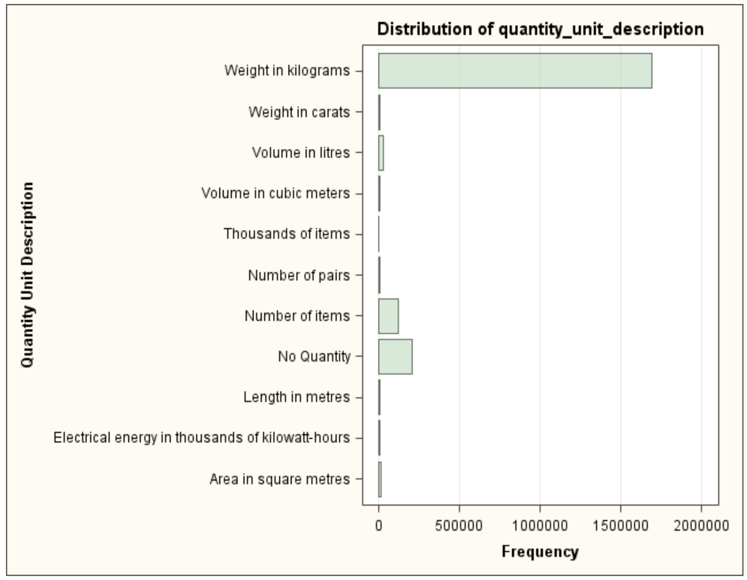
It should be noted that beyond the outliers that have been adjusted, other disruptions within the datasets have been identified. In these cases however they have not been removed from the database since it was impossible to define whether they contain useful information.

**Total trade: How complete is the database?**

Total trade has been checked for its completeness in terms of data reported in kg. In this case too frequency tables have been used and the results are illustrated graphically and in a table in figure 4.2.

Annex-Figure IV-2: Total trade data coverage

| Quantity Unit Description | |
|---|---|
| Quantity_unit_description | Frequency |
| Area in square meters | 8367 |
| Electrical energy in thousands of kilowatt-hours | 719 |
| Length in meters | 807 |
| No Quantity | 202220 |
| Number of items | 119650 |
| Number of pairs | 2354 |
| Thousands of items | 9 |
| Volume in cubic meters | 2521 |
| Volume in litres | 24387 |
| Weight in carats | 1129 |
| Weight in kilograms | 1690255 |




The 80 per cent coverage of total trade in the unit of kg is accepted. Future research will explore potential improvements on the four digit level. Nevertheless there is a limit to achieving full coverage of the database in kilograms due to the nature of the products themselves.

**Total trade: What has been done with the outliers?**

The quality assessment for the total trade level was a tedious process due to problems in tracing outliers and hence identifying their "true nature", as either a result of database errors or of true import behaviour. Additionally, differences in total patterns were observed depending on the source of data and the reporter of imports as explained in chapter four.3. This is observed in differences noted when the same data are sourced by the UNCOMTRADE directly, or the World Bank system WITS and imports sourced as exports of the world to the European countries under consideration instead of direct import of the European countries from the world.

The approach in the adjustments performed, was based on a comparison of the aforementioned databases. Hence, when substantial differences between the graphical patterns were identified the databases were compared and when judged as being appropriate adjusted according to the database with what appeared to be the correct values. This process took into account the comparison between value and volume. This means that when quantity demonstrated extreme volatility while value grew or declined within a certain range that value of quantity was classified as an outlier.

In tables 4.3 and 4.4 all the adjustments made are being reported and highlighted in grey. The reason why they are reported in two different tables is due to the methodology used for their adjustment. In table 4.3 the outliers have been identified by observing the value of trade and adjusted according to the average unit value. In particular it has been noted that in the cases reported, the value did not vary in accordance with the dramatic quantity change. For this reason an average unit value was calculated by taking the ratio of value to quantity, which was then used to calculate the quantity for the year demonstrating the outlier. On the other hand the outliers in table 4.4 have been contrasted between the differently sourced datasets and adjusted accordingly. In particular, in the cases reported, while the database of exports from the world to the country of interest was chosen as the primary database, its outliers have been adjusted according to the database of the specific country acting as a reporter of imports from the world. Although it would seem more appropriate to always use the database with the country acting as a reporter for its imports, in the cases of the Eastern European countries it has been considered more appropriate to source them in the indirect way. The reason was the improvement of the data quality and the possibility to extend the series back in the early 1980's since these countries do not themselves report on trade for those early years. It should be stressed here that ideally the database for total trade should have been investigated in at least the level of dig 2 in order to be able to more accurately trace the outliers. Such a process however goes beyond the scope of this research.

Annex Table IV-2: Total trade outliers – adjustments according to value

| Year | Country | Quantity | Value | Unit value | Average Unit value | Adjusted quantity |
|---|---|---|---|---|---|---|
| 1999 | CHE | 42377466992 | 79857071075 | 1.884423 | 1.665589 | 42377466992 |
| 2000 | CHE | 18351536975 | 82486613092 | 0 | | 49523996695 |
| 2001 | CHE | 19442677239 | 84101794013 | 0 | | 50493732408 |
| 2002 | CHE | 45162555510 | 87326868124 | 1.933612 | | 45162555510 |
| 1996 | CYP | 3912872986 | 3912872986 | 1.01763269 | 0.868522 | 3912872986 |
| 1997 | CYP | 10601782666 | 4257872672 | 0 | | 4257872672 |
| 1998 | CYP | 4122307678 | 4122307678 | 0.89422643 | | 4122307678 |

Annex Table IV-3: Total trade outliers - adjustments according to database comparison

| Year | Country | Quantity country partner (exports from world) | Value country partner (exports from world) | Quantity country reporter (imports from world) | Value country reporter (imports from world) |
|---|---|---|---|---|---|
| 2001 | BGR | 441454184415 | 6240863 | 11137643711 | 7278130102 |
| 2002 | BGR | 425774429620 | 6986140 | 10818797830 | 7987018960 |
| 2003 | BGR | 293741689587 | 9064487 | 14158164838 | 10901031209 |
| 2001 | ROM | 763207071672 | 15726513 | 26339098914 | 15551366960 |
| 2003 | ROM | 241836850387 | 24271458 | 32800384619 | 23983672552 |

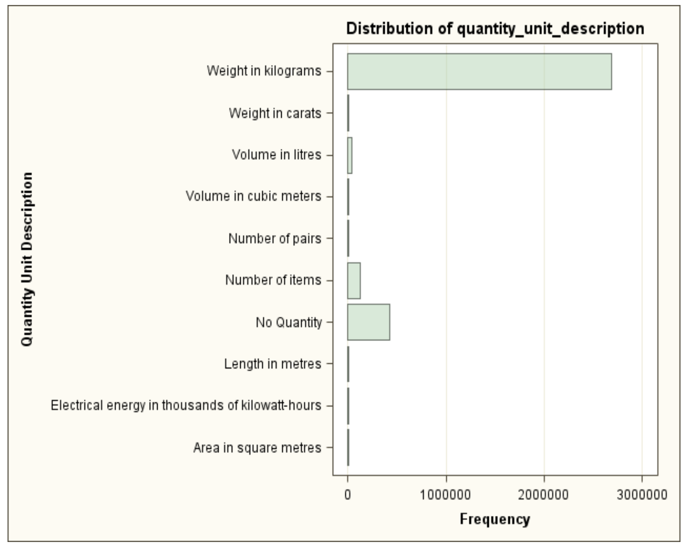
**Extra Trade: How complete is the database?**

The coverage for the extra trade included multiple databases. The ones which have not been previously examined are the intra trade and total exports databases. The intra imports and intra exports databases are described in the frequency tables in figure 4.3.

Annex Figure IV-3: Intra trade coverage

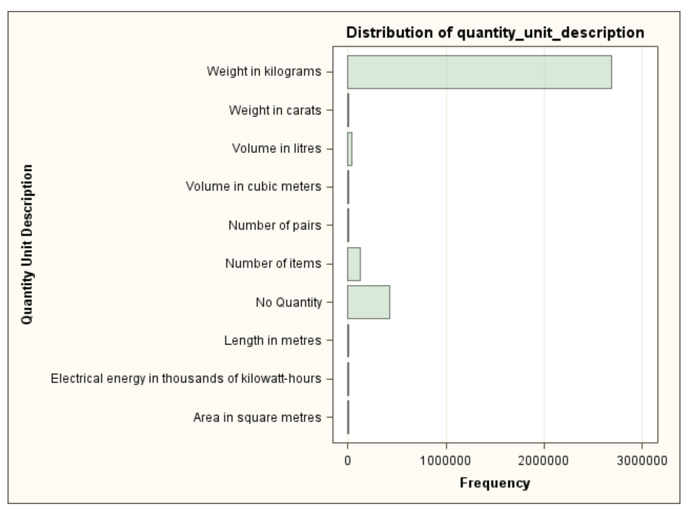
**Imports**

| Intra_Imports | |
|---|---|
| **quantity_unit_description** | **Frequency** |
| **Area in square metres** | 7315 |
| **Electrical energy in thousands of kilowatt-hours** | 1449 |
| **Length in metres** | 3578 |
| **No Quantity** | 425509 |
| **Number of items** | 131674 |
| **Number of pairs** | 7787 |
| **Thousands of items** | 1 |
| **Volume in cubic meters** | 4124 |
| **Volume in litres** | 39359 |
| **Weight in carats** | 558 |
| **Weight in kilograms** | 2738548 |




**Exports**

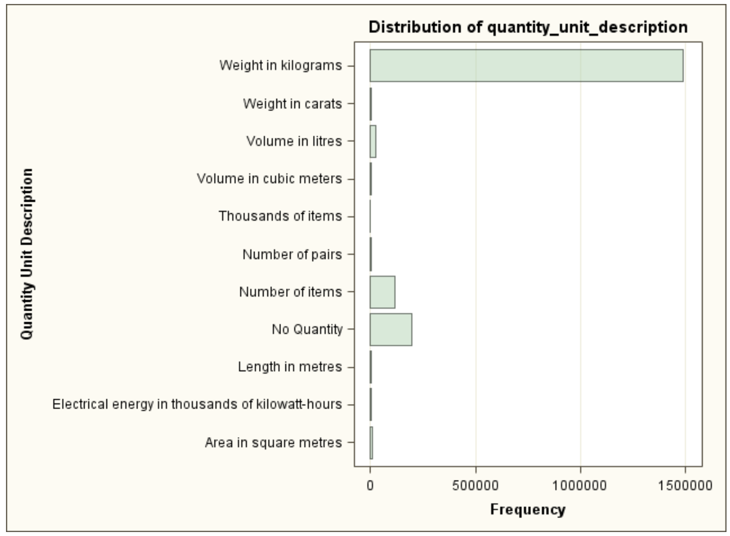
| Intra_Exports | |
|---|---|
| **quantity_unit_description** | **Frequency** |
| **Area in square metres** | 5812 |
| **Electrical energy in thousands of kilowatt-hours** | 1402 |
| **Length in metres** | 3495 |
| **No Quantity** | 419662 |
| **Number of items** | 125533 |
| **Number of pairs** | 7929 |
| **Volume in cubic meters** | 3676 |
| **Volume in litres** | 39303 |
| **Weight in carats** | 606 |
| **Weight in kilograms** | 2689334 |




In both cases of intra imports and intra exports trade reported in kg is well represented. The improvement of coverage is limited due to the fact that coverage in kg is limited by the nature of the products themselves. The total exports database is described in figure 4.4. In the case of total exports kg is also the most appropriate measurement of unit. Same limitations in terms of achieving full coverage hold in this case too.

Annex Figure IV-4: Total Exports coverage

| Quantity Unit Description | |
|---|---|
| **quantity_unit_description** | **Frequency** |
| **Area in square metres** | 8071 |
| **Electrical energy in thousands of kilowatt-hours** | 687 |
| **Length in metres** | 860 |
| **No Quantity** | 194528 |
| **Number of items** | 117710 |
| **Number of pairs** | 2439 |
| **Thousands of items** | 2 |
| **Volume in cubic meters** | 2117 |
| **Volume in litres** | 22008 |
| **Weight in carats** | 817 |
| **Weight in kilograms** | 1491199 |

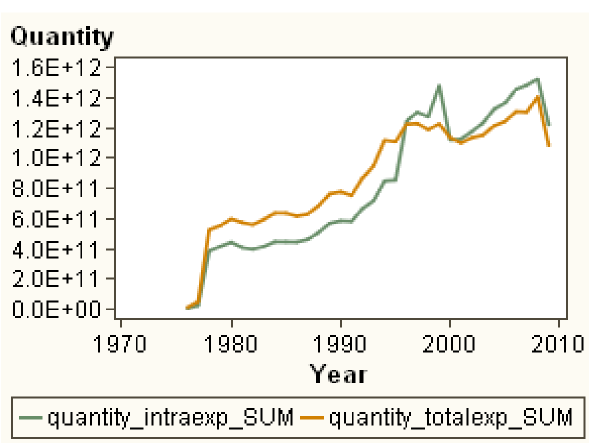



**Extra Trade: What has been done with the outliers?**

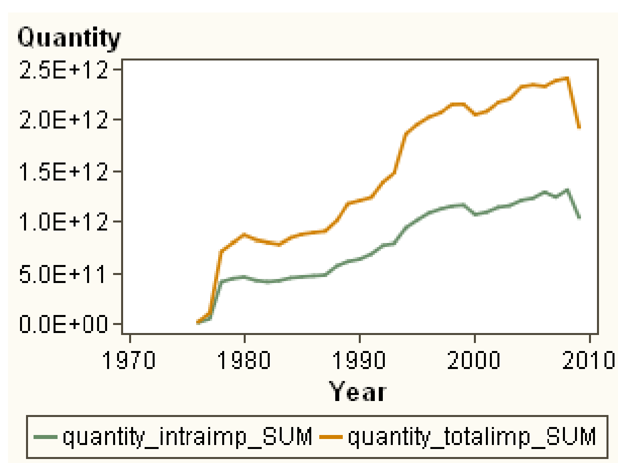
Outliers have not been adjusted for the extra trade database. The problem has been identified in the intra exports database where intra exports exceed total exports from the year 1995 onwards. This is illustrated in graph 4.11 and contrasted with the case of imports. For the reason of insufficient data quality, extra trade has not been considered for the modeling applications.

Annex graph IV-1: Total versus Intra Trade

**Exports**



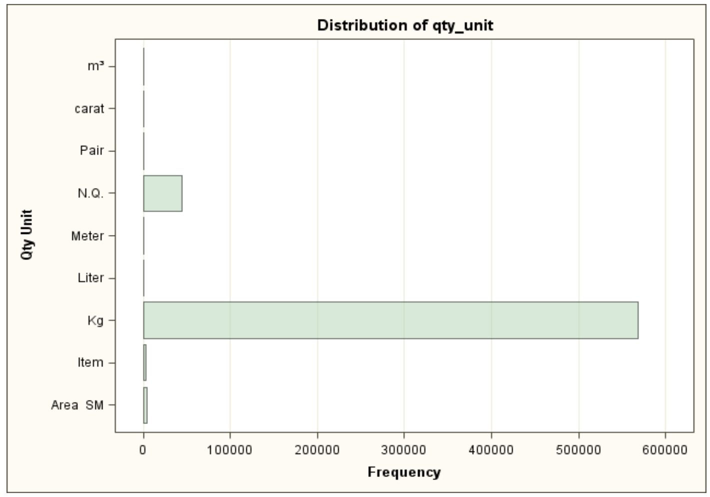

**Imports**



Annex Figure IV-5: Total Exports coverage

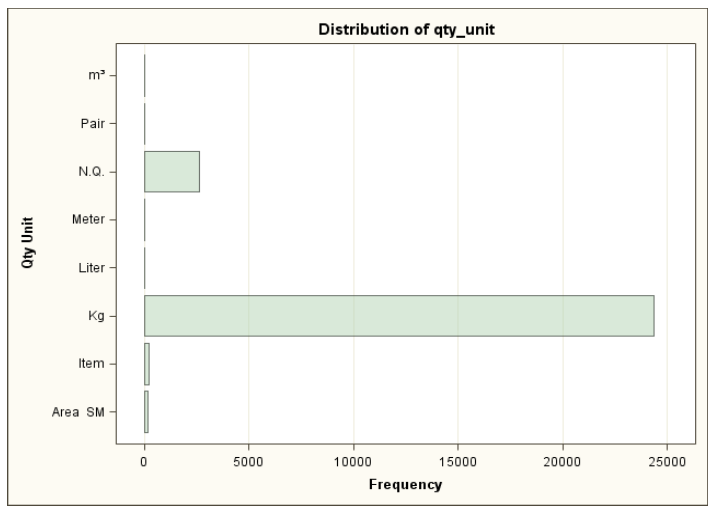
**Intra trade data**

| Qty Unit | |
|---|---|
| **qty_unit** | **Frequency** |
| **Area SM** | 3937 |
| **Item** | 2384 |
| **Kg** | 568638 |
| **Liter** | 348 |
| **Meter** | 493 |
| **N.Q.** | 44371 |
| **Pair** | 60 |
| **Carat** | 307 |
| **m³** | 131 |




**China data**

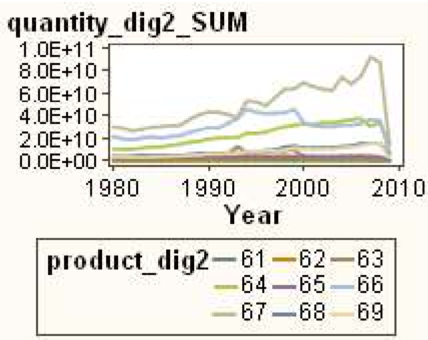
| Qty Unit | |
|---|---|
| **qty_unit** | **Frequency** |
| **Area SM** | 188 |
| **Item** | 216 |
| **Kg** | 24349 |
| **Liter** | 5 |
| **Meter** | 29 |
| **N.Q.** | 2650 |
| **Pair** | 6 |
| **m³** | 3 |

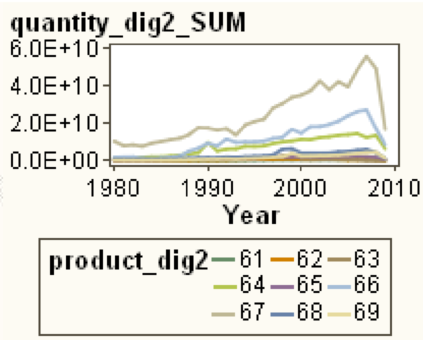


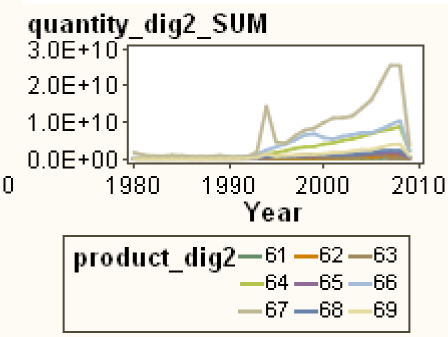
## ANNEX V – Category six descriptive graphics

Annex Graph V-1: Category 6 dig2 per country group

**Graph HW** **Graph HS** **Graph HE**

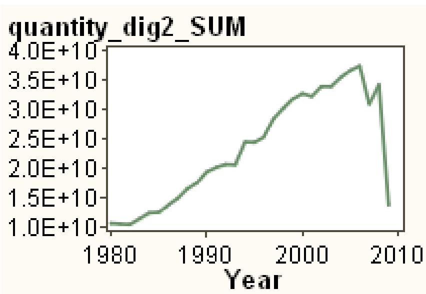


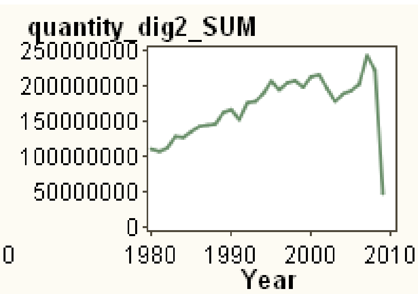



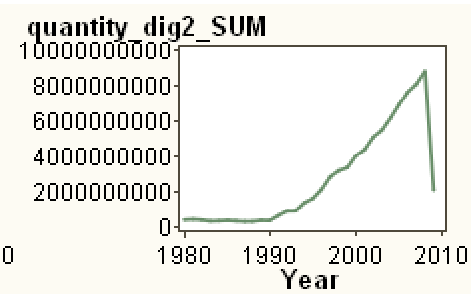




Annex Graph V-2: Example-category 64 total within group (Paper, paperboard, and articles of pulp/paper /paperboard)

**Graph HW** **Graph HS** **Graph HE**

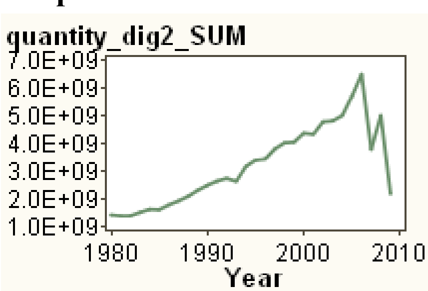


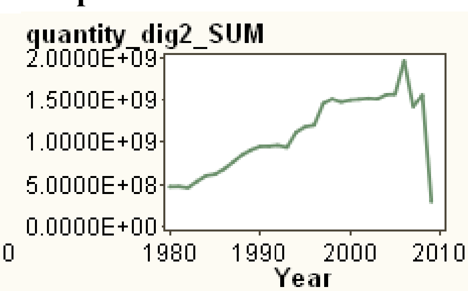



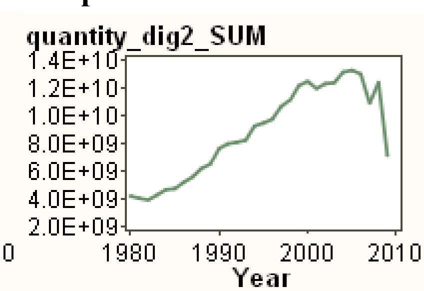




Annex Graph V-3: Example-category 64 per country within group

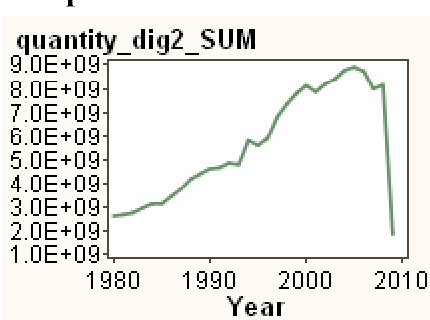
**Graph BLX** **Graph CHE** **Graph DEU**

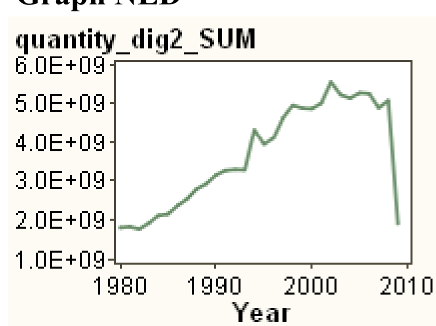


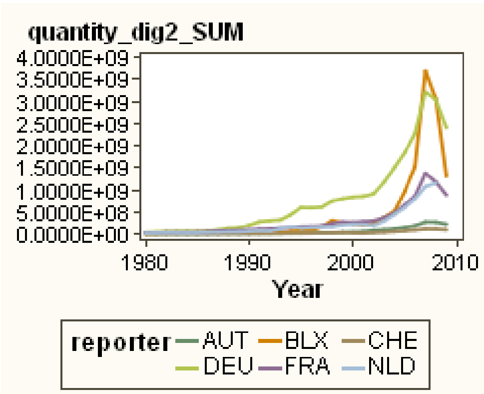

**Graph FRA** **Graph NLD**

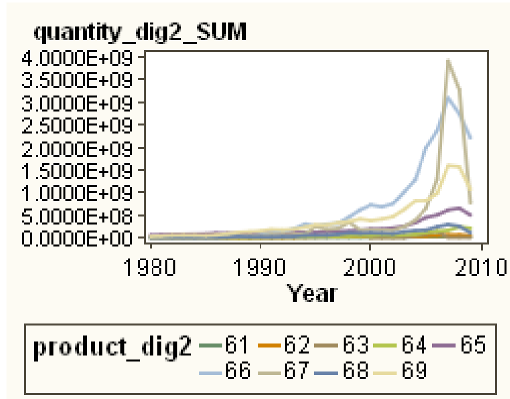


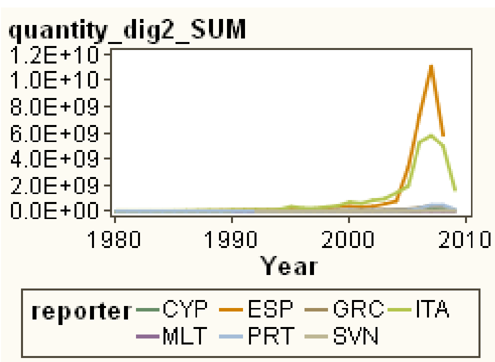
Annex Graph V-4: China total and dig2 exports per country group

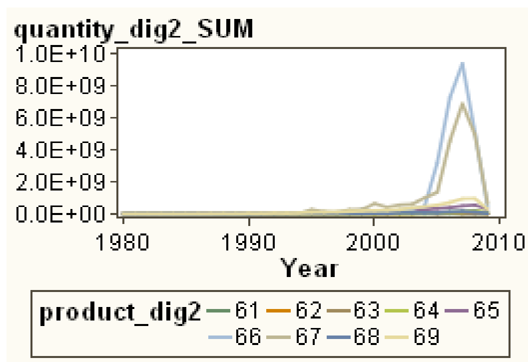
HW



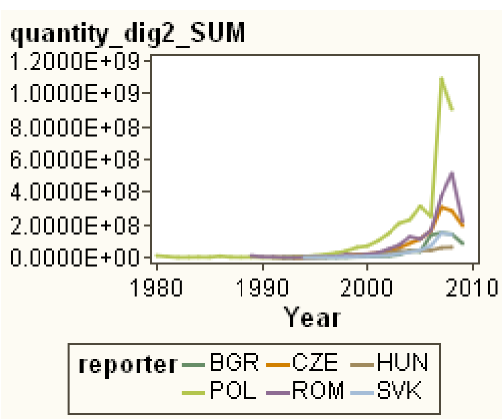



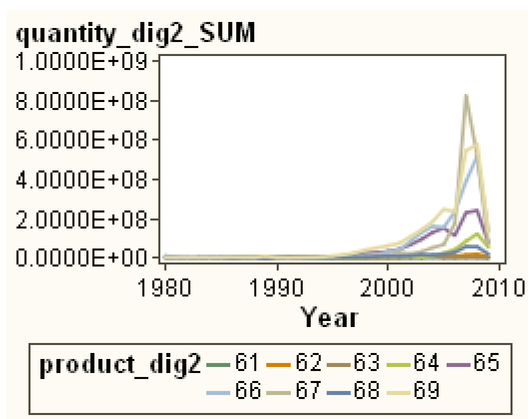

HS




HE



# ANNEX VI – The link between trade and container flows

Annex Table VI-1: Aggregated Method-Containerization degree

| Detail | | Transport characteristic | | |
|---|---|---|---|---|
| 0 | Food and live animals | | | |
| 00 | Live animals other than animals of division 03 | | low | |
| 01 | Meat and meat preparations | high | | |
| 02 | Dairy products and birds' eggs | high | | |
| 03 | Fish (not marine mammals), crustaceans, molluscs and aquatic invertebrates, and preparations thereof | high | | |
| 04 | Cereals and cereal preparations | | | medium |
| 05 | Vegetables and fruit | high | | |
| 06 | Sugars, sugar preparations and honey | | | medium |
| 07 | Coffee, tea, cocoa, spices, and manufactures thereof | | | medium |
| 08 | Feeding stuff for animals (not including unmilled cereals) | | low | |
| 09 | Miscellaneous edible products and preparations | high | | |
| 1 | Beverages and tobacco | | | |
| 11 | Beverages | high | | |
| 12 | Tobacco and tobacco manufactures | high | | |
| 2 | Crude materials, inedible, except fuels | | | |
| 21 | Hides, skins and furskins, raw | | | medium |
| 22 | Oil seeds and oleaginous fruits | | | medium |
| 23 | Crude rubber (including synthetic and reclaimed) | | | medium |
| 24 | Cork and wood | | | medium |
| 25 | Pulp and waste paper | | | medium |
| 26 | Textile fibres (other than wool tops and other combed wool) and their wastes (not manufactured into yarn or fabric) | high | | |
| 27 | Crude fertilizers, other than those of division 56, and crude minerals (excluding coal, petroleum and precious stones) | | | medium |
| 28 | Metalliferous ores and metal scrap | | | medium |
| 29 | Crude animal and vegetable materials, n.e.s. | high | | |
| 3 | Mineral fuels, lubricants and related materials | | | |
| 31 | Coal, coke and briquettes | | | medium |
| 32 | Petroleum, petroleum products and related materials | | | medium |
| 33 | Gas, natural and manufactured | | low | |
| 34 | Electric current | | low | |

Annex Table VI-1: Aggregated Method-Containerization degree (continued)

| | | | | |
|---|---|---|---|---|
| 4 | Animal and vegetable oils, fats and waxes | | | |
| 41 | Animal oils and fats | high | | |
| 42 | Fixed vegetable fats and oils, crude, refined or fractionated | | | medium |
| 43 | Animal or vegetable fats and oils, processed; waxes of animal or vegetable origin; inedible mixtures or preparations of animal or vegetable fats or oils, n.e.s. | | | medium |
| 5 | Chemicals and related products, n.e.s. | | | |
| 51 | Organic chemicals | | | medium |
| 52 | Inorganic chemicals | | | medium |
| 53 | Dyeing, tanning and colouring materials | high | | |
| 54 | Medicinal and pharmaceutical products | high | | |
| 55 | Essential oils and resinoids and perfume materials; toilet, polishing and cleansing preparations | high | | |
| 56 | Fertilizers (other than those of group 272) | | | medium |
| 57 | Plastics in primary forms | high | | |
| 58 | Plastics in non | high | | |
| 59 | Chemical materials and products, n.e.s. | high | | |
| 6 | Manufactured goods classified chiefly by material | | | |
| 61 | Leather, leather manufactures, n.e.s., and dressed furskins | high | | |
| 62 | Rubber manufactures, n.e.s. | high | | |
| 63 | Cork and wood manufactures (excluding furniture) | high | | |
| 64 | Paper, paperboard and articles of paper pulp, of paper or of paperboard | | low | |
| 65 | Textile yarn, fabrics, made-up articles, n.e.s., and related products | high | | |
| 66 | Non-metallic mineral manufactures, n.e.s. | high | | |
| 67 | Iron and steel | | low | |
| 68 | Non-ferrous metals | | | medium |
| 69 | Manufactures of metals, n.e.s. | | low | |
| 7 | Machinery and transport equipment | | | |
| 71 | Power generating machinery and equipment | | low | |
| 72 | Machinery specialized for particular industries | | | medium |
| 73 | Metalworking machinery | | | medium |
| 74 | General industrial machinery and equipment, n.e.s., and machine parts, n.e.s. | | | medium |
| 75 | Office machines and automatic data processing machines | high | | |
| 76 | Telecommunications and sound recording and reproducing apparatus and equipment | high | | |
| 77 | Electrical machinery, apparatus and appliances, n.e.s., and electrical parts thereof (including non electrical counterparts, n.e.s., of electrical household type equipment) | high | | |
| 78 | Road vehicles (including air cushion vehicles) | | low | |

Annex Table VI-1: Aggregated Method-Containerization degree (continued)

| | | | | |
|---|---|---|---|---|
| 79 | Other transport equipment | | low | |
| 8 | Miscellaneous manufactured articles | | | |
| 81 | Prefabricated buildings; sanitary, plumbing, heating and lighting fixtures and fittings, n.e.s. | high | | |
| 82 | Furniture, and parts thereof; bedding, mattresses, mattress supports, cushions and similar stuffed furnishings | high | | |
| 83 | Travel goods, handbags and similar containers | high | | |
| 84 | Articles of apparel and clothing accessories | high | | |
| 85 | Footwear | high | | |
| 86 | Professional, scientific and controlling instruments and apparatus, n.e.s. | high | | |
| 87 | Photographic apparatus, equipment and supplies and optical goods, n.e.s.; watches and clocks | high | | |
| 88 | Miscellaneous manufactured articles, n.e.s. | high | | |
| 9 | Commodities and transactions not classified elsewhere in the SITC | | | |
| 91 | Postal packages not classified according to kind | high | | |
| 92 | Special transactions and commodities not classified according to kind | high | | |
| 93 | Coin (other than gold coin), not being legal tender | | | medium |
| 94 | Gold, non monetary (excluding gold ores and concentrates) | | low | |

Annex Table VI-2: Aggregated Method-Data coverage assessment

| Qty unit | Total imports | | Total exports | | Intra_imports | | Intra_Exports | |
|---|---|---|---|---|---|---|---|---|
| | Frequency | % | Frequency | % | Frequency | % | Frequency | % |
| 1000 KW/H | 381 | 0.18 | 201 | 0.17 | 1580 | 0.04 | 1497 | 0.04 |
| Area SM | 246 | 0.12 | 196 | 0.16 | 8122 | 0.22 | 5850 | 0.16 |
| Item | 6834 | 3.31 | 4033 | 3.33 | 153804 | 4.2 | 135890 | 3.81 |
| Kg | 162667 | 78.81 | 95638 | 79.03 | 2983369 | 81.42 | 2928071 | 82.03 |
| Liter | 2804 | 1.36 | 1864 | 1.54 | 46158 | 1.26 | 45348 | 1.27 |
| Meter | 352 | 0.17 | 233 | 0.19 | 3782 | 0.1 | 3578 | 0.1 |
| N.Q. | 32495 | 15.74 | 18507 | 15.29 | 453095 | 12.37 | 435449 | 12.2 |
| Pair | 354 | 0.17 | 217 | 0.18 | 8953 | 0.24 | 8861 | 0.25 |
| Carat | 13 | 0.01 | 9 | 0.01 | 620 | 0.02 | 643 | 0.02 |
| $m^3$ | 250 | 0.12 | 114 | 0.09 | 4655 | 0.13 | 4463 | 0.13 |
| 1000u | | | | | | | 3 | 0 |

Annex Table VI-3: Aggregated Method-Outliers

| Country | Year | Action |
|---|---|---|
| BGR | year<=1997 | Deleted |
| RUS | year<=1996 | Deleted |
| GEO | year<=1999 | Deleted |
| ROM | year<=1991 | Deleted |
| SVK | year<=1994 | Deleted |
| SVN | year<=1993 | Deleted |
| MDA | year<=1998 | Deleted |

Figure VI-1: Error Analysis-VEC Conversion model

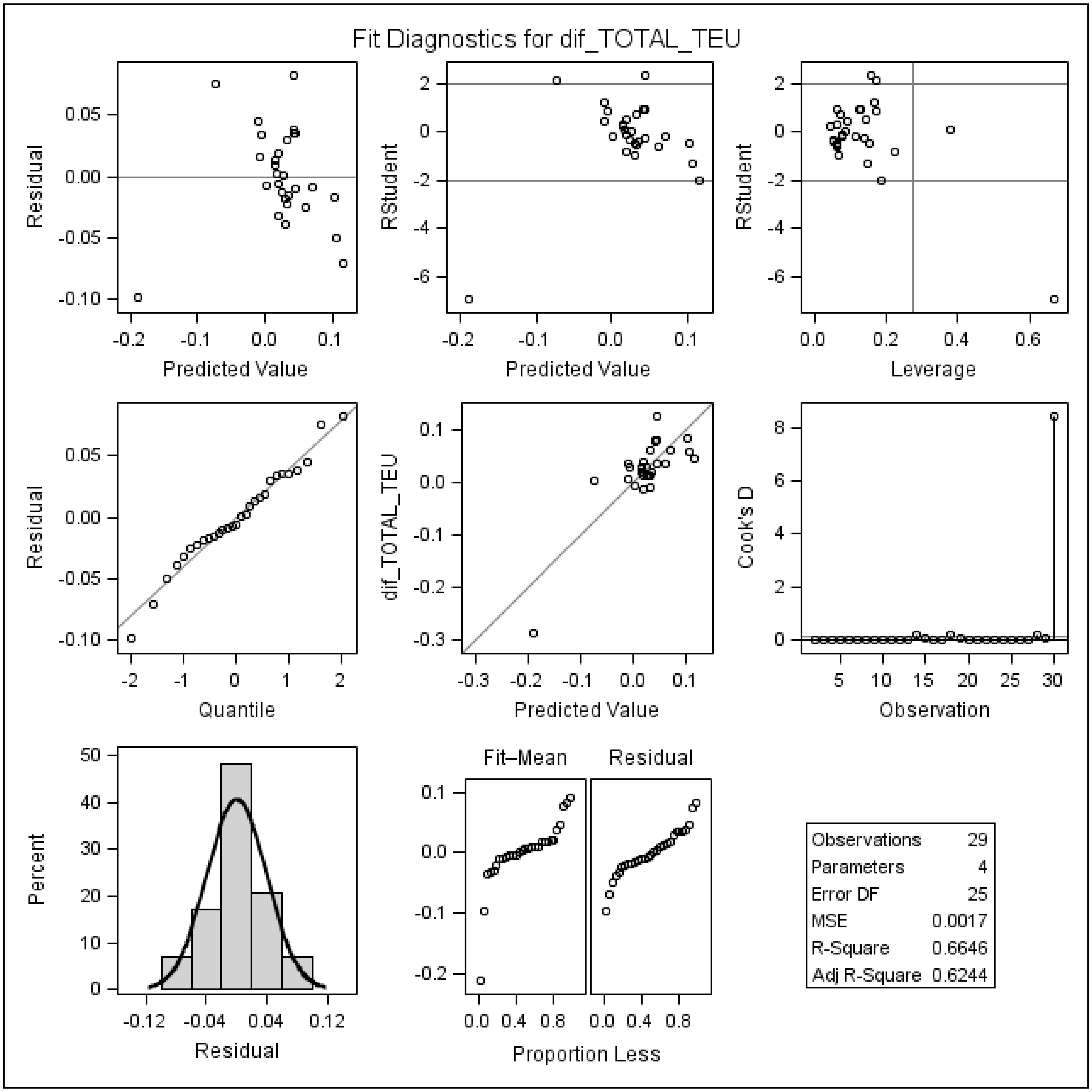
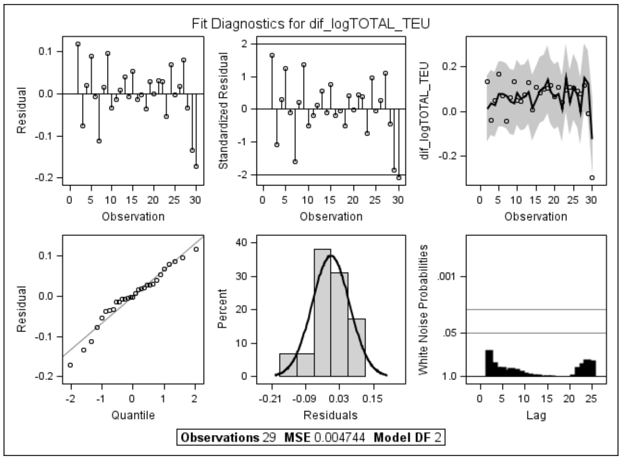


Figure VI-2: Error Analysis – Y-W model

MODEL II




MODEL III

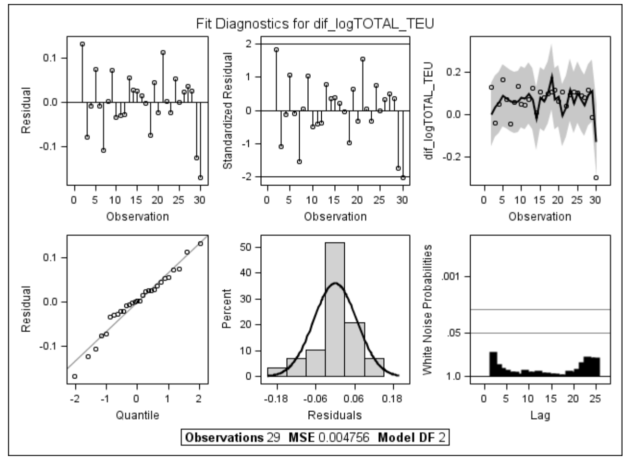



Table VI-4: diagnostic statistics

**Yule-Walker**

| Statistics | Model I-a | Model I-b | Model II | Model III |
|---|---|---|---|---|
| SSE | 0.04992414 | 0.05547871 | 0.12334613 | 0.12365086 |
| MSE | 0.00192 | 0.00213 | 0.00474 | 0.00476 |
| SBC | -92.051692 | -89.069183 | -65.928587 | -65.868187 |
| MAE | 0.0270158 | 0.03074447 | 0.04828937 | 0.04852664 |
| MAPE | 112.179505 | 202.877754 | 93.8105976 | 97.8506986 |
| Durbin-Watson | 1.2239 | 1.3425 | 1.5236 | 1.5876 |
| DFE | 26 | 26 | 26 | 26 |
| Root MSE | 0.04382 | 0.04619 | 0.06888 | 0.06896 |
| AIC | -96.153579 | -93.171071 | -70.030475 | -69.970075 |
| AICC | -95.193579 | -92.211071 | -69.070475 | -69.010075 |
| Regress R-Square | 0.5611 | 0.5332 | 0.3829 | 0.3874 |
| Total R-Square | 0.6124 | 0.5693 | 0.3931 | 0.3916 |

**VEC**

| | Model I-a | Model I-b | Model II | Model III |
|---|---|---|---|---|
| Root MSE | 0.04744 | 0.04157 | 0.06692 | 0.06336 |
| Dependent Mean | 0.02415 | 0.02415 | 0.06317 | 0.06317 |
| Coeff Var | 196.42295 | 172.12076 | 105.93086 | 100.30134 |
| R-Square | 0.5633 | 0.6646 | 0.4491 | 0.5061 |
| Adj R-Sq | 0.5109 | 0.6244 | 0.3830 | 0.4469 |

Annex box VI-1: ECM derivation

**Annex box VI-1: ECM derivation**

Suppose the long run equation (or co-integration equation) is given by

$$y_t = a_0 + a_1 x_t \qquad (1)$$

Then the deviation from the equilibrium zt is defined by

$$z_t = y_t - a_0 - a_1 x_t \qquad (2)$$

Intuitively, since the equation (1) will be true in the limit it can be postulated that *z* is an AR(1) process say

$$z_t = \gamma z_{t-1} + \varepsilon_t$$

Where ε is a Gaussian white noise process. It is now found

$$\Delta y_t = \Delta z_t + a_0 + a_1 \Delta x_t$$
$$= (\gamma - 1) z_{t-1} + a_0 + a_1 \Delta x_t + \varepsilon_t$$
$$= (\gamma - 1) y_{t-1} - (\gamma - 1) a_0 - (\gamma - 1) y_{t-1} a_1 x_{t-1} + a_0 + a_1 \Delta x_t + \varepsilon_t$$

Define $\delta_0=(2-\gamma)\alpha_0$ , $\delta_1=(\gamma-1)$ and $\delta_2= - (\gamma-1)\alpha_1$, then this reads

$$\Delta y_t = \delta_0 + \delta_1 y_{t-1} + \delta_2 x_{t-1} + a_1 \Delta x_t + \varepsilon_t \qquad (3)$$

Using the fact that y isan *I(1)* process, it can be postulated that Δ*y* in itself can also be expressed using an AR(k) process

$$\Delta y_t = \sum_{i=1}^{k} \rho \Delta y_{t-i} + v_t \qquad (4)$$

Where *v* is a stationary process. A similar argument can be used for the process Δx. Granger proves in the Granger representation theorem that combining (3) with the AR representations for Δy and Δx and given the long run relationship (1) the general Error Correction Model (ECM) is given by

$$\Delta y_t = a_0 + v_1 z_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \sum_{i=0}^{m} \psi_i \Delta x_{t-i} + \varepsilon_t \qquad (5)$$

Writing out the ECM (5) for k=0, m=0 the simplest possible ECM is obtained

$$\Delta y_t = a_0 + v_1 z_{t-1} + \psi_0 \Delta x_t + \varepsilon_t \qquad (6)$$

Or when substituting in the long run relationship (1)

$$\Delta y_t = a_0 + v_1 y_{t-1} - v_1 a_0 - v_1 a_1 x_{t-1} + \psi_0 \Delta x_t + \varepsilon_t \qquad (7)$$

**Annex box VI-1 (continued): ECM derivation**

Instead of using a classical two step approach where first (1) is estimated and then the ECM equation (6), it is shown that the equation can directly be estimated using the specification

$$\Delta y_t = \beta_0 +_1 \beta_1 \Delta x_t + \beta_2 x_{t-1} + \beta_3 y_{t-1} + \varepsilon_t \tag{8}$$

Comparing (8) and (7) the following relationships are found:

$$\beta_0 = a_0 - v_1 a_0 \tag{9}$$
$$\beta_1 = \psi_0 \tag{10}$$
$$\beta_2 = -v_1 a_1 \tag{11}$$
$$\beta_3 = v_1 \tag{12}$$

Solving the equation (9-12) for the parameters in (7) it is found

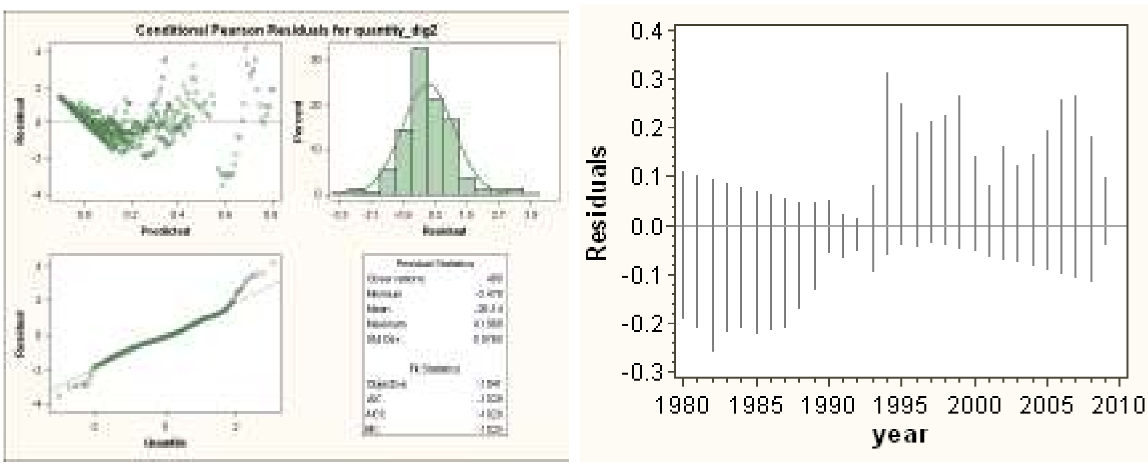
$$v_1 = \beta_3 \tag{13}$$
$$a_0 = \frac{\beta_0}{1 - \beta_3} \tag{14}$$
$$a_1 = -\frac{\beta_2}{\beta_3} \tag{15}$$
$$\psi_0 = \beta_1 \tag{16}$$

Hence, the long run equilibrium (1) is now found as

$$y_t = \frac{\beta_0}{1 - \beta_3} - \frac{\beta_2}{\beta_3} x_t$$

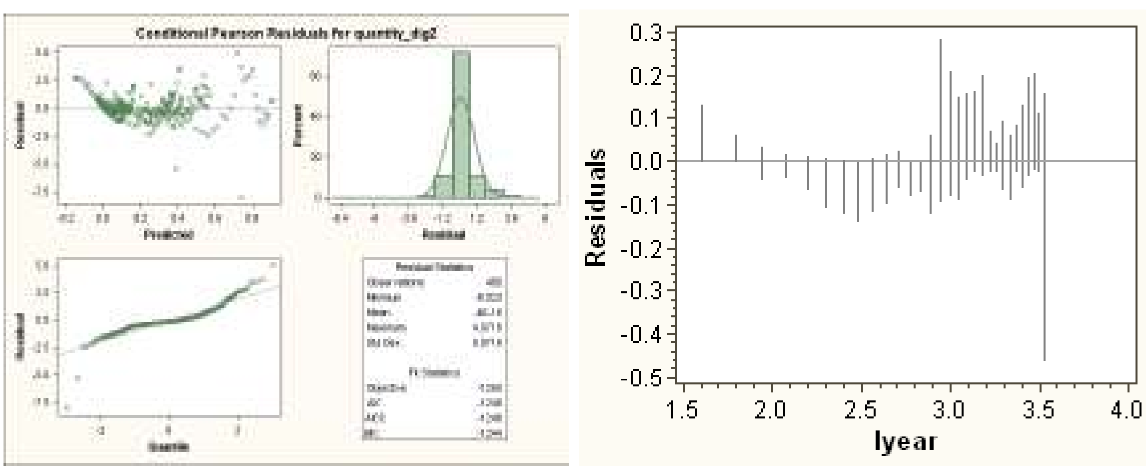
# ANNEX VII - Growth models

Annex figure VII-1: Linear growth model tests



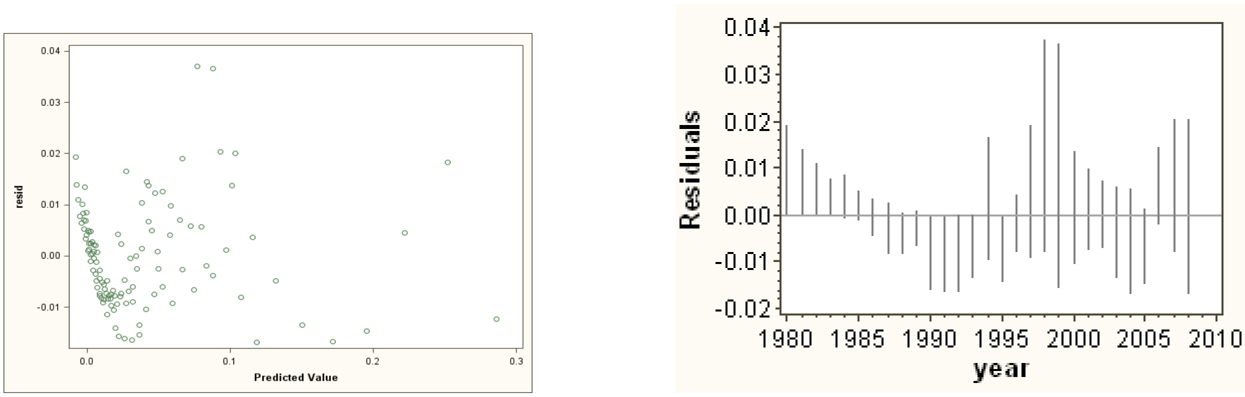

| Fit Statistics LINEAR | HW_TOTAL | HS_TOTAL | *HE_TOTAL* |
|---|---|---|---|
| -2 Log Likelihood | -365.3 | -455.3 | *-553.3* |
| AIC (smaller is better) | -353.3 | -445.3 | *-543.3* |
| AICC (smaller is better) | -352.8 | -445.1 | *-542.9* |
| *BIC (smaller is better)* | *-354.5* | *-445.6* | *-545.2* |

Annex figure VII-2: Logarithmic growth model tests

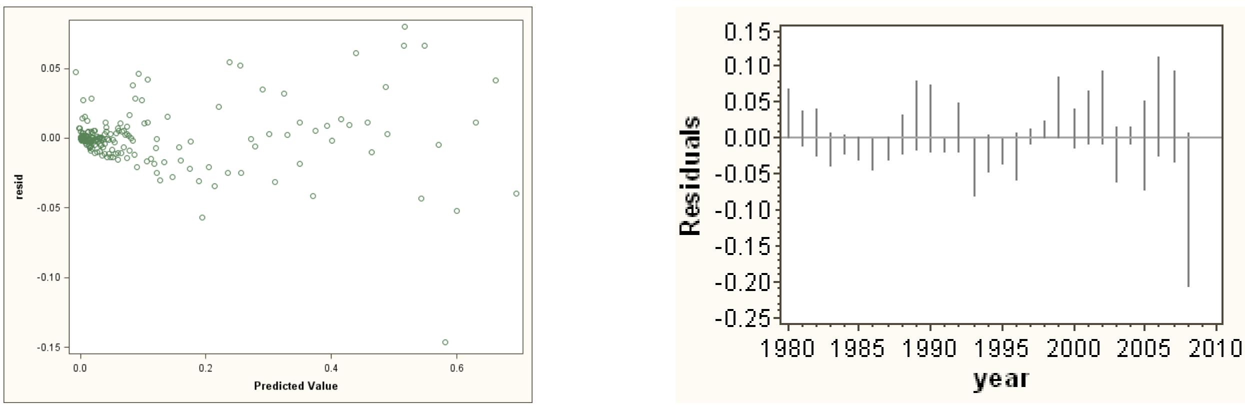



| Fit Statistics LOGARITHMIC | HW_TOTAL | HS_TOTAL | *HE_TOTAL* |
|---|---|---|---|
| -2 Log Likelihood | -437.6 | -529.7 | *-562.9* |
| AIC (smaller is better) | -423.6 | -515.7 | *-548.9* |
| AICC (smaller is better) | -423.0 | -515.0 | *-548.1* |
| *BIC (smaller is better)* | *-425.1* | *-517.1* | *-551.6* |

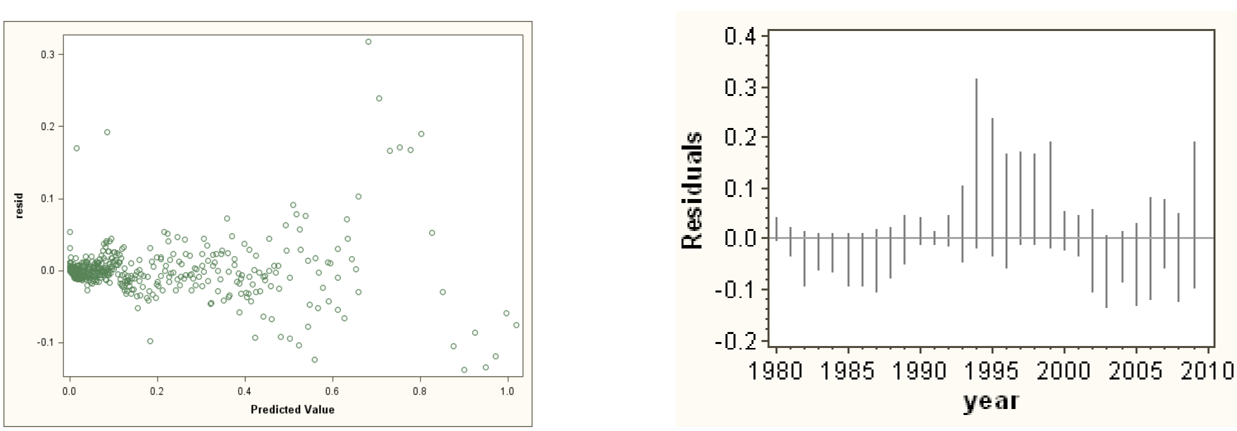
Annex figure VII-3 (a): Exponential HE growth model tests




Annex figure VII- (b): Exponential HS growth model tests

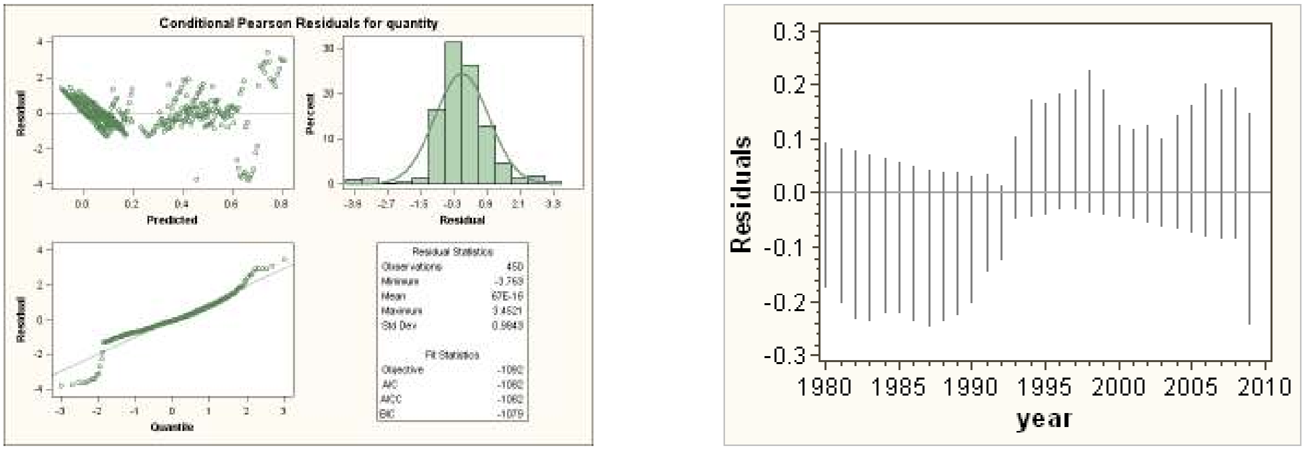



Annex figure VII-4: Logistic growth model tests



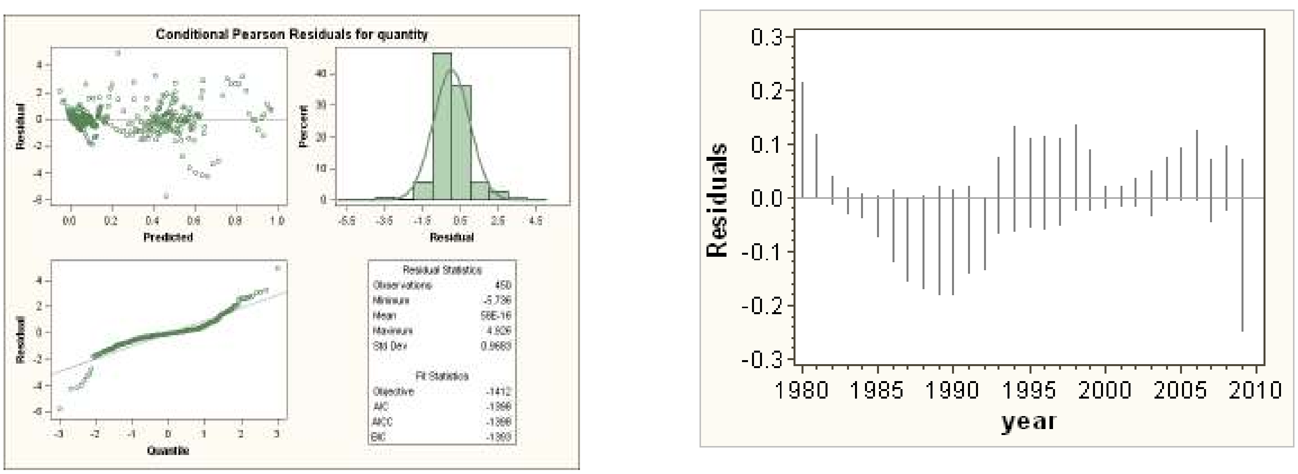

| Fit Statistics LOGISTIC | HW_TOTAL | HS_TOTAL | *HE_TOTAL* |
|---|---|---|---|
| -2 Log Likelihood | -531.6 | -948.9 | *-734.8* |
| AIC (smaller is better) | -517.6 | -934.9 | *-720.8* |
| AICC (smaller is better) | -516.9 | -934.3 | *-720.0* |
| *BIC (smaller is better)* | *-519.1* | *-935.2* | *-723.6* |

Annex figure VII-5: Linear growth model tests



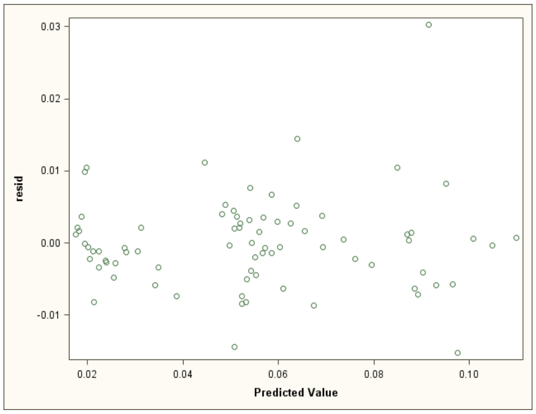

| Fit Statistics LINEAR | HWHSHE_cat6 | HW_TOTAL | HS_TOTAL | *HE_TOTAL* |
|---|---|---|---|---|
| -2 Log Likelihood | -1333.3 | -349.1 | -616.2 | *-651.0* |
| AIC (smaller is better) | -1321.3 | -339.1 | -606.2 | *-641.0* |
| AICC (smaller is better) | -1321.2 | -338.8 | -605.9 | *-640.5* |
| *BIC (smaller is better)* | *-1316.0* | *-340.2* | *-606.5* | *-644.1* |

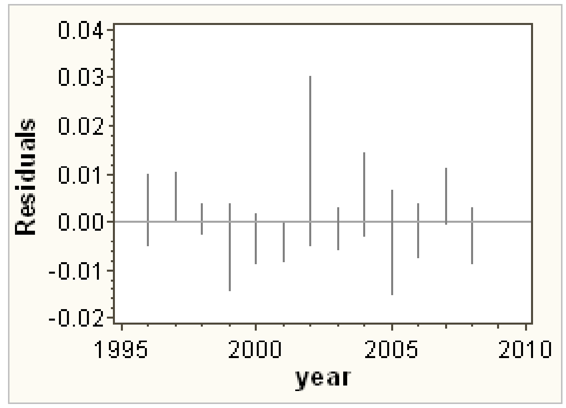
Annex figure VII-6: Logarithmic growth model tests



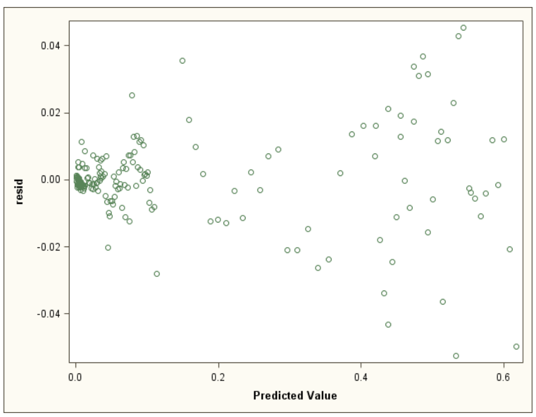

| Fit Statistics LOGARITHMIC | HWHSHE_cat6 | HW_TOTAL | HS_TOTAL | *HE_TOTAL* |
|---|---|---|---|---|
| -2 Log Likelihood | -1453.7 | -463.4 | -455.8 | *-691.3* |
| AIC (smaller is better) | -1439.7 | -449.4 | -441.8 | *-677.3* |
| AICC (smaller is better) | -1439.5 | -448.7 | -440.8 | *-676.3* |
| *BIC (smaller is better)* | *-1433.5* | *-450.9* | *-446.1* | *-681.6* |

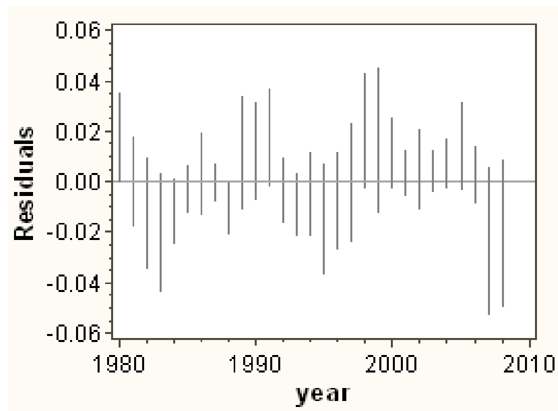
Annex figure VII- (a): Exponential growth model tests



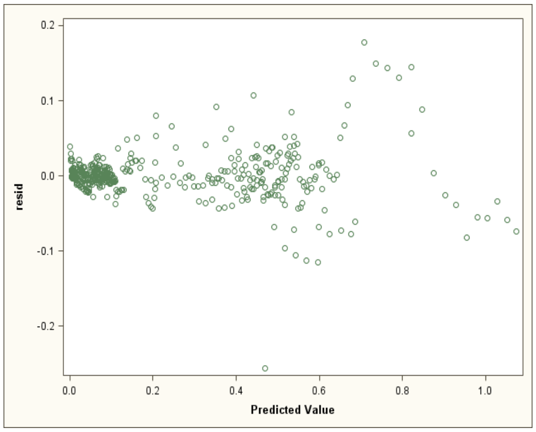

Annex figure VII- (b): Exponential growth model tests

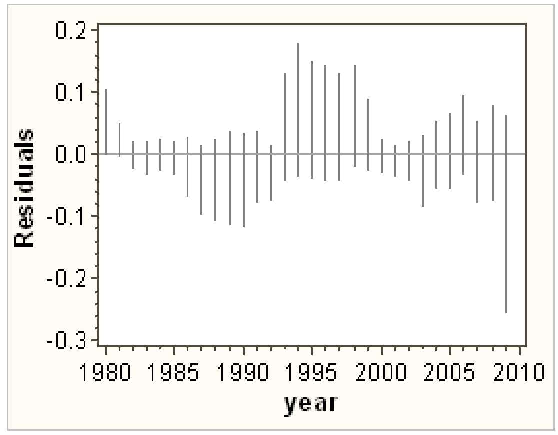



| ***Null Model Likelihood Ratio*** | | | |
|---|---|---|---|
| **Model** | **DF** | **Chi-Square** | ***Pr > ChiSq*** |
| linear_dummy_6 | 2 | 858.89 | *<.0001* |
| logarithmic_dummy_6 | 2 | 1082.91 | *<.0001* |
| logarithmic_dummy_total | 3 | 1395.35 | *<.0001* |
| *Linear_dummy_total* | *1* | *1277.80* | *<.0001* |

Annex figure VII-8: Logistic growth model tests




| Fit Statistics LOGISTIC | HWHSHE TOTAL | HWHSHE cat6 | HW TOTAL | *HS TOTAL* |
|---|---|---|---|---|
| -2 Log Likelihood | -1623 | -1853 | -547.8 | *-673.2* |
| AIC (smaller is better) | -1607 | -1837 | -533.8 | *-659.2* |
| AICC (smaller is better) | -1606 | -1837 | -533.2 | *-658.5* |
| *BIC (smaller is better)* | *-1601* | *-1830* | *-535.3* | *-660.7* |

# ANNEX VIII – Dynamic forecasts

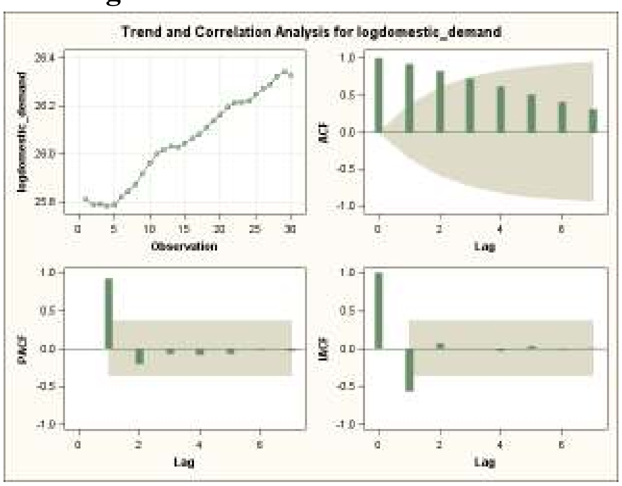
Annex table VIII-1: Panel VAR Fit statistics

| Fit Statistics_ dynamic no2009 | | | | *Fit Statistics_ dynamic VAr Dummy2009* | | | |
|---|---|---|---|---|---|---|---|
| **SSE** | 0.2355 | **DFE** | 348 | **SSE** | 0.4036 | **DFE** | *356* |
| ***MSE*** | *0.0007* | ***Root MSE*** | *0.0260* | ***MSE*** | *0.0011* | ***Root MSE*** | *0.0337* |

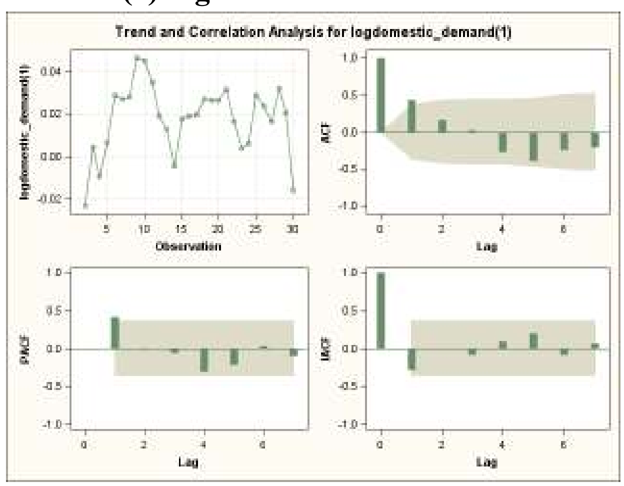
| Sargan Test _dynamic VAr No 2009 | | | *Sargan Test _dynamic VAr Dummy2009* | | |
|---|---|---|---|---|---|
| **DF** | **Statistic** | **Prob > ChiSq** | **DF** | **Statistic** | ***Prob > ChiSq*** |
| *79* | *11.69* | *1.0000* | *81* | *11.31* | *1.0000* |

Figure VIII-1: BLX - ARIMA identification

**BLX-log Levels**




**BLX(1)-log differenced**




**White noise- levels**

| Autocorrelation Check for White Noise_logquantity | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **To Lag** | **Chi-Square** | **DF** | **Pr > ChiSq** | **Autocorrelations** | | | | | |
| **6** | 85.99 | 6 | <.0001 | 0.910 | 0.793 | 0.662 | 0.545 | 0.419 | 0.304 |

**White noise-differenced**

| Autocorrelation Check for White Noise_logquantity(1) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **To Lag** | **Chi-Square** | **DF** | **Pr > ChiSq** | **Autocorrelations** | | | | | |
| **6** | 8.92 | 6 | 0.1783 | -0.074 | 0.467 | -0.089 | 0.076 | -0.164 | 0.011 |

## Diagnostics check

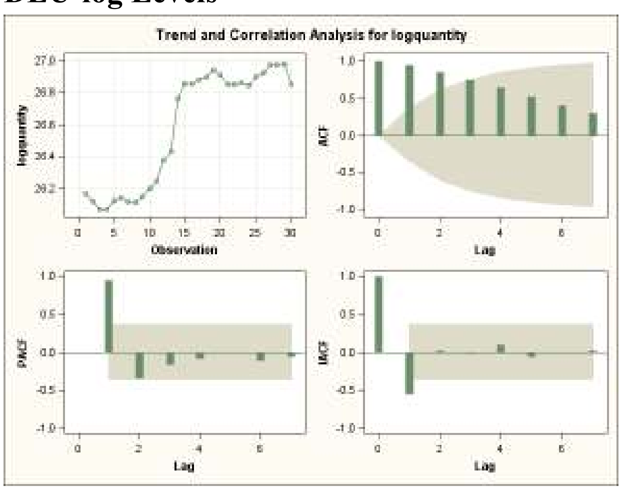
| ARMA(p+d,q) Tentative Order Selection Tests | | | | | |
|---|---|---|---|---|---|
| SCAN | | | ESACF | | |
| P+d | q | BIC | p+d | q | BIC |
| 0 | 0 | 46.25134 | 0 | 0 | 46.25134 |
| | | | 1 | 0 | 46.34117 |
| | | | 2 | 0 | 46.32927 |
| | | | 4 | 1 | 46.59801 |
| | | | 5 | 1 | 46.55456 |

## VEC –Augmented Dickey Fuller tests

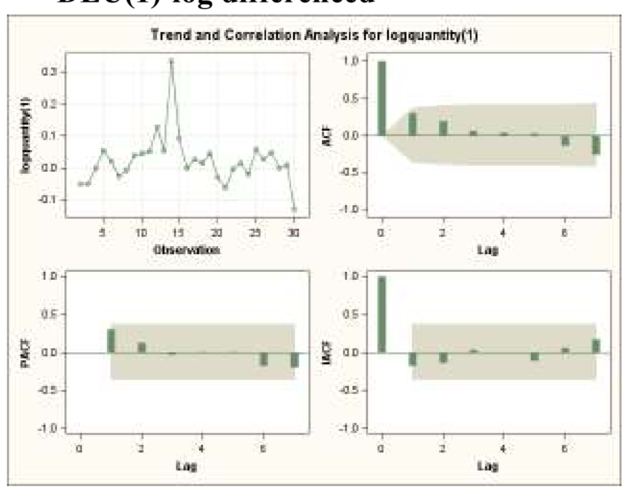
| Augmented Dickey-Fuller Unit Root Tests | | | | | | | |
|---|---|---|---|---|---|---|---|
| Type | Lags | Rho | Pr < Rho | Tau | Pr < Tau | F | Pr > F |
| **Zero Mean** | 0 | -11.2274 | 0.0137 | -2.55 | 0.0127 | | |
| | 1 | -11.9473 | 0.0104 | -2.14 | 0.0330 | | |
| | 2 | -30.2831 | <.0001 | -2.23 | 0.0273 | | |
| **Single Mean** | 0 | -11.0352 | 0.0737 | -2.47 | 0.1328 | 3.37 | 0.2381 |
| | 1 | -11.3098 | 0.0667 | -2.04 | 0.2681 | 2.44 | 0.4649 |
| | 2 | -28.2072 | <.0001 | -2.16 | 0.2240 | 2.54 | 0.4417 |
| **Trend** | 0 | -11.1567 | 0.2832 | -2.43 | 0.3559 | 2.96 | 0.5996 |
| | 1 | -12.1795 | 0.2219 | -2.02 | 0.5647 | 2.08 | 0.7661 |
| | 2 | -27.7581 | 0.0009 | -1.87 | 0.6397 | 2.24 | 0.7362 |

Figure VIII-2: DEU - ARIMA identification

**DEU-log Levels**




**DEU(1)-log differenced**



### White noise- levels

| Autocorrelation Check for White Noise_logquantiy | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **To Lag** | **Chi-Square** | **DF** | **Pr > ChiSq** | **Autocorrelations** | | | | | |
| **6** | 107.20 | 6 | <.0001 | 0.945 | 0.858 | 0.752 | 0.637 | 0.524 | 0.409 |

### White noise- differenced

| Autocorrelation Check for White Noise_logquantity(1) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **ToLag** | **Chi-Square** | **DF** | **Pr > ChiSq** | **Autocorrelations** | | | | | |
| **6** | 6.82 | 6 | 0.3383 | 0.325 | 0.192 | 0.087 | 0.034 | 0.042 | -0.227 |

### Diagnostics check

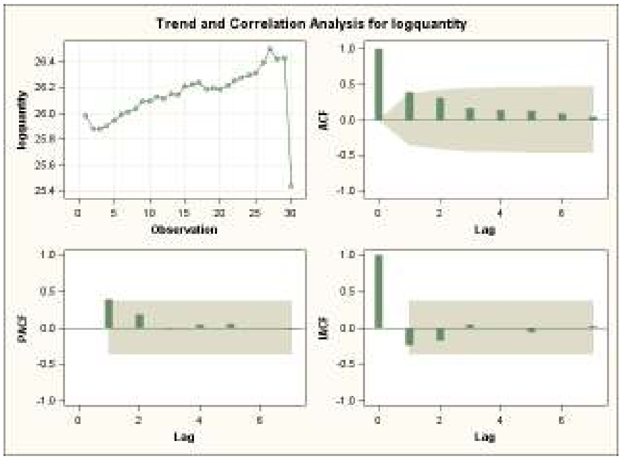
| ARMA(p+d,q) Tentative Order Selection Tests | | | | | |
|---|---|---|---|---|---|
| **SCAN** | | | **ESACF** | | |
| **p+d** | **Q** | **BIC** | **p+d** | **Q** | **BIC** |
| 0 | 0 | -5.38844 | 0 | 0 | -5.38844 |
| | | | 1 | 0 | -5.36257 |
| | | | 2 | 0 | -5.27142 |
| | | | 3 | 0 | -5.15547 |
| | | | 5 | 0 | -4.99654 |

### VEC –Augmented Dickey Fuller tests

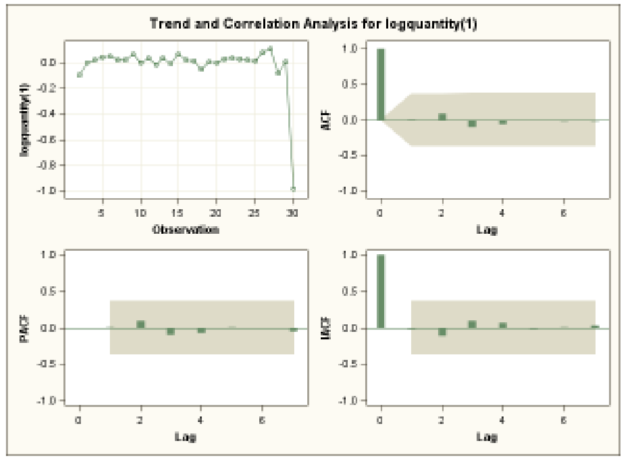
| Augmented Dickey-Fuller Unit Root Tests | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Type** | **Lags** | **Rho** | **Pr < Rho** | **Tau** | **Pr < Tau** | **F** | **Pr > F** |
| **Zero Mean** | 0 | -7.4200 | 0.0506 | -2.11 | 0.0353 | | |
| | 1 | -11.5411 | 0.0121 | -2.35 | 0.0206 | | |
| | 2 | -19.0717 | 0.0006 | -2.53 | 0.0134 | | |
| **Single Mean** | 0 | -7.4033 | 0.2111 | -2.07 | 0.2570 | 2.22 | 0.5186 |
| | 1 | -11.5040 | 0.0629 | -2.31 | 0.1771 | 2.69 | 0.4045 |
| | 2 | -18.9927 | 0.0044 | -2.49 | 0.1299 | 3.12 | 0.3007 |
| **Trend** | 0 | -7.3993 | 0.5798 | -2.04 | 0.5580 | 2.13 | 0.7569 |
| | 1 | -11.5075 | 0.2592 | -2.27 | 0.4354 | 2.58 | 0.6713 |
| | 2 | -18.9764 | 0.0312 | -2.45 | 0.3476 | 3.01 | 0.5909 |

Figure VIII-3: NLD - ARIMA identification

**NLD-log Levels**




**NLD(1)-log differenced**




### White noise- levels

| Autocorrelation Check for White Noise | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **To Lag** | **Chi-Square** | **DF** | **Pr > ChiSq** | **Autocorrelations** | | | | | |
| **6** | 11.20 | 6 | 0.0825 | 0.393 | 0.314 | 0.165 | 0.146 | 0.130 | 0.086 |

### White noise-differenced

| Autocorrelation Check for White Noise | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **To Lag** | **Chi-Square** | **DF** | **Pr > ChiSq** | **Autocorrelations** | | | | | |
| **6** | 0.77 | 6 | 0.9930 | 0.013 | 0.093 | -0.095 | -0.065 | -0.007 | -0.014 |

### Diagnostics check

| ARMA(p+d,q) Tentative Order Selection Tests | | | | | |
|---|---|---|---|---|---|
| **SCAN** | | | **ESACF** | | |
| **p+d** | **q** | **BIC** | **p+d** | **q** | **BIC** |
| 2 | 0 | -9.08023 | 2 | 0 | -9.08023 |
| 0 | 5 | -5.8568 | 1 | 1 | -8.92105 |
| | | | 0 | 2 | -4.89751 |
| | | | 4 | 1 | -9.03249 |
| | | | 5 | 0 | -8.96299 |

**VEC –Augmented Dickey Fuller tests**

| Augmented Dickey-Fuller Unit Root Tests | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Type** | **Lags** | **Rho** | **Pr < Rho** | **Tau** | **Pr < Tau** | **F** | **Pr > F** |
| **Zero Mean** | 0 | -7.8900 | 0.0431 | -2.11 | 0.0358 | | |
| | 1 | -12.0543 | 0.0101 | -2.48 | 0.0152 | | |
| | 2 | -38.0825 | <.0001 | -3.01 | 0.0041 | | |
| **Single Mean** | 0 | -7.8912 | 0.1839 | -2.07 | 0.2593 | 2.13 | 0.5405 |
| | 1 | -11.9883 | 0.0542 | -2.42 | 0.1454 | 3.01 | 0.3278 |
| | 2 | -37.4086 | <.0001 | -2.92 | 0.0557 | 4.34 | 0.0782 |
| **Trend** | 0 | -8.0078 | 0.5246 | -2.06 | 0.5456 | 2.16 | 0.7503 |
| | 1 | -11.9364 | 0.2349 | -2.35 | 0.3946 | 2.84 | 0.6221 |
| | 2 | -47.5256 | <.0001 | -2.99 | 0.1548 | 4.54 | 0.3021 |